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ORIGINAL

Detection and segmentation of Meningioma Tumors using improved cloud empowered visual geometry group (CLOUD-IVGG) deep learning structure

Detección y segmentación de Tumores Meningioma utilizando una estructura mejorada de aprendizaje profundo del grupo de geometría visual potenciada por la nube (CLOUD-IVGG)

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ABSTRACT

Detection and segmentation of meningioma brain tumor is a complex process due to its similar textural pattern with other tumors. In this paper Meningioma Tumor Detection System (MTDS) approach is proposed to detect and classify the meningioma brain images from the healthy brain images. The training work flow of the proposed MTDS approach consists of Spatial Gabor Transform (SGT), feature computations and deep learning structure. The features are computed from the meningioma brain image dataset images and the normal brain image dataset images and these features are fed into the classification architecture. In this paper, the proposed CLOUD-IVGG architecture is derived from the existing Cloud empowered Visual Geometry Group (VGG) architecture to improve the detection rate of the proposed system and to decrease the computational time complexity. The testing work flow of the proposed system is also consist of SGT, feature computation and the CLOUD-IVGG architecture to produce the classification result of the source brain images into either normal or meningioma. Further, the tumor regions in this meningioma image have been located using the Morphological segmentation algorithm. In this research work, two independent resource brain imaging datasets has been involved to estimate and validate the performance efficiency of the proposed MTDS. The datasets are Kaggle Brain Imaging (KBI) and BRATS Imaging 2020 (BI20). The performance efficiency has been analyzed with respect to detection rate, precision, recall and Jaccard index.

Keywords: Brain; Tumors; Meningioma; CLOUD-IVGG Architecture; Datasets.

RESUMEN

La detección y segmentación del tumor cerebral meningioma es un proceso complejo debido a su patrón de textura similar con otros tumores. En este trabajo se propone un Sistema de Detección de Tumores de Meningioma (MTDS) para detectar y clasificar las imágenes cerebrales de meningioma a partir de imágenes cerebrales sanas. El flujo de trabajo de entrenamiento del enfoque MTDS propuesto consiste en la transformada espacial de Gabor (SGT), el cálculo de características y la estructura de aprendizaje profundo. Las características se calculan a partir de las imágenes del conjunto de datos de imágenes cerebrales de meningioma y de las imágenes del conjunto de datos de imágenes cerebrales normales, y estas características se introducen en la arquitectura de clasificación. En este trabajo, la arquitectura CLOUD-IVGG propuesta se deriva de la arquitectura existente Visual Geometry Group (VGG) potenciada por Cloud para mejorar la tasa de detección del sistema propuesto y disminuir la complejidad del tiempo de cálculo. El flujo de trabajo de prueba del sistema propuesto también consiste en SGT, el cálculo de características y la arquitectura CLOUD-IVGG para producir el resultado de la clasificación de las imágenes del cerebro de origen en normal o meningioma. Además, las regiones tumorales en esta imagen de meningioma se han localizado utilizando el algoritmo de segmentación morfológica. En este trabajo de investigación se han utilizado dos conjuntos de datos de imágenes cerebrales independientes para estimar y validar la eficacia del MTDS propuesto. Los conjuntos de datos son Kaggle Brain Imaging (KBI) y BRATS Imaging 2020 (BI20). Se ha analizado la eficiencia del rendimiento con respecto a la tasa de detección, la precisión, la recuperación y el índice de Jaccard.

Palabras clave: Cerebro; Tumores; Meningioma; Arquitectura CLOUD-IVGG; Conjuntos de Datos.

INTRODUCTION

Tumours in humans result from aberrant cell growth in the brain, and there are several varieties of these growths according to factors including size, location, and other characteristics.[1] Gliomas, glioblastomas, and meningiomas were the most common types of brain tumours.[2] Compared to gliomas and glioblastomas, meningiomas are a less aggressive form of brain cancer.[3] Primary tumours of the central nervous system, meningiomas develop in the meninges, the tissue that links the brain and spinal cord.[4] In time, it metastasises to additional brain regions, as well as the brain's nerves and blood arteries.[5] Over the course of several years, they grow in the human brain asymptomatically.[6]

It manifests as mild, moderate, or severe symptoms, depending on the individual's state of health.[7] Older individuals and female patients accounted for the majority of meningioma brain tumour cases.[8] Signs and symptoms often experienced by patients with meningioma tumours included blurred vision, headache, memory loss, and hearing loss.[9] A better prognosis and lower treatment costs are the results of early detection. There is a chance of human error in the standard ways of recognising brain tumours since they rely on the abilities of medical professionals.[10] Traditional methods are costly because they need a lot of human labour. Several imaging techniques, such as computed tomography (CT) and magnetic resonance imaging (MRI), may identify brain tumours.[11] By facilitating visualisation, computer-aided diagnostic procedures are advancing medical imaging research.[12]

Automated tumour segmentation using clustering allows for precise tumour identification, which in turn aids in risk reduction and efficient treatment.[13] To improve upon previous methods of segmenting MRI images, this research suggested using MTDS.[14] The most important form, texture, and colour characteristics are chosen to simplify the process.[15] When it comes to the diagnosis and treatment of brain tumours, the medical professionals come across an issue. Such options may suggest good possibility of improving the survival of Individuals with brain tumours, if they are reconed with and early treatment starts. However, image identify techniques are able to accurately locate, outline and define the size of the tumours in the brain which is quite laborious and full of errors when done by the human eyes. Computer aided diagnosis can reliably identify brain tumors using medical image detection, segmentation and classification.

Motivation: Diagnostic concerns are aggravated by the fact that meningiomas have different texture patterns but look radiologically like other tumors sitings making the menace hard to eliminate. Brain tumours with a systemic occurrence, meningiomas are common. For successful management of meningiomas, their diagnosis should be rapid and accurate. However, techniques available today still experience pressure in trying to merge the computational perspective and accuracy of detection that is high. This paper presents the MTDS based on fusion of SGT and new designed CLOUD-IVGG architecture to increase detection but decrease computing burden. For better detection, accuracy, true positive rate, false positive rate, and segmentation quantification, two different brain images databases KBI and BI20 were employed to test the robustness of the model.

Problem Statement: The striking intra-tumoral and related extra-tumoral characteristics among meningiomas and other brain tumours poses a great difficulty in their precise location, outlining, and segmentation. When it comes to differentiating between brain pictures with and without tumours, current methods aren't always very accurate and may involve high speed computation. It demands a system which would be able to recognize meningiomas in a matter of minutes not hours and accurately as well. For this purpose, MTDS has been proposed in this current investigation to augment overall diagnostic efficiency of the system. It engages the use of an innovative CLOUD-IVGG architecture enhanced by SGT for optimal identification, categorization, and localization fills the gaps.

The main contribution of the paper is as follows:

- Development of MTDS: The technique proposed which is called the MTDS incorporates a new CLOUD-IVGG architecture with SGT. It aims to reduce processing time for every detection and classification of meningioma brain tumours in comparison with normal brain imaging.
- Implementation of CLOUD-IVGG Architecture: Presents an CLOUD-IVGG, an improved VGG architecture, specifically for the detection of brain tumours. The new design is more efficient than the old one due to its high detection rate and low computing time consumption requirements.

- Morphological Tumor Segmentation Methods for Treatment Planning: More specifically, the processes used in this article entail the use of a morphological image segmentation method for precise identification and segmentation of tumor regions in images affected by meningiomas to improve the management of tumor locations and help in planning the treatment.

The remaining of this paper is structured as follows: In section 2, the related work of meningioma tumor is studied. In section 3, the proposed methodology of MTDS is studied. In section 4, the efficiency of MTDS is discussed and analysed. Finally, in section 5 the paper is concluded with the future work.

Related work

Magnetic resonance imaging scans have proved useful in the detection of brain tumours due to its accuracy and ability to precisely segment the tumorous region. It is feasible to predict brain tumours using MRI images by extracting accurate and relevant characteristics. According to research, cluster-based segmentation classifies MRI scans into subsets and highlights the ROI in each one. Clustering allows for the accurate measurement of tumour size, which in turn allows for more targeted therapy and a lower risk of death. A distinct area is created, with high-similarity pixels contained inside, and low-similarity pixels kept apart.

Convolutional Neural Networks based Meningioma Tumor Detection (CNN-MTD)

Any kind of abnormal, unchecked cell development might be considered a tumour. The intricacy of the brain's structure and function makes brain tumours among the most lethal illnesses. deep learning models based on convolutional neural networks with transfer learning. Tyagi, M. et al.[18] utilise a dataset of 5712 photos obtained from the open-source website Kaggle. After a Gaussian filter is applied to the input picture for pre-processing, snake segmentation is used for segmentation. Another round of de-noising using PNLM filters is applied to the segmented picture. Ultimately, the two classifier models are combined, trained, and evaluated using metrics like F1-score, recall, accuracy, and precision.

Brain Tumor via Reversing Hexagonal Feature Pattern (BT-RHFP)

Brain tumour diagnosis is laborious and highly reliant on the radiologists' skills. A number of quick and accurate algorithms have been created for the purpose of BT detection and classification. In recent years, deep learning has gained a lot of traction, particularly for the purpose of creating automated systems that can faster and more precisely diagnose and categorise BT by Anlin Sahaya Infant Tinu, M. et al.[19] This study proposes a new RHPN for cancer classification using MEG and PET scans, which can distinguish between benign, malignant, and normal tumours. To eliminate artefacts caused by noise, the acquired MEG and PET pictures undergo pre-processing using a bilateral filter.

Data Mining Technique for Meningioma Tumor Detection (DMT-MTD)

The primary focus of the research was to examine potential risk factors for MM. Data collected from mesothelioma patients helped in the detection of the disease's symptoms. Yet, the dataset included both individuals without mesothelioma and those who had the disease. Computationally effective data mining approaches were used to implement classification algorithms for MM disease diagnosis. In a MTD test, the support vector machine showed better results than the MLPE method by Alali, A. M. F. et al.[20]

Meningioma Tumor Detection using Support Vector Machine (MTD-SVM)

Improving agricultural sustainability and production via accurate plant health monitoring is the driving force behind this work. To accomplish accurate disease identification and classification in fig leaves, Alzoubi, S. et al.[21] aim to provide a novel method that combines SVM with state-of-the-art image processing approaches. Digital colour photos of sick leaves are the starting point for our methodology's sequential procedure that includes denoising using the mean function and augmentation with contrast-limited adaptive histogram equalisation.

Meningioma Tumor Detection using Fuzzy Logic (MTD-FL)

The importance of clinical diagnosis in modern healthcare systems has grown tremendously. This article presents a strategy for detecting brain tumours using fuzzy logic based on edge detection. To segregate tumours, the suggested method uses image enhancement, classification, and edge detection based on fuzzy logic. The source photos are pre-processed with contrast enhancement and then an edge detection approach based on fuzzy logic is used to find the edge by Maqsood, S. et al.[22]

Curvelet Transform in Meningioma Tumor Detection (CT-MTD)

Because brain tumours and their surrounding areas have many structural similarities, detecting aberrant tumour locations in MRI scans is a challenging process. This study proposes a classification approach based

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on curvelet transform for the identification of meningiomas, brain tumours by Anitha, R.[23] There are four steps to the suggested process: preprocessing, transformation, feature extraction, and classifications. The preprocessing step involves improving the brain MR images and then utilising the Curvelet transform to turn the spatial domain picture into a multi resolution image. The modified coefficients are used to extract the statistical characteristics and texture.

Meningioma Tumor Detection using grey level Co-occurrence Matric (MTD-GLCM)

Feature extraction, classification, segmentation, and diagnosis are the main components of the suggested system. Here, use the ANFIS classifier to determine if a brain picture has normal or pathological characteristics by extracting GLCM and Grid features. The aberrant areas of the brain imaging are further segmented using morphological techniques. The segmented tumour areas are detected by locating these aberrant patches in brain tissues by Kathirvel, R. et al.[24]

Tumor Detections using K-means Clustering (TB-K-C)

Anterior to the spinal cord and brain lies the central nervous system. An abnormal development resulting from cells replicating uncontrollably is known as a brain tumour. The most typical method for detecting brain tumours is MRI. Obtaining and analysing a huge quantity of data manually is not feasible in MRI. The presence of noise in the input pictures makes segmentation a difficult but essential procedure in medical image analysis. For the purpose of biomedical picture segmentation, clustering is an effective technique. Meenakshi, S. R. et al.[25] suggest implementing MIP using the K-means clustering technique.

Table 1. Summary of related works

S. No	Methods	Advantages	Limitations
1	CNN-MTD (Convolutional Neural Networks)	High detection accuracy; automatic feature extraction; effective with large datasets.	Requires large training data; computationally intensive; may overfit small datasets.
2	BT-RHFP (Reversing Hexagonal Feature Pattern)	High precision and recall; effective in distinguishing between benign, malignant, and normal tumors.	Noise in scans can affect performance; specialized for MEG and PET scans.
3	DMT-MTD (Data Mining Technique)	Efficient data mining techniques; good at identifying risk factors and symptoms.	Limited in handling image data; performance may depend on dataset quality.
4	MTD-SVM (Support Vector Machine)	High classification accuracy; works well with smaller datasets.	Not ideal for large, complex datasets; sensitive to feature scaling.
5	MTD-FL (Fuzzy Logic)	Effective in edge detection and segmentation; handles uncertainty well.	Less accurate with noisy data; slower processing time.
6	CT-MTD (Curvelet Transform)	Good at detecting fine details and texture in images; multi-resolution image analysis.	High computational cost; sensitive to noise.
7	MTD-GLCM (Grey Level Co-occurrence Matrix)	Robust feature extraction; combines with ANFIS classifier for accurate detection.	Complex to implement; may struggle with noisy or poor-quality images.
8	TB-K-C (Tumor Detection with K-means Clustering)	Simple and efficient segmentation technique; works well with large datasets.	Sensitive to noise and initial clustering parameters; less effective in complex images.

Existing literature on meningioma brain tumor detection methods, focusing on the Implementation of CNN models, feature extraction techniques, and use of Machine learning algorithms. Modern methods of diagnosing brain tumors such as BT-RHFP and CNN-MTD offer other alternatives. Other techniques follow including but not limited to the use of SVMs, fuzziness, curvelets and K-means clustering. The aim of these methods is primarily classification, segmentation and denoising of medical images. Their performance on different datasets based on metrics like accuracy, precision, recall, F1-score is discussed in the research.

METHOD

This paper provides a new method for better segmentation and classification of meningioma tumours using deep learning. The CLOUD-IVGG architecture integrated with MTDS-SGT technique provides more effective identification and segmentation of meningioma tumours in head MRI images. This new framework aims to enhance detection rates, improve feature computation, and enable appropriate segmentation of tumours with a combination of morphological and advanced feature modelling techniques. Using the KBI and BI20 datasets the method is tested with accuracy, recall, detection rate and segmentation border enhancement.

Contribution 1: Enhanced Detection Rate with CLOUD-IVGG Architecture

The paper presents a deep learning framework improving the original concept of the Cloud empowered Visual Geometry Group. The current VGG design forms the foundation for the building of this framework. This innovation improves the performance of the system by lowering the false positives and raising the general detection rate. By improving the feature extraction and classification process, this helps to achieve this and increases the accuracy of meningioma tumour detection in brain images.

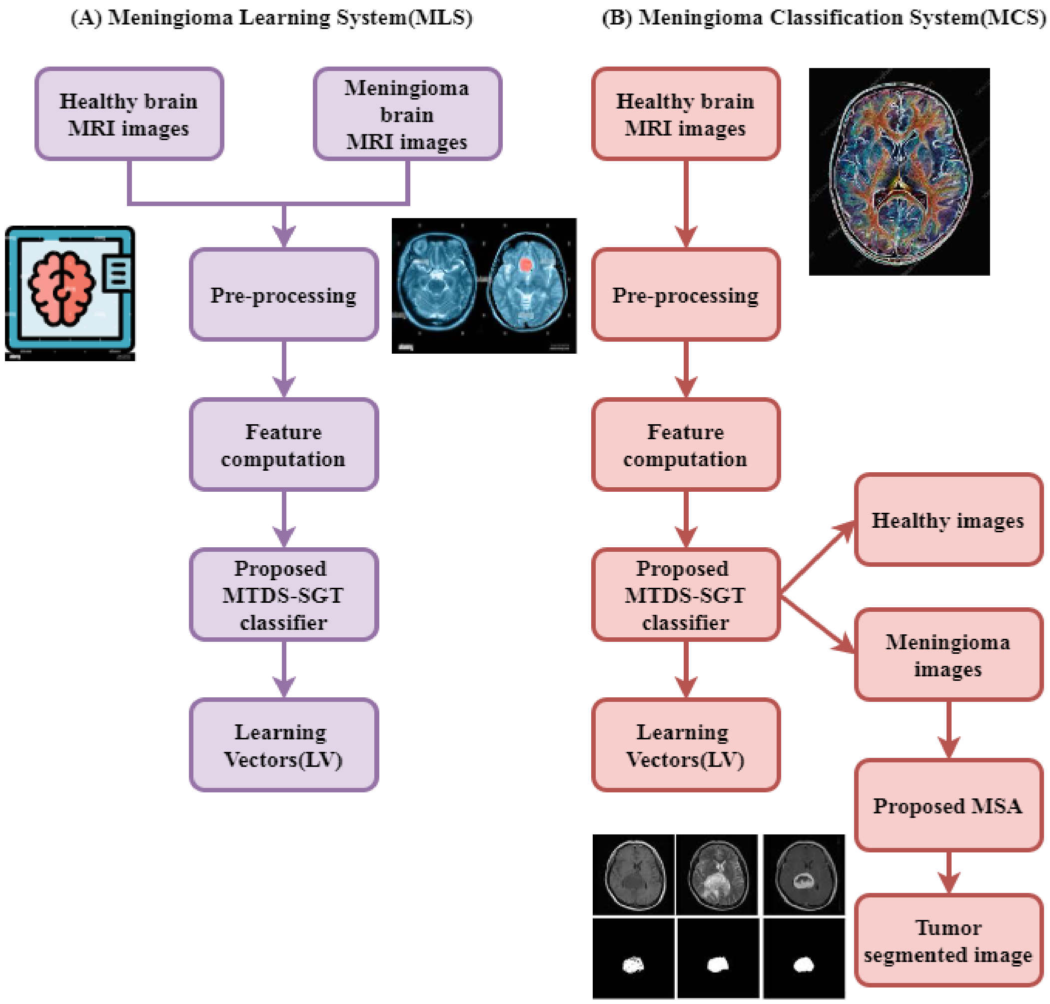

Figure 1. A Novel Approach for Meningioma Classification and Segmentation using MRI Images

Figures 1 provide a MCS recommended system its aim is to correctly segment meningioma tumours generated using brain MRI data. Respectably, it is Proposed Multi-Task Deep Supervised Generative Transformer and Meningioma Learning System. Taken together, it form the two most crucial components of the system. Following pre-processing MRI images to improve picture quality, the MLS then computes features to extract relevant information. Then the MLS makes quite good use of the gathered data. These features enable the MTDS-SGT classifier to be trained to detect meningioma-affected from healthy brains. The things are then classified. Moreover directed is the classifier to generate Learning Vectors (LV) able to authentically represent the special properties of meningioma tumours for classification. MTDS-SGT is a new deep learning classifier among the most recent developments. The many advantages of generative modelling and supervised learning are compiled by this classifier. Training more discriminative representations is one way the MTDS-SGT improves meningioma classification accuracy. We simultaneously optimise the categorisation and generating techniques to do this. Generation of an image segmentation depending on tumour volume marks the final step of the MCS. Using the taught LV will enable to attain this goal. For surgical treatment administration, planning, and treatment execution, this split picture provides required information.

$$-N^{\mp}_{\forall,R} * (E^2 p) = n^Q \; in \; \forall \equiv S^{t-r}, R \leq 4 \; (1)$$

This equation 1 can be used to represent intensity features (such as (E^2p)) in medical images $\forall \equiv S^{t-r}$, where the distribution of pixel/voxel intensities across various areas (n^Q) is modeled by ($-N^{\mp}_{\forall,R}$) and is connected to the deep learning structure of the (CLOUD-IVGG) to detect $R \leq 4$ and segment meningioma tumors. The model's performance is enhanced by the equation, which implies a connection between the accuracy of tumor segmentation and local image attributes.

$$T\_ = \frac{\forall}{Er}(R-2) + 2, F_w^q (D-2) + 4 \; (2)$$

The spatial resolution $\forall/Er$ and rate $T\_$ are represented by the equation, while the filtering or weight application in various layers is represented by $R - 2$, with modifications dependent on $F_w^q \; (D\text{-}2)$ dimensional parameters and regions. Maximizing processing efficiency without sacrificing segmentation accuracy is the goal of equation 2.

$$\min\left\{\frac{L *}{F * -(4n * q)}\right\} = Q > E(f^2 - Wd) \; (3)$$

While taking into account feature mapping $F^* - (4n^*q)$, the number of neurons $Q > E$, and weight adjustments $f^2 - Wd$, equation 3 may be connected to minimizing loss in the CLOUD-IVGG model. This equilibrium aids in the enhancement of the accuracy of meningioma tumor detection.

$$f_{vp} \leq J(b - rw^2) < R - \frac{2v}{4} + Ed \; (4)$$

The change of features affected by parameters such as bias ($J(b - rw^2)$), weight (R), and region size ($2v/4$) is measured by the equation feature propagation (f_{vp}) within the CLOUD-IVGG deep learning model. This aids in managing the efficiency of feature extraction. By controlling the correlation between velocity and the segmentation edge, equation 4 guarantees that the segmentation performance stays constant.

Figure 2 shows the suggested brain tumour detecting and classifying structure. Further discussed below are four phases to it: picture preparation, segmentation, feature extraction, and classification. It collected photographs of brain tumours from many databases. In the primary step, one can suggested to increase the contrast of the brain tumour pictures by means of an enhanced hybrid contrast based on the absolute mean deviation and the kurtosis function. In the following step, one can suggested the enhanced fuzzy model to segment the pictures of brain tumours. The feature extraction procedure gathers the forms, textures, and colours of the segmented brain tumour pictures in the following step. The improved ELM model properly recognised four varieties of brain tumours in the last stage: pituitary, no tumour, meningioma, and glioma tumours.

$$v'' = N(+\forall(K-2) * q' * un^{-2} - p'') \; (5)$$

The variables that the equation 5 can explain are v'' for spatial coverage, for kernel size, $+\forall(K - 2)$ for feature scaling and neuron interaction, and $q' * un^{-2}$ for possible p''. To improve the accuracy of meningioma tumor segmentation by adaptive learning, this equation controls the dynamic modification of feature propagation.

$$Y(v-p) = -wp'(s) * r(f' - tb) * Mgt(j - rt) \; (6)$$

In the CLOUD-IVGG deep learning model, the weight parameter $Y(v - p)$ serves to account for spatial fluctuations, the link between feature values $j - rt$ and bias $r(f' - tb)$ is reflected by $-wp'(s)$, and the equation represents a response function in the model. For more consistent and precise segmentation results while detecting meningioma tumors, equation 6 probably regulates the feature-weight balance.

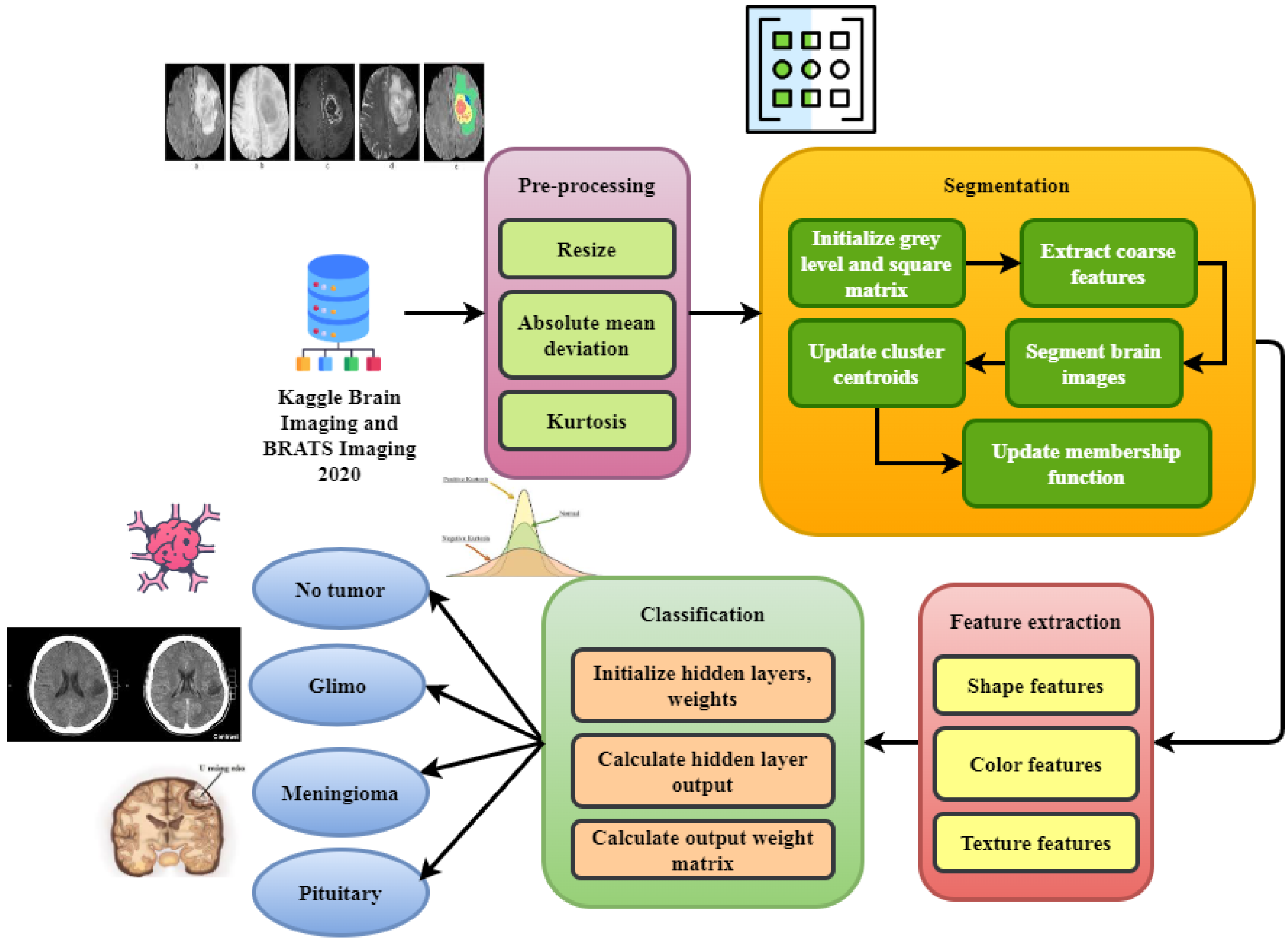

Figure 2. Brain Tumor detection flow diagram

$$r - M = \{(Y, mt)\}: E = w(P - q)\ for\ - N^{\mp}_{\forall,R}\ (7)$$

Represented by *r - M* during meningioma tumor identification, the equation may be used to characterize the residual *Y, mt* in the CLOUD-IVGG model. The energy is modified by the weight *w*(*P - q*), and the optimization between the predicted and actual values is shown by the difference $-N^{\mp}_{\forall,R}$. Tomaximize accuracy and minimize mistakes in segmentation, equation 7 ensures that features are normalized across spatial areas.

Contribution 2: Efficient Feature Computation Using Spatial Gabor Transform (SGT)

By use of the Spatial Gabor Transform (SGT), the system can faithfully extract spatial and textural information from brain imaging datasets. This is made possible by technological advancement. Its advanced feature extraction technique lets it separate meningioma from normal photos. The result is a quite significant increase in the accuracy and recall rates of the classification ability.

Figure 3 shows a better MRI-based tumours diagnosis and segmentation workflow. This pipeline makes use of an updated form of the VGG architecture, the CLOUD-IVGG. Reducing noise, normalising, and scaling the image before it is sent to an MRI scanner falls to a preprocessing unit. The CLOUD-IVGG model consists then of five convolutional layers triggered by ReLU and max-pooling over images. Skips links between layers and batch normalisation after convolutional blocks helps to improve learning accuracy and efficiency. After that, densities follow for progressive feature extraction; the completely connected layers flatten the feature maps into a 1D vector after feature extraction. The softmax layer places the image either in non-tumours or tumours. Concurrent with this generates a segmentation mask from a segmentation network linked with up-sampling layers to identify the tumour location. Tumour border refinement of conditional random fields helps to further increase the accuracy of the segmented region even in postprocessing. At end, the segmented image with the marked tumour shows precisely and unambiguous identification of the cancer's margins. This approach could greatly improve cancer detection and segmentation performance of MRI scans.

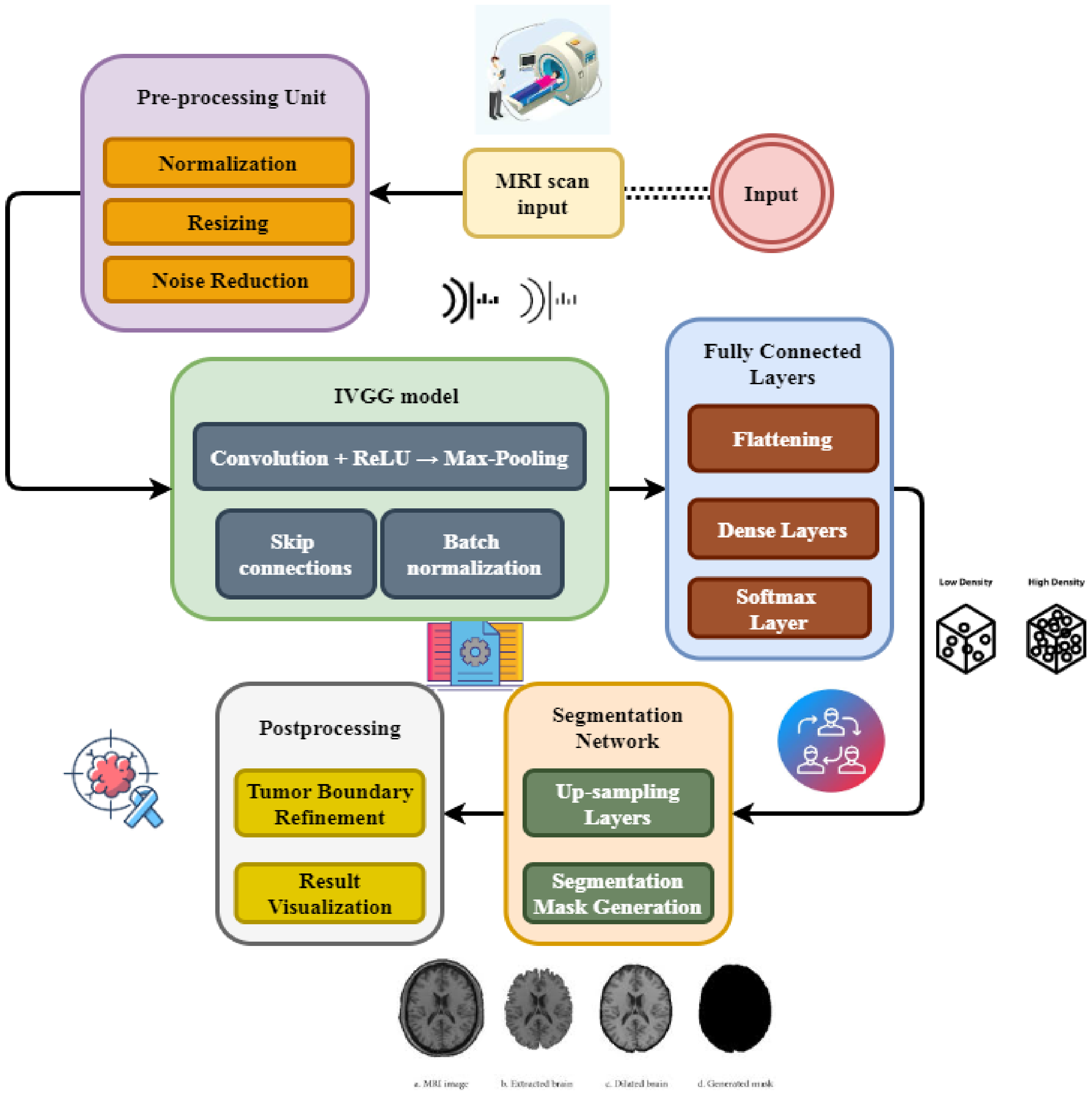

Figure 3. Improved VGG Model for MRI Scans

$$E_{v-z} = \{(Y', zq) * F = B(r - qA)\} * C - B(-k, m') \; (8)$$

The link between output predictions and scaled features is defined by the equation 8, E_{v-z} in the CLOUD-IVGG deep learning model for meningioma tumour identification, which represents the function Y', zq. Adjusting feature responses $B(r - qA)$ is done using bias $C - B$ and weight $(-k, m')$. The accuracy of tumour segmentation is enhanced by equation 8, which improves error management.

$$Qmn_2 = \left(R\left(J_{-r} + Za(b^2 - Cf)\right) - Rv_2 s\right) \; (9)$$

The CLOUD-IVGG model's spatial complexity is related to the equation 9, Qmn_2 which accounts for the quadratic interaction of features $(b^2 - Cf)$ and correction factors Za, and regional adjustments J_{-r} are denoted by $Rv_2 s$. Because the reaction to fluctuations in spatial data is controlled, collecting features for meningioma tumor identification is more accurate.

$$R_f\left(N^2 * L(m * rt)\right) = d_k * Q(wr^2 - V) \; (10)$$

The refinement factor is represented by the equation 10,d_k the squared normalization of feature maps is R_f and kernel adjustments are $N^2 * L(m * rt)$ applied. The feature weighting d_k about threshold V is controlled by the wr^2. By maximizing feature refinement and kernel dynamics, this equation aids in fine-tuning the detection accuracy.

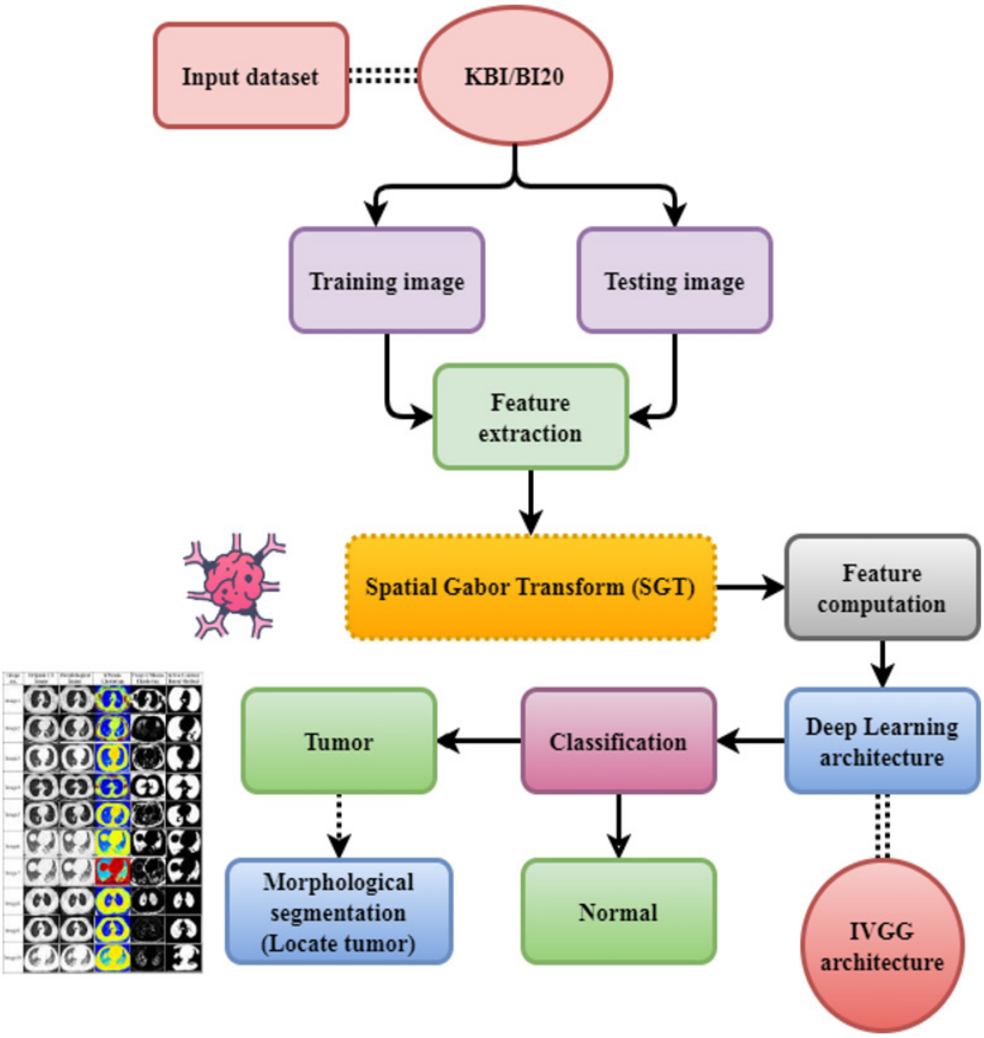

Figure 4. Workflow of Meningioma Tumor using SGT

The MTDS is shown fully from input to tumours classification and segmentation (figure 4). Starting with split training and testing pictures, KBI and BI20 form the input datasets. Image sets both undergo feature extraction producing the SGT. Above all, SGT emphasises textural and spatial characteristics to distinguish normal from malignant tissues. Features derived feed the Deep Learning component in charge of classification—the CLOUD-IVGG. Meningioma tumours are separated from normal brain pictures using the classification system. Images found to show tumours are segmented morphologically so that the tumour area within the picture can be exactly found. Combining deep learning with current feature extraction and segmentation techniques guarantees the outstanding performance of the system in terms of detection rate, accuracy, recall, and Jaccard index. It thus ensures accurate and rapid diagnosis and classification of meningioma brain tumours.

$$D = \{q < 1: for\ E_r = (W_Z, D_t)\} * Z_0 \ (11)$$

The features are kept within a normalized range using the equation where $q < 1$ and the dataset's dimensionality is represented by D. The E_r includes the connections between weights Z_0, and time data W_z,D_t serving as a reference point for baseline. The accuracy of tumor segmentation, this equation stresses the need to normalize and keep data intact during feature extraction.

$$Q_2 = \left(y_2, H(Z-2)\right), R_{vt} = \left(m_2.J(y-2)\right) \ (12)$$

The function $H(Z - 2)$ accounts for spatial offsets in the input data and the output from particular features y_2 is represented by the equation 12,Q_2. The connection between the modulation factor m_2 and the feature adjustment R_{vt} is captured. Better segmentation outcomes for meningioma tumor detection are the goal of these equations, which attempt to improve the extraction of attributes and response accuracy.

$$\forall(F,L) = Y^b * E(m^2 - pk), \partial = 2 - \frac{pk}{w} * 2v \ (13)$$

A link between feature functions $\forall(F,L)$ and layer Y^b is denoted by the equation 13, $E(m^2 - pk)$, where $\partial=2$ modifies the output according to pk/w that represents differences in model predictions. The model's performance sensitivity concerning weight 2v and component variance is examined using the metrics. The meningioma tumor detection equation guarantees effective learning and improves segmentation accuracy.

$$b' = E_2 * M * Fz(m' - gh), A'_2 = Fd(v_2 Q) \ (14)$$

The updated bias, affected by $E_2 * M$, matrix b', and feature interactions $Fz(m' - gh)$, is represented by the equations associated with A'_2, while the corrections required for successful learning are accounted for by Fd. The output feature adjustments are determined by the input variations and scaling factor, and this is represented by the equation (v_2Q). The model's capacity to precisely segment tumors is improved by the equation, which refines the learned characteristics.

$$b = r\left(T_2, z(4n - w)\right); V_n * EZ(r^2) \ (15)$$

This interaction between time series data and feature weights is shown in the equation, which shows the bias that is defined by the response function r and its connection to parameters T_2,$z(4n - w)$. The significance of variance V_n and energy normalization $EZ(r^2)$ in increasing feature representation. The equation 15 model's segmentation accuracy for tumor detection is illustrated.

Contribution 3: Accurate tumor segmentation with morphological techniques

The technique accurately locates tumours inside the brain images of meningiomas that have been identified using morphological segmentation. Extensive testing on the KBI and BI20 datasets shows this method greatly improves tumour boundary identification. This helps the segmentation procedure to be more generally accurate and efficient.

Figure 5 presents from MRI images the segmentation process of meningioma tumours using the CLOUD-IVGG deep learning architecture. Beginning with MRI image gathering, the system moves via a preprocessing layer normalising and resizing the images to standard input dimensions. Running the input through many convolutional blocks, the CLOUD-IVGG architecture extracts ever abstract and detailed elements of the tumour. Block 1 and Block 2 use convolution and ReLU (Rectified Linear Unit) activation functions to capture early visual patterns after a max pooling layer that reduces spatial dimensions, therefore preserving significant features and minimising computational overhead. Focussing on deeper hierarchical patterns in the MRI images, intermediary convolution blocks (Block 3 and Block 4) enhance the acquired characteristics even further. For classification, a fully connected dense layer gathers this information. At end, a softmax layer generates a tumour segmentation mask distinguishing tumours from non-tumours. The result is then post-processed to enhance the segmentation limits, therefore ensuring accurate identification of meningioma tumours. The end effect is a well defined tumour segmentation suited for subsequent diagnostic activities or clinical review.

$$q < t(b), w(v - r) = cT^{2p} - A_2C(m - f) \ (16)$$

By indicating a cutoff for feature quality relative to bias q, the equations $t(b)$ guarantee that the features that are extracted have any significance. The link between weights cT^{2p} and the difference between variables $w(v - r)$ is represented by the second equation 16, which is balanced by factors $(m - f)$, and adjustments for features A_2C. Improved tumor identification and segmentation accuracy is the goal of this framework, which seeks to optimize model performance and feature selection on analysis of detection rate.

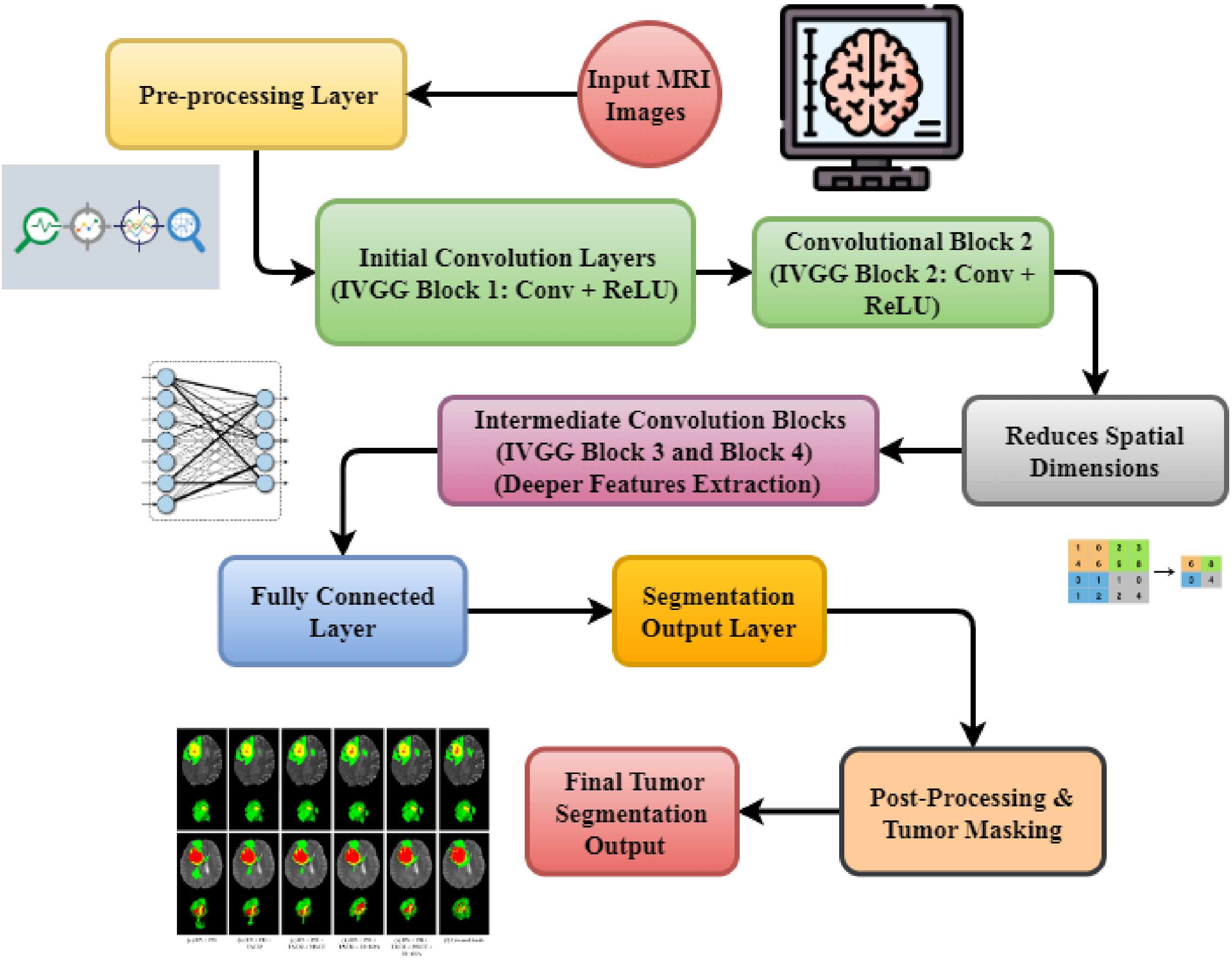

Figure 5. Process of Meningioma Tumor Segmentation

$$\partial(\mathrm{R},\mathrm{s}') = \{Y^{b-z}, z^{c-rt} * \mathrm{v}'\mathrm{w}\} \ (17)$$

The equation $\partial(R,s')$ shows how the output Y^{b-z} varies when the segmented features z^{c-rt} are changed $v'w$. Tooptimize feature extraction and guarantee more accurate tumor segmentation findings, show the influence of biases and spatial adjustments on the overall performance on analysis of precision.

$$r = -q(T-2) + \frac{E-z}{A}q - 2 * Y^{b-r} - \forall(2n-e) \ (18)$$

The scaling of these effects is controlled by the equation 18, $-q(T - 2)$ which includes the threshold r, and adjustments $\forall(2n - e)$ depending on bias $(E\text{-}z)/A$ and feature interactions Y^{b-r}. Improving tumor segmentation results is the goal of this equation, which incorporates dynamic adjustments depending on feature performance on analysis of recall.

$$+Q(v_2-3) - \left(F_2W - ty(p-nm)\right) = \forall * Er(a-b') \ (19)$$

The output is adjusted according to a particular feature F_2W in the equation $+Q(v_2 - 3)$, and the impact of weights and feature discrepancies is shown by $ty(p - nm)$. Normalization balanced feature $(a - b')$ representation is emphasized by the symbol $\forall * Er$. This equation is useful for optimizing the model’s parameters, which in turn increases the accuracy by segmentation on analysis of performance.

$$-e(T-ypo)b + w(v'-mt) = q - 2w > 0 \ (20)$$

In this equation, the interplay of time factors ($-e(T - ypo)$) and anticipated outputs ($b + w$) concerning feature variations ($v' - mt$) and model thresholds ($q - 2w$) is reflected. It is necessary to effectively adjust the weights and biases to improve the segmentation accuracy in tumor detection since the model's positive performance metrics are guaranteed by lessanalysis of time complexity.

The proposed method provides the following main advancement in the field of meningioma tumour detection and segmentation. CLOUD-IVGG architectural design Enhanced Rate of Detection: By use of improved feature extraction and classification methods, the CLOUD-IVGG-based system reduces false positives and increases overall detection rates. This ensures higher accuracy in the meningioma tumours identification in brain MRI pictures. By use of SGT, effective feature computation is accomplished; this helps the system to effectively extract spatial and textural information, hence enhancing classification performance and generating higher accuracy and recall rates. Applied morphologically, precisely segmented tumours: The technique improves segmentation accuracy particularly in cancer border recognition by accurately detecting cancers in brain images using morphological techniques.

RESULT AND DISCUSSION

This report provides an in-depth evaluation of the Meningioma Tumour Detection System, with an emphasis on how well it uses cutting-edge approaches to identify and categorise brain tumours that are thought to be meningiomas. Improved detection rate, accuracy, recall, and performance metrics across several datasets, such as BRATS Imaging 2020 and Kaggle Brain Imaging, are achieved by integrating the unique CLOUD-IVGG architecture with Spatial Gabor Transform for feature extraction in the system.

Dataset Description: A mass of aberrant brain cells is known as a brain tumour. The bone that covers the brain, the skull, is rather hard. Any kind of development in such a confined area might lead to complications. Tumours in the brain may be either benign or malignant. Increased intracranial pressure may be a symptom of tumour growth, whether benign or malignant. Brain damage and even death might result from this. Brain tumour early identification and categorisation is a significant area of study in medical imaging since it aids in choosing the most practical treatment option for patients, which ultimately saves their lives.[26]

Analysis of detection rate

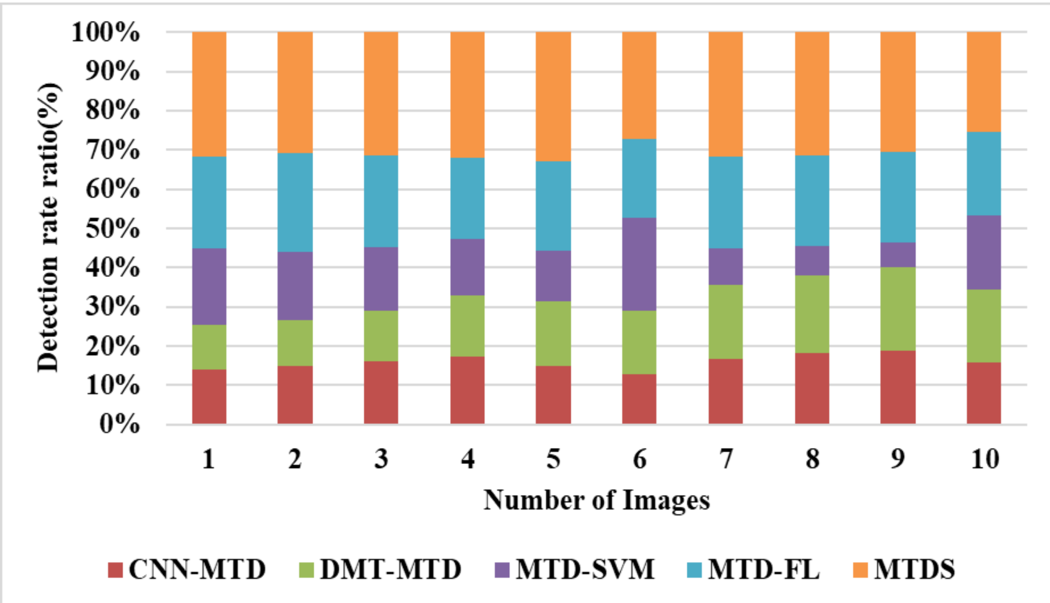

Figure 6. The Analysis of detection rate

One of the most useful measures of the effectiveness of the MTDS is the rate of detection. It measures the ability of the system to differentiate meningioma brain tumours from normal brain images. The proposed MTDS method enhances the accuracy of detection by utilizing the CLOUD-IVGG novel architecture with Spatial Gabor Transform for feature extraction. The performance of the algorithm as detected rate was investigated in detail using two different sets of data which includes BRATS Imaging 2020 and Kaggle Brain Imaging is illustrated with equation 16. One of the ways to amine computing complication and raise detection rate is the CLOUD-IVGG model, a redesigned VGG framework. Empirical evidence from exhaustive testing of the system has shown that the system is effective and reliable due to the consistent and high detection rate of both datasets. The morphological segmentation method also contributed towards the determination of the tumours thus improving the performance of the system for meningioma detection and classification enhancing its reliability. The rate of detection was found to improve by 98,65 % is depicted in figure 6.

Analysis of precision

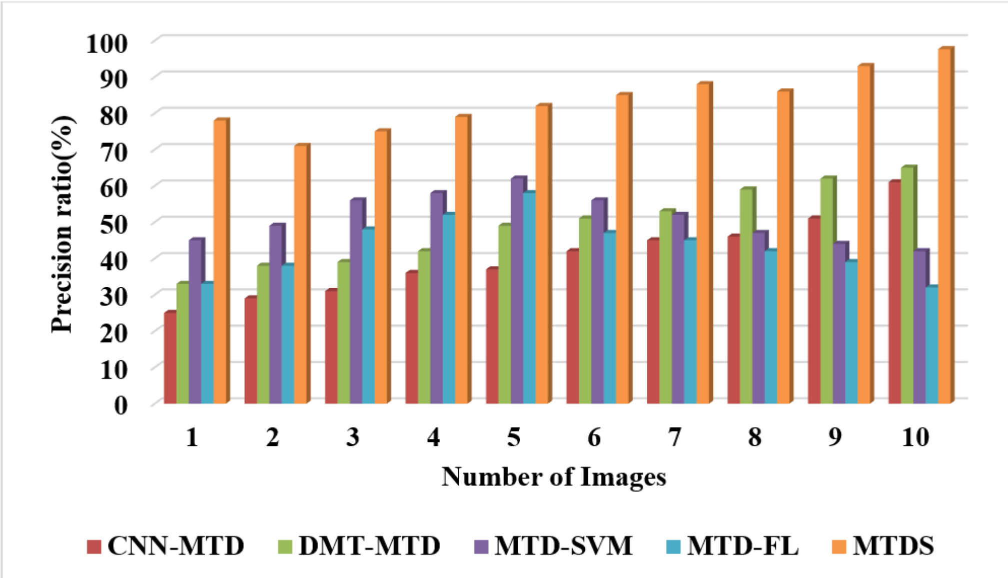

Figure 7. The graphical Representation of Precision

In figure 7, which is important in determining the effectiveness of MTDS, precision, is one of the other parameters analyzed. Precision is defined as the number of meningioma cases detected as positive out of all positive cases. The more advanced addition of the CLOUD-IVGG architecture and SGT for feature extraction has been noted to provide an impact with respect to accuracy in the Exploration of various parameters of the MTDS which is given in equation 17. By decreasing the number of false positives and increasing the probability of tumour identification, the deep learning architecture of the CLOUD-IVGG model enhances the feature selection process. To check its precision, the MTDS was performed on two databases namely, BRATS Imaging 2020 and Kaggle Brain Imaging. The findings were such that the algorithm was able to distinguish tumour cases as well as areas without tumours. By this system, the tracking accuracy was further enhanced by correctly identifying the tumor regions based on the morphological segmentation algorithm. Therefore, the MTDS pulled up the overall reliability of the system because a high accuracy rate was achieved which means that meningioma detection is achieved with very few member misclassifications. The improvement in the precision ratio of 97,65 % in the proposed method of MTDS is projected in figure 7.

Analysis of recall

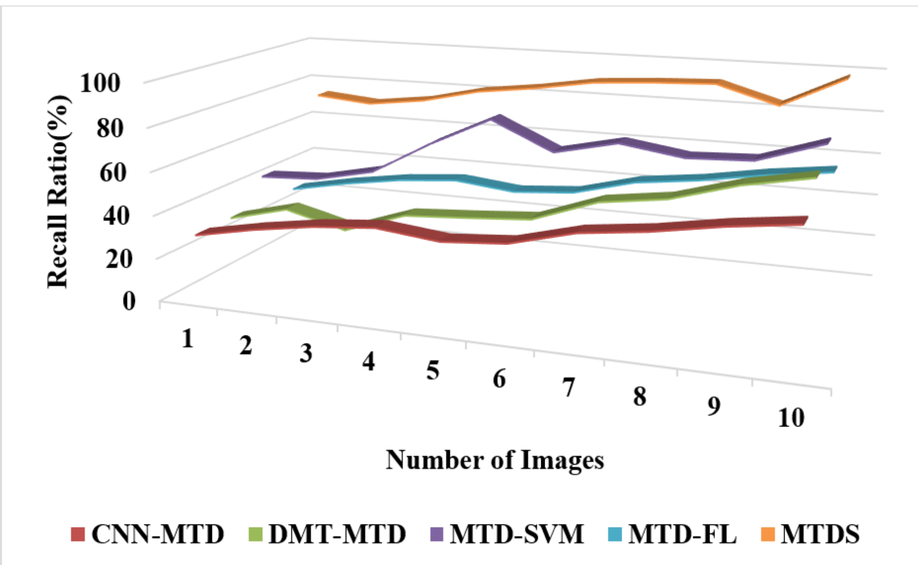

Figure 8. The Graphical illustration of Recall

In this paper, the MTDS has been validated through its recall, which measures the degree to which the system can find all specimens of meningioma instances in truth. Recall is also referred to as true positive rate. An important element of the proposed MTDS technique for increasing the recall of the system is the incorporating the advanced CLOUD-IVGG structure and the SGT to achieve accurate feature extraction. The purpose of the method is to restrict false negatives so that most of meningioma cases are appropriately detected. Recall able to be achieved by MTDS is high enough as to how it is able to test in two datasets of Kaggle Brain Imaging and BRATS Imaging 2020 as represented in equation 18. This validates that indeed indeed the system performs well in true positive even in images where meningioma is not conspicuous or resembles another brain tumor. Morphological segmentation techniques further enhance the makeup such identifying success by accurately classifying tumor outlines computer. It's because of this high recall that the MTDS system can be relied upon for early disease detection and treatment in the clinics which makes it possible to minimize missed diagnoses. In figure 8, the recall value is obtained by the proposed method of MTDS which is 97,57 percentage.

Analysis of performance

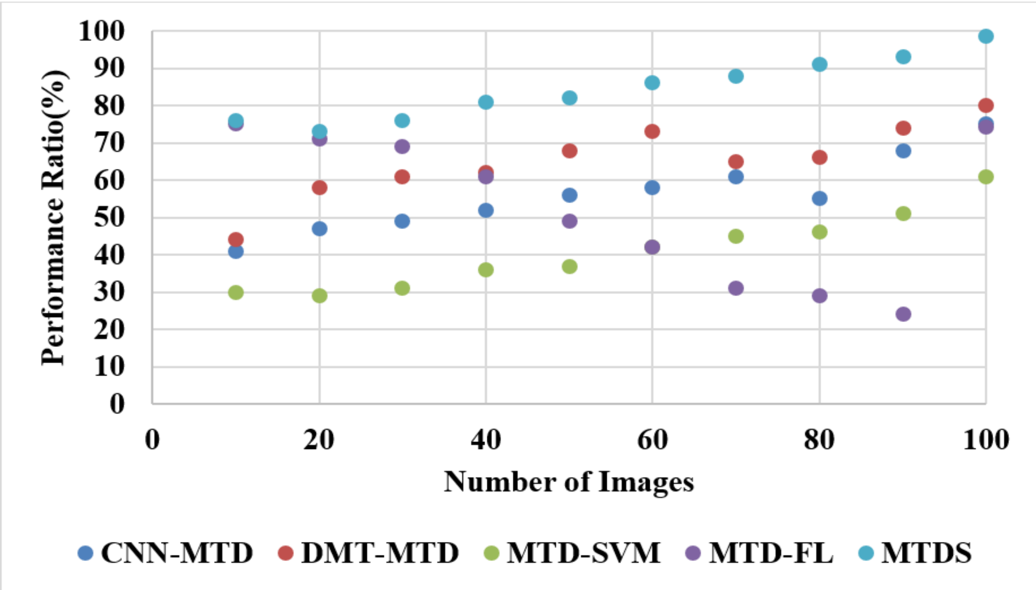

Figure 9. The Analysis of performance

In figure 9, the performance of the Meningioma Tumour Detection System (MTDS) in detecting and classifying Meningioma brain tumor is assessed. Detection rate, recall, precision, and the Jaccard index were some of the variables that were considered during the assessment. As explained in equation 19, two datasets, BRATS Imaging 2020 and Kaggle Brain Imaging were utilized to test the system to ensure it accommodates various forms of brain imaging. The efficiency of the system was significantly enhanced by synthesising the novel CLOUD-IVGG structure while that of the spatial gabor transformation feature extraction was slightly improved. Operating on the more assimilated conceptual structure of the team's design, the CLOUD-IVGG model enabled increased precision and computing efficiency. In particular, to enhance the picture classification accuracy of the system further, separation of tumor blocks was performed using morphological segmentation techniques. Generally, MTDS showed favorable outcomes in performance in that it was carried out with good sensitisation, low false positives and a balance between sensitivity and accuracy. This reliable performance at this level of the system makes it appropriate for the detection and diagnosis of the tumors in the clinical environment. The performance ratio is improved by 98,73 % in MTDS.

Analysis of time complexity

There is a direct relationship between MTDS speed and its real-life usability, as this is governed by time complexicity. In other works, none were performed that would decrease time complexity of computation without losing in detection efficacy, in regards to the proposed MTDS the use of modified CLOUD-IVGG architecture aids in achieving such a goal. CLOUD-IVGG which is modified from VGG model seeks to increase the efficacy of deep learning models by shortening the lengthy processes of carrying out the feature extraction and classification is stated in equation 20. Additionally this method also improves the computational efficiency of the Spatial Gabor Transform for the purpose of neoplastic feature extraction. SGT shortened the amount of time required to prepare the images for analysis by making it possible to extract the texture heterogeneity that distinguishes a meningioma from normal brain tissue. The MTDS was able to achieve significant time complexity reductions because of these optimizations particularly when tested using large datasets such as BRATS Imaging 2020 and Kaggle Brain Imaging. Consequently, this allows the system to process brain images much faster making it very useful in a clinical situation where it is important to make a quick diagnosis. This is how much time complexity is decreased by 30 % is seen in figure 10.

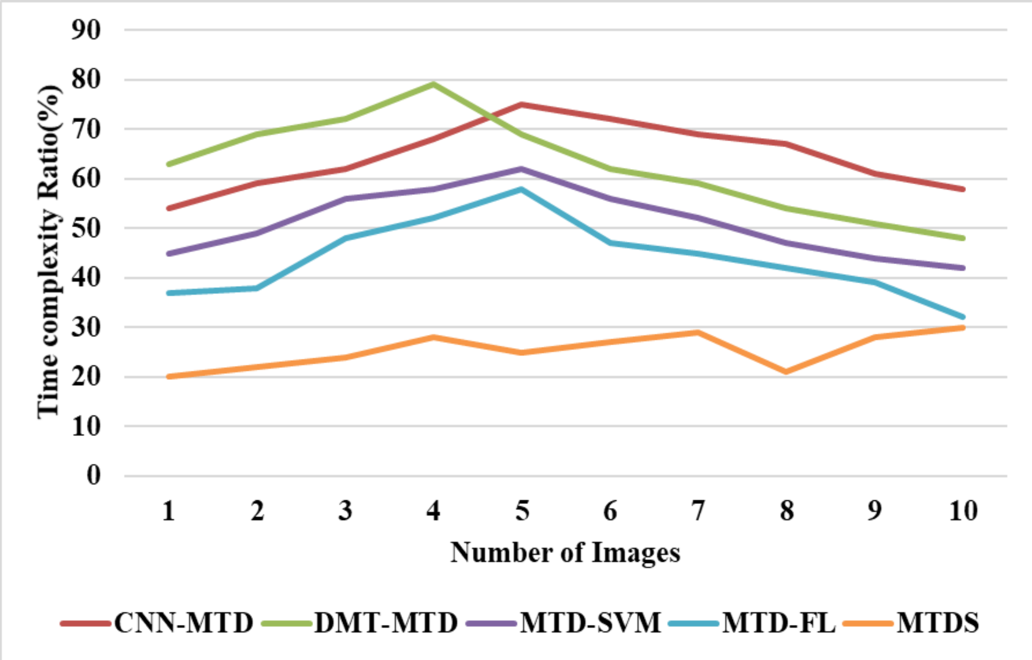

Figure 10. The Graphical Representation of Time Complexity

Table 2. Comparison table of finding parameters			
S. No	**Aspects**	**MTDS**	**Ratio (%)**
1	Detection Rate	Proportion of true positive meningioma detections	98,65 %
2	Precision	Percentage of correctly identified meningioma cases	97,65 %
3	Recall	Sensitivity; ability to detect all actual meningioma cases	97,57 %
4	Performance	Overall system performance across multiple metrics	98,73 %
5	Time Complexity	Reduction in computational time complexity	30 %

In summary, identifying and categorising meningioma brain tumours, the MTDS shows remarkable effectiveness. Results on datasets such as BRATS Imaging 2020 and Kaggle Brain Imaging show that the system achieves good detection rates (98,65 %), accuracy (97,65 %), and recall (97,57 %) by merging the CLOUD-IVGG architecture with Spatial Gabor Transform for feature extraction. Notable in clinical applications, its total performance score of 98,73 % demonstrates dependability. The technology also improves its usefulness for quick diagnosis by reducing computing time complexity by 30 %. So, the MTDS is clearly an excellent resource for finding brain tumours quickly and accurately.

CONCLUSION

Using the enhanced deep learning method, this work demonstrates a method for detecting and classifying brain tumours. when reducing computing complexity for detecting lesion details, the suggested FCM minimises uncertainty concerns when segmenting the MRI images. The suggested approach enhanced the identification of brain tumours by extracting parameters such as colour, shape, and texture, resulting in quicker, more accurate detection times. The classification performance is enhanced by the enhanced ELM model. It will use the suggested approach to assess the massive MRI datasets. As a means of further improving the model, it will investigate deep learning models. The suggested MDSS method gave substantial tumour segmentation outcomes based on the efficient analysis and comparisons of experimental findings from two separate datasets. Designed for use in clinical diagnostic procedures, this document primarily identifies tumour areas. Future diagnostics of the segmented tumour areas will make use of the suggested MDSS method. When training the new model, fewer epochs are needed than when using pre-trained models. This model outperforms competing pre-trained models on a brain tumour classification challenge, demonstrating its primary emphasis on medical picture classification problems. A new model with tailored architecture is needed to get superior results, despite the fact that the pre-trained models were trained with much bigger datasets for certain applications, particularly medical imaging.

Future Work

Integrating further sophisticated approaches like ensemble learning and transfer learning would enhance the Meningioma Tumour Detection System's capabilities, particularly in terms of detection accuracy and resilience. To improve the model's generalisability to other imaging modalities, it is worth investigating the usage of more varied datasets. Immediate clinical applications made possible by real-time processing might also lead to faster diagnosis. To improve the accuracy of tumour localisation, future studies may also include enhancing the morphological segmentation method. Last but not least, validating the system's efficacy in various healthcare contexts will need substantial clinical studies.

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Supervision: Sivamurugan V.
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Display: Swathika R.
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