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A Comprehensive Review on Image Segmentation and Classification Algorithms for Tumor Detection in Smart Healthcare Systems

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Abstract: Recent innovations in imaging technologies have brought about improved benefits for smart health care systems in enabling earlier detection and diagnosis of tumors and other diseases through imaging techniques. To develop effective treatment guidelines, tumor images must be accurately and precisely segmented and classified. To overcome limitations in current tumor image segmentation and classification algorithms regarding high levels of computational overhead, low levels of accuracy, and inability to classify complex tumor architectures correctly, this paper proposes enhancements to current algorithms for smart health care tumor classification. In particular, this paper discusses a tumor image segmentation algorithm that combines thresholding and region-growing methods, designed to reduce the computational overhead of current tumor segmentation algorithms while increasing the accuracy of tumor region identification. In addition, this paper presents a novel approach to feature extraction that focuses on the textural and geometric characteristics of tumor areas segmented. Compared with earlier algorithms for segmentation and classification, the RBF kernel has improved the accuracy of both segmentation and classification when used in conjunction with SVMs for tumor image recognition. Furthermore, the RBF kernel has increased the SVM's ability to recognise complex structures in tumour images. Consequently, the speed of determining whether a person has a tumour has increased, enabling patients to receive care earlier.

Keywords: Tumor Structures; Region-Growing; Segmentation Algorithm; Medical Imaging; Image Recognition; Feature Extraction; Textural Features; Computational Efficiency; Radial Basis Function (RBF).

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1. Introduction

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Image segmentation and classification algorithms are crucial for detecting tumors in medical imaging. Segmentation and classification algorithms segment and classify the image, enabling the identification of specific areas, including non-cancerous tissues and tumors. Unfortunately, current image segmentation and classification algorithms are neither very effective nor very accurate. Therefore, there is a need for improved tumour detection and more accurate results when using these algorithms [1]. This has led to the development of additional approaches that combine artificial intelligence, machine learning, and deep learning. Clinicians can increase the precision and effectiveness of picture segmentation by combining these technologies with classification algorithms used in cancer detection and diagnosis. Many of them integrate convolutional neural networks (CNNs), enabling these tools to learn to swiftly and accurately extract and interpret the primary features of images. CNNs, or convolutional neural networks, were trained on large amounts of medical imaging data to recognize different anatomical structures, including tumors [2]. An important aspect of developing these algorithms was the ability to generate additional training data through advanced image augmentation techniques, thereby improving their robustness [3].

Table 1: List of abbreviations used in this research

No.	Classification	Referred To
1	SVM	Support Vector Machine
2	RBF	Radial Basis Function
3	CNN	Convolutional Neural Networks
4	DNA	Deoxyribonucleic Acid
5	RNA	Ribonucleic Acid
6	IHC	Immuno Histo Chemistry
7	ER	Estrogen Receptor
8	PR	Progesterone Receptor
9	CT	Computed Tomography
10	MRI	Magnetic Resonance Imaging
11	PET	Positron Emission Tomography
12	GLCM	Gray Level Co-Occurrence Matrix
13	GM	Gray Matter
14	WM	White Matter
15	CSF	Cerebrospinal Fluid

Continued technological advances in medical image acquisition and machine vision are likely to lead to more precise algorithms for detecting tumours and other abnormalities [4]. Image segmentation is the process of dividing images into distinct regions (or portions) so that meaningful data can be extracted; this is a critical stage in cancer discovery, as it enables the correct identification and delineation of the tumour region [5]. Regarding algorithms for image segmentation and classification, improving accuracy and efficiency, and achieving the most accurate results possible when identifying tumours, several technical issues must be addressed [6]. Perhaps the most prevalent issue is noise and artefacts in medical imagery, which significantly degrade image quality and detail, as well as the ability to identify the tumour region accurately [7]. Therefore, to address this problem, the image denoising and artefact removal phases must be incorporated into segmentation and classification techniques to ensure that all potential data can be extracted from the images and to improve the overall precision and reliability of the results [8]. A further challenge faced by analysts is the variety of shapes/sizes/textures that types vary dramatically among cancerous masses or tumors. All tumor types have distinct features, which pose a challenge for developing a single algorithm that can accurately identify them [9].

A viable solution may include implementation (in an organization) of many different methods for both segmentation and feature extraction, to create greater strength and versatility within the examining algorithm to provide accurate detection/classification for all tumor types, including tumour variability, respectively [10]. An example of the various stages associated with tumours is depicted in Figure 1. Medical imaging has shown some weaknesses in low contrast tumour versus non-tumour image differentiation leading to false positive tumour detection or missing a small tumour, such as the use of advanced imaging methods (like Contrast Adjustment and Histogram Equalization) for improving the level of contrast between the tumour(s) and surrounding area(s) to provide the needed contrast for accurate tumour detection [11]. These algorithms require significant time and computational complexity, especially when used in real time [12]. Many traditional imaging enhancement algorithms require substantial time and energy to process high-resolution medical images and are therefore not suitable for timely, accurate tumour detection. Thus, an urgent need exists for algorithms that process high-volume datasets more quickly, more effectively, and at lower computational cost, yielding results in real time [13].

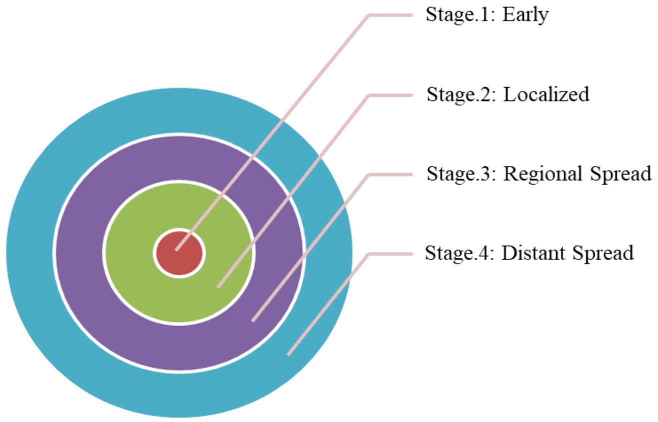

Figure 1: Different stages of tumor

To improve tumor identification, given the diversity of tumor characteristics, the degree and intensity of contrast enhancement, the reduction of computational processing time, and image quality enhancement (removal of noise and artifacts) are some of the technological aspects that need to be addressed in medical imaging using segmentation and classification [14]. By tackling the many fields of study, Researchers will develop new algorithms that yield more trustworthy, accurate findings in the diagnosis and treatment of malignancies. This will lead to improved clinical outcomes for patients.

1.1. Importance of Tumor Segmentation and Classification

Tumor Segmentation and Classification are two highly significant components of the Medical Imaging domain, as they both help in the cancer detection process. The primary objective of tumor segmentation is to provide the radiologist with an accurate outline of all abnormal areas (the tumour) in the image. This allows the radiologist to determine the tumour size and track its rate of growth. Tumors vary greatly in size and location, and these two characteristics will affect how they can be treated and the likelihood of successful treatment. In addition, tumor classification assists the radiologist in grouping the identified tissue/diagnosis into established categories that can be used to develop predictive responses to treatment and to serve as prognostic indicators of overall health status. Tumor segmentation and classification require sophisticated, computer-assisted, supervised Machine learning algorithms and image processing techniques to precisely and effectively assess and interpret large volumes of medical images, thereby improving diagnosis and treatment outcomes for people with cancer.

1.1.1. Signs and Symptoms

The signs and symptoms indicating the presence of a tumour depend on its size, type, and location. However, some general signs and symptoms could indicate a tumour is present:

- **Local Symptoms:** Local symptoms will appear if a tumour develops in a particular area of your body. For example, persistent coughing or chest pain is common in someone with a lung tumour, whereas headaches or changes in your eyesight may occur if you have a brain tumour. In many cases, local symptoms result from either the pressure exerted by the tumour on surrounding tissue or the body's effort to fight the tumour.
- **Systemic Symptoms:** Systemic symptoms are signs that your entire body has been affected, which might suggest that the tumour has spread to other parts of your body. Examples of systemic signs and symptoms include night sweats, fever, weakness, and unintentional weight loss. These systemic signs and symptoms may not only be seen in individuals who have tumours but can also occur with many other illnesses and diseases. Therefore, when these systemic signs and symptoms develop alongside local signs and symptoms, they serve as red flags for a possible tumour.
- **Compression Symptoms:** Tumours that grow to a large size or to a location near vital organs may become large enough to impede other areas of the body, leading to "compression symptoms." For example, if you have a large abdominal tumour, it may compress your intestinal system, leading to abdominal bloating and pain. If the tumour is located in your spine, it may put pressure on your spinal nerves, causing weakness, numbness, or pain in your arms or legs.
- **Hormonal Imbalances:** Some tumors secrete hormones that alter hormone levels, leading to multiple symptoms. For example, a pituitary tumor can lead to excess growth hormone production, resulting in accelerated growth and acromegaly. An adrenal gland tumor can cause increased cortisol production, resulting in Cushing's syndrome.

- **Cognitive and Behavioral Changes:** Brain tumors can affect how well someone thinks and remembers, how well they can focus or pay attention, and how they behave. The cognitive and behavioral effects of a brain tumor can differ depending on where in the brain the tumor is placed. A brain tumor may cause behavioral and cognitive abnormalities in a person, including confusion, difficulty understanding and dealing with things, mood disorders, and changes in their personality.
- **Changes in Skin Appearance:** Some tumors (e.g., skin tumors) may also alter the skin's appearance. Different skin variations (including changes in pigmentation and texture, and the emergence of new moles or lesions) are observed in skin tumors. Additionally, skin tumors may cause itching, bleeding, or discomfort in the affected area.
- **Unexplained Pain:** Pain can result from tumors in several different ways. Tumors may compress nerves, release chemicals that trigger the pain response, and provoke inflammation. A medical doctor should evaluate ongoing discomfort with an unknown cause; this may indicate the presence of a tumor.

In addition to the typical indicators and symptoms listed above, specific tumors may produce unique symptoms. For example, colon cancer may result in changes in bowel habits (constipation and/or diarrhea). In contrast, breast cancer may manifest itself as a breast lump or changes to the appearance of the breast. It is critical to inform your doctor of any new, different, or ongoing symptoms, as the earlier you seek out cancer treatment, the better your chances of survival will be.

1.1.2. Methods of Tumor Segmentation

Finding and separating the areas in medical imaging that indicate tumor tissue from surrounding normal tissue is known as tumor segmentation. It is an important aspect of diagnosing and treating cancer, as well as of tracking cancer patients over time. There are various methods for tumor segmentation, each with its own advantages and disadvantages. This paper will discuss the four main types of tumor segmentation techniques: manual segmentation, threshold-based approaches, machine-learning-based methods, and hybrid methods (Table 2 depicts the role of Tumor Segmentation in different applications). The original technique for tumor segmentation involved allowing a qualified physician to visually identify and define the tumor region directly on the medical image (manual segmentation). This was a very labor-intensive and subjective technique because it relied on the physician's judgment and expertise in rendering the image. However, it remains the ultimate standard for the accuracy and interpretability of medical images and is often used to assess the efficacy of automated segmentation methods. Various intensity-based methods, also called thresholding methods, assess pixel intensities in an image using a threshold value to differentiate tumor regions from surrounding normal tissue. This segmentation relies on the assumption that a tumor's pixel intensity differs from that of the surrounding normal tissue; hence, the threshold is determined by this difference. Employing thresholding approaches requires multiple methodologies to compute the threshold value; for example, Otsu's approach determines the cutoff by minimizing the intra-class variance between tumor and normal tissue classifications. These approaches are straightforward to use and offer speedy segmentation results. However, their susceptibility to noise might lead to erroneous segmentation, and their effectiveness depends on the threshold value used for heterogeneous tumors with differing intensity characteristics (Figure 2).

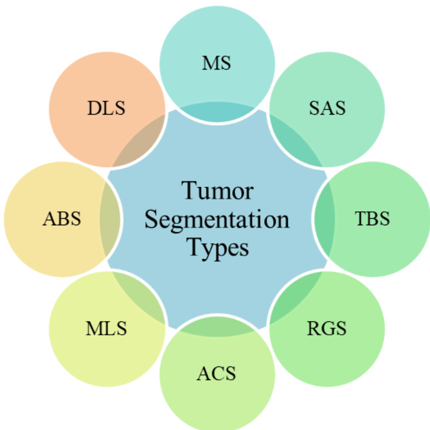

Figure 2: Types of tumor segmentation

Machine Learning-based or Automated Segmentation Methods leverage machine learning techniques that learn to segment the characteristics and profiles of tumorous tissue types and incorporate that knowledge into the segmentation of new images. Supervised and unsupervised learning are two additional categories of machine learning techniques. In supervised learning, the core procedure for training the algorithm is to use labeled training data, where each tumor area is manually segmented and used as a 'ground truth' against which to compare. In addition, the tumor locations in the labeled data provide a basis for classifying tumor and normal tissue based on the characteristics extracted from the labeled training data. Conversely, Unsupervised Learning does not use labeled data in its training process and instead uses various clustering techniques to detect and segment patterns within images. These methods most often outperform threshold-based methods and can develop models that account for heterogeneity or variation within tumor tissue; however, they require extensive amounts of training data to construct a good prediction model and, unfortunately, have less interpretability and generalizability than supervised learning-based models. Hybrid Models combine the advantages of threshold-based approaches and machine learning to improve tumor segmentation accuracy. To prepare input data for a machine learning model, hybrid models employ threshold-based techniques to detect and classify probable tumor areas of interest, then use a machine learning model to perform more precise, robust segmentation of the tumor region. The combined advantages of these two methods yield a more precise and robust tumor region segmentation solution in the presence of complex, heterogeneous tumor masses and underscore the importance of tumor segmentation across a variety of applications.

Table 2: Importance of tumor segmentation in various applications

No.	Segmentation Type	Segmentation Details	Applications
1	Manual Segmentation (MS)	The traditional way of segmenting tumors uses manual tracing to determine the tumor boundaries on medical images or other types of images. This method takes a great deal of time and can introduce human error into the results. However, it is still frequently used for a limited number of patients where computer-based diagnosis is not possible.	Manual segmentation is used to assess tumor size, location, and shape for treatment planning and monitoring.
2	Semi-Automatic Segmentation (SAS)	Combining manual segmentation with image processing speeds up the overall process. When manual segmentation is used, the user selects several points on the tumor, and the computer program uses them as a basis to complete the segmentation.	Semi-automatic segmentation is used in areas where the tumor's shape is irregular, making manual segmentation more difficult.
3	Threshold-Based Segmentation (TBS)	Histograms are used to determine the cut-off point (threshold) that distinguishes the background from the tumor in an image. Pixels above the threshold value will be considered part of the tumor, while pixels below the threshold will be classified as background.	Threshold-based segmentation is commonly used for tumors with well-defined boundaries and sufficient contrast from the surrounding tissue.
4	Region Growing Segmentation (RGS)	Using this iterative segmentation process, a user creates a 'seed' pixel and builds on that pixel based on the similarity of the pixels around it. As new pixels are added to the segmentation, the user will stop the process if there is a sufficiently large difference in the properties of the new and existing pixels.	Region-growing segmentation is appropriate for tumors with homogeneous intensities in medical images, as it can effectively differentiate tumors from surrounding tissue.
5	Active Contour Segmentation (ACS)	Curves or contours are used to estimate the tumor boundaries based on the features of the pixels along the curve/contour that are not directed toward the tumor.	Active contour segmentation is beneficial when tumors have irregular shapes and poorly defined boundaries, as it enables greater accuracy in locating and defining tumor boundaries.
6	Machine Learning Segmentation (MLS)	This approach involves training a machine learning system to categorize tumors automatically based on attributes extracted from medical images.	There is a rising interest in the application of machine-learning-based approaches for segmenting tumors in terms of being able to generate a higher accuracy and a more efficient segmenting system for tumors, with the potential to be used in many different ways (tumor detection, monitoring, and classification).

7	Atlas-Based Segmentation (ABS)	Pre-segmented atlases (also known as labeled images) are used in this approach for tumor segmentation of new images. The atlas is aligned with the new image, and the segmenting information found within the atlas is directly copied to the new image.	The advantages of atlas-based segmentation become evident when a large number of segmented-image datasets are available; this enables accurate segmentation of lesions, even in images with little or no distinction or contrast between the tumour and the surrounding structure or tissue.
8	Deep Learning Segmentation (DLS)	Using a form of machine learning called deep learning, this segmentation leverages deep neural networks to identify and segment tumors across multiple 2D medical images (e.g., CT scans, MRIs). Deep learning algorithms use large collections of thousands, or even hundreds of thousands, of 2D radiographs to develop and refine learning rules that recognize and differentiate features associated with tumors from those of other structures visible in the images.	Deep learning segmentation is employed in various applications, including tumor detection, classification, and monitoring, as it can deliver highly accurate and efficient segmentation results.

1.1.3. Methods of Tumor Classification

Tumor classification is the process of categorizing tumors based on their appearance, behavior, and other characteristics. This provides an accurate means to diagnose tumors and develop an appropriate treatment plan, as different tumor types will likely have different prognoses and treatment options. There are many ways to classify tumors, based on various factors and methodologies. The types of tumor classification methods are shown in the diagram below, and the chart below details the importance of tumor classification in its various applications (Figure 3).

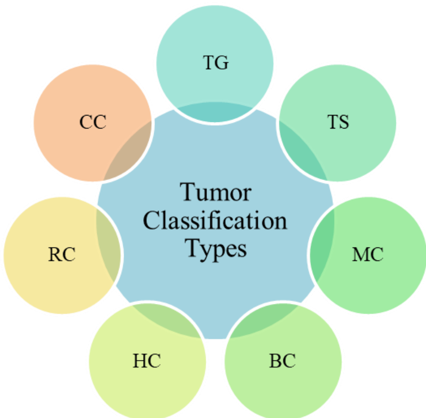

Figure 3: Types of tumor classification

1.1.4. Histological Classification

Histological classification is one of the oldest methods of classifying tumors; it is based on histological assessment, or assessment of the microscopic structure of the tumor, using a pathologist's techniques in examining the tumor tissue. As part of the histological classification process, a biopsy sample will be obtained and evaluated for specific histological characteristics, including cell type, tissue type (the type of tissue the tumor is within), and histological architecture. Histologic attributes can enable the pathologist to determine the tumor type, evaluate its grade, and assess its aggressiveness.

1.1.5. Molecular Classification

Molecular classification is a relatively recent, advanced classification technique. This method is based on the tumor's unique genetic and molecular features and is a sophisticated approach for evaluating cancer cell molecular characteristics. Molecular classification evaluates the DNA, RNA, and protein expression profiles of tumors to identify mutations or other genetic alterations in tumor cells that may promote tumor development and progression. In addition to tumor subtype identification, molecular classification offers forecast capabilities for evaluating the impact of various therapeutic options on tumor response.

1.1.6. Immunohistochemical Classification

Immunohistochemistry (IHC) uses antibodies to identify specific proteins in tissue samples. IHC identifies tumor classification and indicates which molecular markers are present or absent in tumors. Information about the presence of specific breast cancer biomarker proteins—ER, PR, HER2—using IHC is important in assisting the oncologist in making therapy recommendations.

1.1.7. Grading and Staging

Grading and staging are not tumor classification methods; however, they are essential for describing and accurately classifying cancers. Grading examines how tumor cells appear and differ from normal cells (e.g., whether they are more "developed"), indicating how aggressive they may be. In contrast, staging examines the size of the tumor and how far it has spread (i.e., to other parts of your body). Thus, through both grading and staging, it can typically provide both a complete and precise classification of the tumor.

1.1.8. Clinical Classification

Clinical classification is based on where the tumor resides within your body and, therefore, what type of tissue or organ the tumor originates from (i.e., breast cancer = breast tissue). This means it will be able to identify the primary source of metastatic tumors that have spread to different parts (e.g., lung cancer = lungs) and, more importantly, the tissues of origin. The Clinical Category is primarily used alongside other tumor categories, such as the Histological and/or Molecular Categories, to provide a full understanding of the entire cancer. The classification of a tumor is a complex process due to the many factors involved in a thorough analysis to determine its type (i.e., cancer type), subtype (i.e., cancer subtype), and grade (i.e., aggressiveness). The classification method will rely on several factors, including tumor type, available resources, and skill level. However, obtaining a thorough and accurate categorization—which is crucial for achieving the best possible care and patient outcomes—usually requires integrating many classification techniques (Table 3).

Table 3: Importance of tumor classifications in various applications

No.	Classification Type	Classification Details	Applications
1	Tumor grading (TG)	The process involves identifying cancers based on how they develop and respond to treatment.	Tumor classification can also help determine which patients may benefit from different types of therapy based on their treatment response.
2	TNM staging (TS)	TNM is a method for assessing the size of the cancer (T), the presence of cancer in nearby lymph nodes (N), and whether the disease has spread to other organs (M).	TNM staging helps doctors determine the stage of cancer, which is essential for determining the most appropriate treatment plan and predicting prognosis.
3	Molecular Classification (MC)	The genetic analysis method for quantifying cancerous tissue characteristics allows us to subdivide them into subtypes based on identified mutations or gene expression patterns. These subtypes can provide insight into the expected progression of the cancer and the most effective treatment options.	Molecular classification can help guide targeted therapies, predict responses to specific treatments, and provide insights into the development of new treatments.
4	Biomarker Classification (BC)	Biomarkers are measurable substances in the body that can be used to identify the types and properties of specific cancers. Biomarkers can help us classify cancers based on their genetic, molecular, or protein characteristics.	Biomarker classification can help detect and diagnose cancer early, determine treatment options, and monitor treatment response.
5	Histological Classification (HC)	Microscopic examinations of tissue structure and cell types allow us to distinguish various tumor types, such as Adenocarcinoma, Squamous cell carcinoma, and Lymphoma.	Histological classification can provide important information about the tumor's origin and type, which can influence treatment decisions and prognosis.

6	Radiological Classification (RC)	This method uses imaging techniques such as X-rays, CT scans, MRIs, and other modalities to assess tumor size, location, and characteristics. Radiological classification can provide valuable information about the extent and stage of a tumor.	Radiological classification can help diagnose, stage, and monitor tumor growth or response to treatment.
7	Clinical Classification (CC)	This method involves classifying tumors based on their clinical features, such as location, size, and symptoms.	By classifying tumors using specific techniques, oncologists can provide patients with more reliable outcomes based on their unique tumor characteristics and clinical classifications.

1.2. Traditional Tumor Segmentation and Classification

The image used in this study will be obtained from a medical imaging modality (e.g., MRI, CT, PET) and will serve as input to the tumor segmentation technique. The diagram below illustrates the function of conventional tumor segmentation and classification (Figure 4).

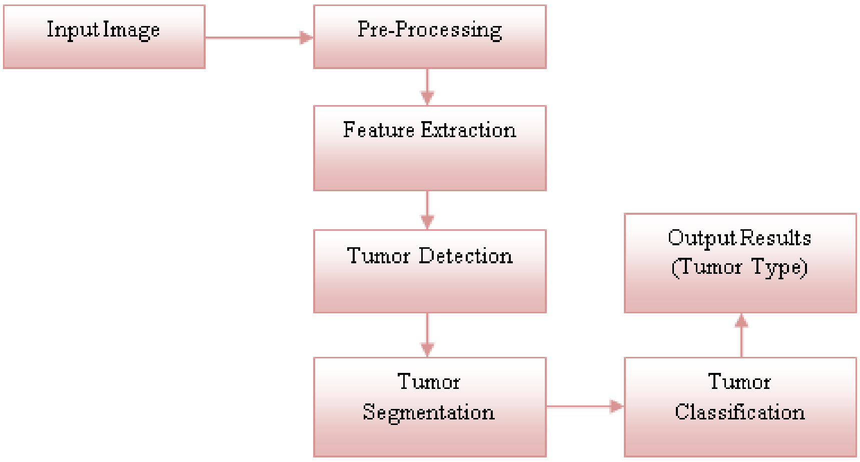

Figure 4: Traditional tumor segmentation and classification

Tumor segmentation begins with pre-processing, which entails filtering out artifacts and noise introduced during image acquisition. The majority of pre-processing involves applying a median/Gaussian filter to create a smoother image with improved contrast, which will aid feature extraction. Feature extraction is the automatic identification of meaningful features present in the filtered image. For instance, height and width, shape, and texture are all typical features used for feature extraction. Tumor Detection includes detecting a "visible tumor" in the input processed by this study using a previously identified feature set, thresholds, or trained machine learning classifiers that assign a label of tumor presence or absence based on an image. Tumor Segmentation is the process of outlining the tumor's edges in an image so they can be defined and separated from adjacent tissues. The most common methods of tumor pixel or voxel segmentation are thresholding of individual pixels or voxels, Region Growing, or Level Set methods. To categorize a tumor properly, experts identify and compare the significant features of the segmented area with pre-established norms for different tumor types. After a radiologist segments an image and identifies its significant characteristics, this information will be used to categorize the segmented area and to provide an individualized treatment plan for the patient. After identifying the tumor type through evaluation of segmented area segmentation and extracting characteristics from the segmented areas, a visual or numerical representation of this information will generally be generated. This information can then be combined with additional clinical data specific to the tumor type, enabling physicians to formulate optimal treatment options to achieve a specific treatment goal.

1.3. Challenges Faced in Tumor Segmentation and Classification

- **Segmentation and Classification Challenges:** Each tumour is unique (in size and shape), thus segmenting and classifying tumours are challenging due to this variation.
- **Different Tissue Types:** Tumours contain multiple tissue types, including necrotic, edematous, and other tissues. This makes the segmentation and classification of tumours difficult.

- **Imaging Technology Limitations:** The accuracy of imaging technologies (MRI and CT) will impact the accuracy of segmentation and classification of tumours.
- **Tumours Overlapping Other Structures:** Tumours can sometimes be found adjacent to other structures. This can make it difficult to segment and classify a tumour accurately.
- **Variance in Tumour Segmentation and Classification by the Operator:** Depending on how the operator segments and classifies a tumour, the results can vary widely.
- There is an inadequate supply of training data; without annotated training data (to train the segmentation/classification algorithms), Tumor classification and segmentation require training on a sufficient number of annotated datasets.
- Each tumor has a unique internal structure unlike any other tumor (i.e., it can contain many heterogeneous regions), so there is no single way to segment/classify a tumor accurately. Intra-tumor diversity of tumors is the variation in cell types, size, density, organization, and shape found within a single tumor.
- This variation will affect the accuracy of the tumor's segmentation/classification. Both MRI and CT imaging data are susceptible to artificial noise and artifacts, which can affect the quality and accuracy of tumor segmentation/classification.
- **Computational Requirements:** The algorithms used for tumor segmentation and classification require substantial computing power and may take a long time to process large datasets.

2. Related Works

Tumor segmentation and classification is the technique through which a medical image is analyzed for signs of abnormal tissue growth. Tumor segmentation is achieved through manually outlining the area of abnormal tissue or by using an automated algorithm. Classification can determine whether an area is benign or malignant based on image characteristics. Two imaging modalities are primarily used for tumor identification: MRI and CT. Identifying tumour boundaries accurately enables accurate diagnosis and assessment of tumour cellular characteristics (degree of malignancy), which in turn supports the development of treatment strategies and the monitoring of patient outcomes. When categorizing these two processes, the characteristics of the shape, texture, and intensity patterns are important for differentiating between tumour types.

2.1. Tumor Segmentation

Khairandish et al. [15] and others have investigated how combining CNNs and SVMs provides automatic tumour identification and classification capabilities from MRI brain data. CNNs can produce what is commonly known as a feature map, and SVMs classify based on that output by setting thresholds. Both techniques achieve high accuracy in detecting or classifying tumours on MRI or CT scans. Lather and Singh [16] have examined the identical approaches and tactics used by medical practitioners to discover and examine tumor cells in the human brain, using sophisticated imaging techniques such as CT or MRI, along with automated algorithms or machine learning tools to support them. The purpose of the investigations is to enhance brain cancer diagnostics by increasing accuracy and efficiency, resulting in improved treatment options and improved quality of life for cancer patients. Through developing new models based on research, Arunkumar et al. [17] and colleagues are developing fully automated computer methods using neural networks to identify and automatically designate tumours in MRI data. Using artificial neural networks, this research accurately detects and classifies tumors in medical imaging (i.e., cardiac) for fast, efficient diagnosis. There is no need for manual intervention, which minimizes human error and maximizes the efficiency of the procedure. Since neural networks continuously adapt and improve as they process more images, they can also lead to earlier tumor detection. Devunooru et al. [18] discuss how this paper reviews the cutting edge of medical image processing, particularly deep learning for brain malignancies. To assist researchers in selecting the best method for a given situation, Devunooru et al. [18] provide a taxonomy that classifies numerous deep learning strategies based on architecture, input data type, and output data type.

Bhanothu et al. [19] emphasized the need to precisely identify and categorize brain cancers using MRI images for the diagnosis and treatment of brain tumors. Using MRI data, several recent studies employing deep convolutional neural network methods have reported encouraging results in detecting and categorizing brain cancers. Deep learning models, which are multilayer neural networks, combine convolution and pooling to accurately categorize and extract meaningful information from images. Healthcare professionals may now swiftly and precisely identify and categorize malignant brain tumors using these technologies, improving patient outcomes through early detection and effective treatment. Islam et al. [20] emphasize the importance of precisely and promptly identifying brain tumors to provide the best possible care. Using superpixels for image segmentation, PCA for feature extraction, and model-based K-means clustering for precise classification, this study suggests a novel approach to identify brain cancers in MRI data. The technique used in this study increases the effectiveness and precision of brain tumor identification when compared to conventional detection methods. He et al. [21] created a model named 'picture Segmentation Algorithm', which is stated as a way of segmenting a picture for subsequent assessment and identification. This neural network-based lung cancer segmentation technique uses deep learning to precisely identify and segment lung cancers from medical images. Preliminary studies indicate that this approach greatly increases the accuracy and efficiency of lung cancer diagnosis. Lung cancer can be diagnosed and treated early thanks to the aforementioned techniques. Studies carried out by Almotairi et al. [22]. In other words, it is frequently challenging to automatically separate tumors with curved or irregular shapes from manual CT scans. Due to laborious procedures and human error, manual segmentation of the liver's blood and/or bile ducts has proven challenging.

It's interesting to note that in recent years, researchers have used artificial intelligence (AI) to implement more automated segmentation techniques. For example, a modified version of the SE-NET architecture (SE-NET-m) that incorporates additional features, such as convolutional and deconvolutional layers, enables more effective automated segmentation of liver tumors. Senet's most recent version has proven to be a helpful tool for precisely segmenting liver tumors, assisting medical professionals in the planning of early liver cancer treatment. Raja and Rani [23] suggest a model (hybrid deep autoencoder) and a segmentation strategy (fuzzy clustering algorithm) to efficiently identify and segment brain tumors by fusing deep learning and Bayesian probabilistic techniques. According to Chattopadhyay and Maitra [24], one of the most crucial elements of medical image processing today is the diagnosis of brain tumors using MRI in October 2020. The most successful way to diagnose brain malignancies has been enabled by analyzing MRI images with CNNs and Deep Learning. The network's ability to recognize cancers using a training dataset is supported by extremely high accuracy. (Sensitivity and Specificity) This can be accomplished through automated imaging and treatment planning. Salama and Aly [25] have described the use of a deep learning-based methodology (a CNN) for mammogram image segmentation and classification, separating breast tissue. This provides for increased confidence and accuracy in determining potential risk and, therefore, provides a better opportunity for assisting in both the early detection and management of breast cancer.

A brain tumor categorization and classification model utilizing an artificial intelligence (AI) system that applies deep learning to magnetic resonance imaging (MRI) data is discussed by Naser and Deen [26]. Naser's AI-based deep learning system employs image processing techniques to locate and categorize brain cancers in MRI scans, leveraging sophisticated algorithms. As a result, the system can also precisely segment the tumor region and assign a categorization grade, enabling more effective treatment planning. Current research suggests that implementing this model will significantly improve the diagnosis and management of brain cancers. Díaz-Pernas et al. [27] suggest employing convolutional neural networks (CNNs) within a multiscale architecture to identify and segment brain cancers. CNNs are often utilized as a technique of boosting the categorization accuracy of brain cancers and the accuracy of segmenting brain tumor images, resulting in greater accuracy when diagnosing and treating brain tumor patients. Dogra et al. [28] evaluate the use of fuzzy graph-cut algorithms for detecting and segmenting MRI brain tumor images. Fuzzy logic provides a method for accurately representing the complex, irregular border shapes and characteristics of brain tumors. Sha et al. [29] conducted research that found that Deep Learning (DL) and Optimization Algorithms provide significant advancements in breast cancer detection, with greater depth of accuracy and higher performance metrics (HMP). By creating large Neural Networks with advanced data analysis capabilities, the AI Systems developed in this paper can automatically identify areas that may be suspicious for breast cancer in Medical Images. Because of this, early detection of malignant disease and or death can occur. Furthermore, with the continued use of AI Systems and advances in M. A. (Machine Learning), Improved performance can be achieved in both the detection and treatment of breast cancer.

Melanoma (skin cancer) is often fatal. Therefore, the earlier melanoma is detected, the better doctors can treat it. Imaging techniques have been developed in combination with imaging techniques (computer-aided diagnosis) to facilitate early detection of melanoma. Using imaging technology, doctors can view images of lesions and determine whether you are at risk for melanoma by identifying patterns or irregularities visible in the images. Using image processing, doctors can quickly and accurately identify melanoma and therefore will have the chance to save a victim's life. Overall, this new technology will increase the likelihood of early recognition of skin cancer and improve treatment outcomes. Karuppusamy [31] presents a technique for identifying brain cancers utilizing a Hybrid Manta Ray Foraging Optimization approach that integrates both Genetic algorithms (GA) and particle swarm optimization (PSO). The precision and effectiveness of brain tumor photodetection may be enhanced by a hybrid strategy to maximize manta ray foraging. Additionally, this strategy may enhance patient care and treatment results by helping healthcare professionals identify and map brain tumors. The Hybrid Manta Ray Foraging Optimization approach is based on how manta rays forage for food, including the complex movement patterns associated with their hunting behavior. The example of Ejaz et al. [32] used a Hybrid Segmentation Method with a Confidence Region Detection method, combined with several methods, to provide a hybrid approach for tumor identification that improves the accuracy and reliability of medical imaging techniques by combining existing imaging methods.

Investigation by Liu et al. [33] into improved performance for the multilevel imaging of breast cancer through a differential evolution algorithm combined with a slime mold-based search for improved performance in the application of multilevel segmentation. The combination of differential evolution optimization and slime mold search efficiency will significantly improve speed and precision in segmenting breast cancer tissue, leading to better diagnosis and treatment for patients diagnosed with breast cancer. Abdel-Gawad et al. [34] developed an improved edge-detection algorithm to produce better MRI images of brain tumors. Compared with standard edge detection approaches, our algorithmic approach has greatly enhanced our capacity to detect and diagnose brain malignancies by employing optimization algorithms to delineate tumor boundaries more accurately. Consequently, the method may enhance the precision of early brain tumor detection and enable appropriate therapy. Furthermore, by removing the requirement for human intervention, this strategy speeds up the discovery process and reduces the possibility of human error. Morphological edge identification and brain tumor segmentation are crucial for the precise and effective diagnosis of brain cancers using MRI data, according to Sheela and Suganthi [35]. The authors of this study offer a fully automated method for brain tumor identification. division that combines region growth with a Mod-FCA (that is, a modified fuzzy c-means). By applying morphological processing to identify edge sites, they reasoned that places discovered by edge detection would be candidates for generating additional tumor regions through an adaptive 'region growth' approach.

Table 4: Comprehensive analysis of tumor segmentation

Author	MS	SAS	TBS	RGS	ACS	MLS	ABS	DLS
Khairandish et al. [15]	✓							
Lather and Singh [16]	✓							
Arunkumar et al. [17]	✓							
Devunooru et al. [18]		✓						
Bhanothu et al. [19]		✓						
Islam et al. [20]		✓						
He et al. [21]			✓					
Almotairi et al. [22]			✓					
Raja and Rani [23]				✓				
Chattopadhyay and Maitra [24]				✓				
Salama and Aly [25]					✓			
Naser and Deen [26]					✓			
Díaz-Pernas et al. [27]						✓		
Dogra et al. [28]						✓		
Sha et al. [29]						✓		
Zghal and Derbel [30]							✓	
Karuppusamy [31]							✓	
Ejaz et al. [32]								✓
Liu et al. [33]								✓
Abdel-Gawad et al. [34]								✓
Sheela and Suganthi [35]								✓

Furthermore, they felt that a modified Fuzzy C-Means clustering (FCM) would help them to refine their tumor segmentation results. Their proposed approach was validated using a set of MR images and compared with several other methods (listed in Table 1), yielding high agreement and accuracy. Their findings suggest that this technique may help medical personnel identify brain tumors earlier and plan treatments accordingly. Figure 5 displays the segmentation results of all methods used. Table 4 presents a comprehensive analysis of tumor segmentation, and Table 5 presents a comprehensive segmentation analysis with Limitations.

Table 5: Comprehensive segmentation analysis with limitations

Author	Advantage	Limitation
Khairandish et al. [15]	By combining the strengths of both CNN and SVM models, the hybrid approach improves tumor detection and classification accuracy and robustness.	Limited generalizability owing to dependence on a specific CNN model and SVM classifier; may not perform well on fresh or diverse datasets.
Lather and Singh [16]	increased precision in the identification and management of brain tumors, leading to better treatment results and patient satisfaction.	The availability of high-quality training data is limited, making it difficult to reliably evaluate the effectiveness of different strategies.
Arunkumar et al. [17]	This method enables MRI-based identification and categorization of brain tumors reliably and effectively, supporting early diagnosis and treatment planning.	The approach may not accurately classify complex or overlapping tumor types, leading to incorrect diagnoses.

Devunooru et al. [18]	enhanced diagnosis and treatment planning due to increased precision and efficiency in brain tumor identification and segmentation.	Limited literature review of only one type of neural network, and focused only on brain tumor segmentation.
Bhanothu et al. [19]	Rapid and accurate identification of tumor type and location can lead to appropriate, timely treatment.	A possible limitation is limited generalizability when applied to different populations or types of brain tumors.
Islam et al. [20]	improved patient outcomes and treatment strategies as a result of increased precision and effectiveness in identifying and diagnosing brain cancers.	The algorithm may not be accurate if the tumor is too small or if overlapping brain structures are present in the MR image.
He et al. [21]	Detect lung cancer accurately and effectively to improve patient outcomes by speeding up diagnosis and treatment.	Difficulties in accurately distinguishing images with high noise levels or unclear boundaries due to disease progression.
Almotairi et al. [22]	It produces more accurate and comprehensive tumor segmentation in CT scans, which can help with monitoring and treatment planning.	Limited ability to accurately segment complex or overlapping tumor structures due to reliance on a pre-trained neural network.
Raja and Rani [23]	Combining deep learning and fuzzy clustering enables more precise and reliable brain tumor categorization.	The method is effective only for brain tumors and may not apply to other tumor types.
Chattopadhyay and Maitra [24]	enhanced brain tumor detection precision and dependability, which lowers the requirement for invasive therapies and patient risk.	Requires large amounts of training data and may not accurately detect rare or atypical brain tumors.
Salama and Aly [25]	The automatic CNN methodology enables faster, more accurate analysis than manual segmentation and classification procedures.	Limited ability to generalize to diverse mammography images due to over-reliance on specific CNN architecture and training data.
Naser and Deen [26]	improved accuracy and efficacy in the diagnosis and treatment planning of lower-grade gliomas in patients with brain tumors.	Limited availability of high-quality MRI images for training and validation of the deep learning algorithm.
Díaz-Pernas et al. [27]	Using a deep learning technique enables proper classification and segmentation of brain tumors across different sizes.	The model's accuracy may be affected by the quality and variability of the input data.
Dogra et al. [28]	This approach employs fuzzy logic to analyze complex medical images with high accuracy.	The limitation is that it requires a high level of expertise to accurately assess the results.
Sha et al. [29]	improved patient outcomes and earlier diagnosis of breast cancer due to increased accuracy and dependability as compared to conventional approaches.	Limited by the quality and size of available datasets, which affects the accuracy and generalizability of the detection results.
Zghal and Derbel [30]	The process is non-invasive, reducing patient discomfort and enabling earlier melanoma detection.	Difficulty in detecting early stages of melanoma through images, as they may not show visible changes from normal skin.
Karuppusamy [31]	One advantage is its potential to improve the accuracy and speed of detecting brain tumors using a combination of manta ray foraging and optimization techniques.	Only applicable to brain tumor detection and is not effective for the detection of other types of tumors or diseases.
Ejaz et al. [32]	By combining two segmentation methods, this approach can provide more accurate tumor identification while also quantifying uncertainty.	It may not accurately identify certain tumor types due to variations in tumor characteristics and imaging quality.
Liu et al. [33]	An efficient, time-saving optimization approach that improves segmentation accuracy for better clinical decision-making.	Lack of applicability to other types of image segmentation due to focus on breast cancer images.
Abdel-Gawad et al. [34]	The optimized edge detection technique results in more accurate and reliable tumor detection in MRI scans.	Limited to detecting brain tumors in MR images, it may not accurately detect tumors in other imaging modalities.

Sheela and Suganthi [35]	Improved accuracy in identifying and delineating brain tumors for more effective diagnosis and treatment planning.	The requirement for manual selection of the seed point in region growing can lead to errors and inconsistencies.

- **MS:** Manual Segmentation
- **SAS:** Semi-Automatic Segmentation
- **TBS:** Threshold-Based Segmentation
- **RGS:** Region Growing Segmentation
- **ACS:** Active Contour Segmentation
- **MLS:** Machine Learning Segmentation
- **ABS:** Atlas-Based Segmentation
- **DLS:** Deep Learning Segmentation.

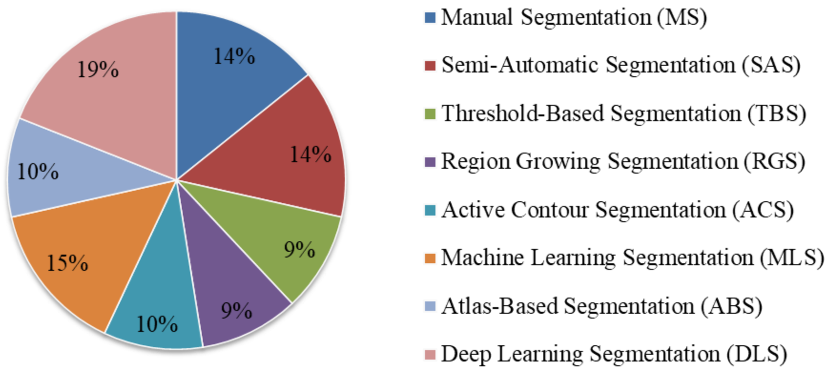

Figure 5: Results obtained by the different types of segmentation techniques

2.2. Tumor Classification

Skin cancer is one of the most prevalent forms of cancer, and early detection is crucial for successful treatment, according to Monika et al. [36]. Automated methods for identifying and categorizing skin cancer will be developed using machine learning technology. Algorithms that scan digital photos of skin lesions are crucial for early detection, as there is currently no reliable, efficient diagnostic method. Advanced image processing methods and machine learning algorithms are used in alternative methods for MRI-based tumor identification and classification. Amin et al. [37] claim that this technique for categorizing and identifying various types of brain tumors using features gleaned from MRI images will enhance the assessment and selection of therapy for individuals with such tumors. According to Madhuri et al. [39] and associates, brain tumors are aberrant growths in the brain that, if untreated, can have major repercussions. MRI scans must usually be analyzed by humans using traditional procedures, which makes diagnosis time-consuming and prone to serious human error. Machine learning algorithms (MLAs) have been developed to accurately diagnose brain cancers and automatically extract information from brain MRI images. A substantial amount of MRI data is used to train MLA. The recently proposed approach combines multi-core SVM and rough K-means for MRI images. Although these two methods have been used independently in the past, combining them yields results that exceed those of either method used separately. The techniques outlined here can help your doctor diagnose brain tumors early on. Deep learning is an artificial intelligence method that learns from digital images and trains computers to recognize specific characteristics and patterns within the data, according to a study by Raut et al. [41].

The researchers conclude that deep learning methods enable the creation of data-rich algorithms capable of precisely distinguishing between healthy and abnormal brain cells, such as tumor cells. In the context of medical image processing, Jia and Chen [42] emphasize the significance of precise evaluation and categorization of brain cancers based on MRI images. These objectives can be met by convolutional neural networks (CNNs) and other deep learning methods. The accuracy and speed of brain tumor diagnosis and classification can be increased by the sophisticated algorithms and processing power employed in this kind of network, as well as by the ability to rapidly recognize common patterns in images from MRI scans. As a result, these techniques can help medical professionals choose the best course of action for their patients. Thus, brain tumor identification is a crucial component of medical image processing for accurate diagnosis and treatment planning, according to Sadad et al. [43]. By leveraging multi-layer neural networks and automatic feature extraction, advanced deep learning techniques improve the accuracy of brain tumor detection and classification. This improves the ability to distinguish between different types of brain tumors and provides precise information about their location and size. Deep learning, a cutting-edge technique, has enabled the identification of brain tumors before they reach extremely large sizes. This enables clinicians to treat patients with a far better success rate by detecting malignancies at an early stage. According to many recent studies, deep learning algorithms may automate tumor identification and classification, greatly reducing human error and freeing up medical professionals' time to treat patients. These ongoing developments in deep learning are being applied to multi-classification and brain tumor detection. For instance, Hussain et al. [44] proposed a novel fusion of two distinct approaches: asymmetric-based tumor segmentation and the unified design of ACO (ant colony optimization).

According to the scientists, this unified method accurately segments and classifies tumors seen on MRI scans by combining both ACO and asymmetry. They assert that ACO improves tumor diagnosis accuracy by optimizing the segmentation of brain tumor regions. Additionally, by differentiating between abnormal and normal brain regions, asymmetry can be used to detect tumors that conventional approaches miss. Because of this combination strategy, doctors may more reliably employ MRI for early tumor identification and treatment planning. Semantic segmentation is a technique that has been developed to detect and label various regions in an image, enabling the categorization of individual regions, as reported by Hussain and Khunteta [45]. When diagnosing brain cancers, this method has been remarkably effective in identifying tumors from MRI images. The tumor must be carefully located in this stage. The GLCM (gray-level co-occurrence matrix) feature is used by the SVM (support vector machine) to classify this area. The connection between a pixel and its surrounding pixels in an image is described by GLCM features, which are texture-based. The SVM classifier may use these GLCM features to identify the tumor's location within the segmented MRI. Compared with conventional techniques, the time required to detect malignancies and treat patients is greatly reduced, enabling quicker diagnosis and improved patient care. The detection of brain tumors is described by Kaur and Oberoi [46], who also emphasize their significance in medicine. For naïve Bayesian data categorization, several classification schemes are useful. Probability theory serves as the foundation for classification. This categorization technique offers a novel, more effective, and precise strategy for identifying brain tumors. Transfer learning and data augmentation techniques are used to train deep neural networks using massive datasets.

To obtain high classification accuracy, a combination classifier (ensemble classifier) is created by combining many classifiers. The procedures outlined here are quite successful in identifying lung cancer and may eventually aid in the diagnosis and treatment of lung cancer in those who are at high risk. The capacity to identify brain cancers (found by MRI) is one of the most crucial components of medical imaging, according to Kumar et al. [50]. The suggested method helps detect brain cancers in MRI videos by combining an adaptive K-nearest neighbor classifier with a fuzzy C-means optimum clustering technique. The researchers claim that this combination increases classification reliability by accounting for data robustness and uncertainty, and doubles the likelihood of successfully detecting brain cancers via MRI. The segmentation of brain tumors in MRI images was highlighted by Khan et al. [51] as a crucial step for precise brain tumor identification and therapy. The researchers employed deep learning techniques in conjunction with K-Nearest Neighbors (KNN) and K-Means clustering algorithms to exclude brain malignancies from MRI scans. They also employed synthetic data augmentation to enhance and broaden the dataset. With the additional data, the authors were able to produce a more precise categorization. Machine learning (ML) and image processing (IP) approaches are increasingly used to assess medical imaging data for breast cancer identification, according to Jasti et al. [47]. Healthcare practitioners can more precisely identify malignant cells by utilizing machine learning-trained computer algorithms to recognize intricate patterns and characteristics in medical images. Health care professionals have been able to detect and treat more breast cancers thanks to this greater confidence, saving lives.

Chowdhary et al. [48] proposed a technique that combines a support vector machine (SVM) algorithm with an intuitive fuzzy C-means clustering method to improve the speed and accuracy of medical image segmentation and classification. Both algorithms provide more accurate and reliable findings by leveraging the inherent ambiguity and uncertainty in medical data. A fuzzy support vector machine classifies each segmented image that results from grouping chest CT images of similar patients using an intuitively defined fuzzy C-means clustering algorithm. The combined output of both algorithms helps healthcare providers manage the extremely complex, heterogeneous nature of lung cancer images. Consequently, the combination of these two algorithms will eventually increase the precision of lung cancer diagnosis and treatment by healthcare providers. Using improved deep neural networks and ensemble classifier models, Shakeel et al. [49] show a similar capacity to automate lung cancer detection using CT scans. Among the resources covered in the section on search repositories, institutional repositories, and social networking sites are digital libraries, social networking sites, and institutional repositories. Libraries connected to research institutes and databases are growing in popularity as useful resources for researchers, alongside the numerous digital libraries and repositories accessible to them. By consistently documenting their research findings and releasing them promptly, researchers may take advantage of the opportunities offered by these two types of repositories to optimize their exposure and impact. Researchers may publish their work in multimedia formats using both types of repositories, and they can examine and download files prepared for publication—often with no assistance.

Even as both types of storage are still widely used, new digital libraries and repositories have emerged from the Internet's explosive growth. Researchers refer to this new kind of storage as a "virtual library." Virtual libraries provide writers with unrestricted access to their "bookshelf," rather than sharing only the experiences of original readers. The number of books each author or publisher can print is almost unlimited, and they can expand their publications indefinitely. Long regarded as a serious public health issue, lung cancer has drawn special attention. Numerous studies on lung cancer's risk factors, stages, therapies, and prevention have been carried out, and a substantial quantity of data about the disease's occurrence in the US has been produced and published. Lung cancer is often identified and treated at an early stage. A limited percentage of individuals will be diagnosed with stage 4 lung cancer and get treatment if proper follow-up care is not provided. Numerous organizations have created recommendations to assist healthcare providers in monitoring and diagnosing lung cancer patients early due to the seriousness of the disease's danger to public health. Fireflies can help optimize segmentation and classification parameters by mimicking their blinking patterns, thereby enhancing the efficiency and precision of lung cancer detection and staging. By detecting, staging, and treating lung cancer quickly and effectively, this combination of technologies improves patient survival through early and precise therapy. According to Saraswat et al. [38], breast cancer is among the most prevalent malignancies in women, and effective treatment of this illness depends on early identification.

Using computer vision technologies, breast cancer can be detected early. Professionals can identify and treat patients more rapidly and precisely thanks to automated analytical techniques. Gu et al. [54] state that the diagnosis of lung cancer depends on the rapid and precise detection, segmentation, and classification of pulmonary nodules. It is crucial to understand how to use these technologies to identify and treat lung cancer promptly. Therefore, the accuracy of these techniques determines a doctor's capacity to diagnose a patient and suggest a course of therapy. Deep learning algorithms and sophisticated imaging technologies can greatly increase the speed and accuracy of cancer detection, improving patient outcomes. According to Patel et al. [55], applying artificial intelligence methods to cancer diagnosis requires sophisticated machine learning algorithms to analyze large volumes of medical data and identify patterns and relationships. Artificial intelligence algorithms can successfully identify and diagnose cancer at an early stage by analyzing vast volumes of medical data, improving patients' chances of receiving a successful course of therapy. AI technology has improved typing speeds and streamlines the entire diagnostic process, reducing errors and diagnostic time. Additionally, Murugesan et al. [56] presented a hybrid deep learning model as a sophisticated method for precisely segmenting and categorizing lung lesions using CT images. This hybrid model offers a more precise and effective way to identify pulmonary nodules by combining the strengths and weaknesses of conventional machine learning and deep learning.

Table 6: Comprehensive analysis (Tumor Classification)

Author	TG	TS	MC	BC	HC	RC	CC
Monika et al. [36]	✓						
Amin et al. [37]	✓						
Saraswat et al. [38]	✓						
Madhuri et al. [39]		✓					
Kanaujia et al. [40]		✓					
Raut et al. [41]		✓					
Jia and Chen [42]			✓				
Sadad et al. [43]			✓				
Hussain et al. [44]				✓			
Hussain and Khunteta [45]				✓			
Kaur and Oberoi [46]					✓		
Jasti et al. [47]					✓		
Chowdhary et al. [48]						✓	
Shakeel et al. [49]						✓	
Kumar et al. [50]						✓	
Khan et al. [51]							✓
Yadav and Yadav [52]							✓
Lavanya et al. [53]							✓
Gu et al. [54]							✓
Patel et al. [55]							✓
Murugesan et al. [56]							✓

This model aids early diagnosis and identification of lung conditions by distinguishing among types of lung nodules. Comprehensive analysis (Tumor Classification) is presented in Table 6, and Comprehensive Analysis of Classification with Limitations is presented in Table 7.

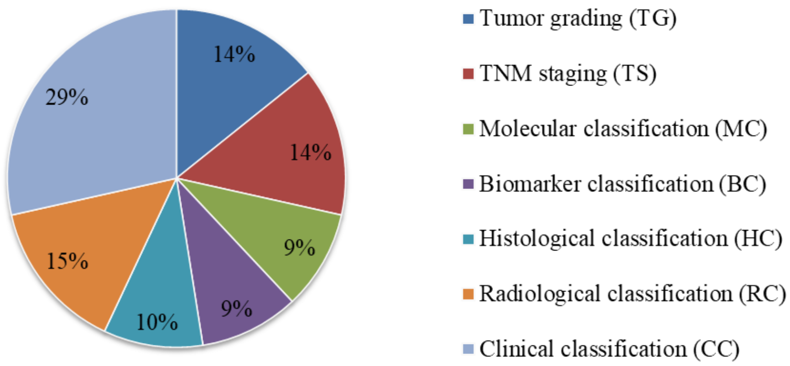

Figure 6: Results obtained by the different types of classification techniques

Table 6 lists the various tumor classification systems and their designations: TG = Tumor Grading; TS = Tumor Node Metastasis (TNM) Staging; MC = Molecular Classification; BC = Biomarker Classification; HC = Histological Classification; RC = Radiological Classification; CC = Clinical Classification. Examples of results from each classification method are shown in Figure 6.

Table 7: Classification with limitations: A comprehensive analysis

Author	Advantage	Limitation
Monika et al. [36]	Detecting skin cancer at an early stage can increase survival rates and improve overall patient outcomes.	Difficulty in detecting early stages of skin cancer and relying on existing datasets for training the models.
Amin et al. [37]	increased precision in tumor identification and categorization, resulting in patient treatment regimens that are more successful.	Limited to only detecting and classifying brain tumors, it cannot detect other abnormalities or diseases.
Saraswat et al. [38]	Improved accuracy and efficiency in identifying brain cancers, perhaps assisting in early identification and treatment.	Limited accuracy due to a lack of diversity in training data.
Madhuri et al. [39]	increased precision in detecting the presence and type of brain tumors, leading to more successful therapeutic approaches.	This approach may not accurately detect rare or uncommon types of brain tumors due to limited training data.
Kanaujia et al. [40]	Compared to conventional techniques, deep learning enables more precise, automated identification and segmentation of brain tumors.	Predictions for new data may be skewed or erroneous, depending heavily on the quant ity and quality of training data utilized.
Raut et al. [41]	Brain cancers can be identified and classified more precisely and automatically by combining deep learning with MRI.	Difficulty in generalization due to limited training data and variation in MRI machines and image quality.
Jia and Chen [42]	enhanced precision and effectiveness in identifying and categorizing brain cancers, enabling more successful treatment strategies.	Requires a large dataset and accurate annotations, which may be time-consuming and costly to produce.
Sadad et al. [43]	enhanced patient diagnosis and treatment planning as a result of more precise and effective brain tumor segmentation and categorization.	Limited to brain tumor segmentation and classification; may not generalize well to other medical imaging tasks.
Hussain et al. [44]	Accurately identifies the boundaries of tumor tissue, allowing for targeted and precise treatment planning.	The method may not work effectively if the images have inconsistent contrast and resolution.
Hussain and Khunteta [45]	The ability to provide reliable, accurate detection of brain tumors with minimal false positives, thanks to its efficient classification method.	Assuming independence of features, which may not necessarily hold for complex and correlated tumor data.

Kaur and Oberoi [46]	Improved accuracy and efficiency in detecting and diagnosing breast cancer, leading to earlier detection and potentially better treatment outcomes.	Limited by the quality and quantity of available medical images and the difficulty in obtaining representative datasets.
Jasti et al. [47]	It can effectively detect and differentiate subtle abnormalities in medical images, enabling more accurate diagnoses and treatment plans.	Requires precise, specific input parameters that may vary across medical image datasets.
Chowdhary et al. [48]	Improved accuracy and efficiency in identifying lung cancer tumors, leading to earlier detection and a greater likelihood of successful treatment.	Limited ability to detect specific types and stages of lung cancer, potentially resulting in false negatives or incorrect diagnoses.
Shakeel et al. [49]	More precise and reliable identification of brain tumors leads to better treatment results and enhanced patient care.	It may not generalize well to new data due to overfitting from using both a clustering and a classification algorithm.
Kumar et al. [50]	It can improve the accuracy of brain tumor classification by combining standard clustering methods with modern deep learning techniques.	Using synthetic data may not accurately reflect real brain tumor images, resulting in lower classification accuracy.
Khan et al. [51]	Improved accuracy and speed of brain tumor identification and classification compared to standard MRI approaches.	Dependency on high-quality MRI images, as the accuracy of the classification results heavily relies on the quality of the input images.
Yadav and Yadav [52]	increased precision in identifying and categorizing lung nodules, resulting in earlier identification and more successful treatment.	Dependency on accurate segmentation of lung nodules and potential for misclassification of nodules due to variability in size, shape, and intensity.
Lavanya et al. [53]	It is relatively simple and cost-effective compared to using more advanced AI technologies.	Difficulty in dealing with variations in breast images, such as size, shape, and density.
Gu et al. [54]	More precise and efficient detection, segmentation, and categorization of lung nodules, leading to improved diagnostic and treatment results.	Possible limitation: Lack of generalizability to real-world clinical settings due to reliance on specific data sets and algorithms.
Patel et al. [55]	Earlier detection and timely intervention can increase survival rates and improve patient outcomes.	Requires large training datasets, which might not be readily available or may be expensive to obtain.
Murugesan et al. [56]	Improved accuracy and precision in identifying and categorizing lung nodules for better diagnosis and treatment planning.	Lack of generalizability, high computational requirements, and reliance on accurate and large training datasets.

3. Analytical Discussion

The processes of segmentation and classification of tumor images are critical steps in medical imaging that help physicians both identify and define tumors. In tumor segmentation, advanced algorithms are used to identify and segment the abnormal tumor area from the surrounding normal tissue. Thus, tumour segmentation is an important process. It can be used to detect, diagnose, and plan treatment for all types of cancer, enabling doctors to offer patients more accurate and effective treatment options. In addition, tumor classification provides additional information about tumor characteristics, allowing clinicians to assess tumor severity and type more accurately. The combined process of tumor segmentation and classification enables clinicians to make more informed decisions, potentially leading to better patient outcomes and improved oncology treatments. Despite the importance and necessity of tumor segmentation and classification, achieving them is often difficult due to the complexity of the algorithms required. This problem is further exacerbated by the reliance on high-resolution medical images for reliable results. Therefore, future research and advances in these areas are of paramount importance to enhance the accuracy and efficiency of tumor segmentation and classification, thereby improving tumor diagnosis and treatment.

3.1. Purpose of the Study

Medical imaging analysis uses both tumor segmentation and classification to identify and locate tumor(s) correctly in the body. Tumor segmentation involves creating a tumor boundary and labeling the tissue regions around the tumor as either benign or malignant, which helps clinicians diagnose and monitor tumor progression, and develop treatment plans and decisions. An important reason to use both tumor segmentation and classification, rather than have a clinician manually measure or visually inspect images, is to achieve the most accurate and consistent tumor assessment, regardless of the individual or the test method used. Instead, by applying computer algorithms to automate assessments of tumor size, shape, and location, the computer can consistently produce reliable and objective measurements. Additionally, tumor segmenting and classification are also used for treatment planning purposes – knowledge of where (the location) and how big (size) and `what shape` (the type of shape), allows for optimization of the radiation dose, and design of the target volume for a radiological procedure.

Tumors undergoing surgical treatment may affect how surgery is performed if they are correctly located, as precise location helps develop the surgical approach and reduces the risk of injury to adjacent normal tissues. By partitioning and labelling tumours at the first error in image transfer during treatment, changes in tumour size and position can be evaluated, treatment response determined, and treatment plan changes or other options considered. Tumours produce the cells which can exhibit unique characteristics termed as pseudo-biomarkers to support clinical prognosis, enabling the physician to evaluate and develop treatment plans accordingly; and, similarly, the ability to predict the patient's outcome allows the development of clinical trials and research about new and innovative therapies through the collection, measurement, and analysis of large amounts of images taken during treatment of tumour cells.

Tumor segmentation and classification are intended tools for quantifying tumor size, assisting with treatment, tracking disease progression, predicting patient outcomes, and aiding clinical and research studies for both the physician and the patient, by providing an objective, precise measurement of tumors and enabling more accurate evaluations, thereby reducing time spent on evaluation and enabling the physician to achieve a higher level of accuracy and control over the quality of care delivered to their patients.

3.2. Impacts of the Study

- **Advanced Imaging Techniques:** Utilizing advanced imaging techniques for tumor segmentation and classification provides a reliable and comprehensive view of the tumor and its associated architecture.
- **Preprocessing of Images:** Before segmentation and classification, the quality and contrast of the images are enhanced via noise reduction, rescaling, and standardization to improve accuracy in tumor segmentation and classification.
- **Automated Algorithms for Segmentation:** Automated algorithms are frequently used to accurately identify and delineate tumor borders for segmentation and classification. Mathematical/statistical-based models based on image analysis will significantly improve the accuracy and speed of segmentation and classification.
- **Standardized Storage and Data for Automated Segmentation Algorithms:** A large volume of data generated by advanced imaging techniques requires a standardized storage mechanism to provide a consistent/reproducible set of results across multiple imaging methods/systematic comparisons. The standardization must include the following categories: image format, image metadata, and image parameters. Some of these elements will affect the accuracy of the information analyzed and compared across experimental sets/studies using different imaging technologies.
- **Image Feature Extraction:** For Tumor Segmentation/Classification, feature extraction provides image characteristics describing the shape, size, texture, and intensity of the image. These features represent a group of important/required "biomarkers" used in the identification and classification of Tumors. Collaboratively, these same features will be instrumental to determining the accuracy of Tumor Classifications.
- The use of Machine Learning and Artificial Intelligence helps facilitate automated, optimized segmentation and classification of tumors while minimizing human error and variability. These technologies continually learn from new data and improve their accuracy.
- High-performance computing and advanced processors provide the computational power and time required to accurately segment and classify tumors from large volumes of imaging data.
- Combining imaging data with clinical data, i.e., patient history and treatment regimens, may increase the accuracy of tumor segmentation and classification. Properly managing and integrating imaging data with clinical data enables comprehensive tumor analysis.
- **Clinical Decision Support:** Correctly segmenting and classifying tumors can materially influence clinical decision-making, including treatment planning and the evaluation of treatment response. Accurate tumor segmentation and classification can provide information on tumors to assist in determining tumor type, size, and location; therefore, the information they provide will play a major role in your decision-making process regarding which treatment to pursue and how you will track the success of your treatment.
- **Research and Development:** Tumor segmentation and classification methods are continually advancing through ongoing research and development to improve efficiency and accuracy. As such, this research can also have a major impact on the design and introduction of new imaging technologies and treatment approaches for different tumor types.

3.3. Identified Issues

- **Segmentation Accuracy:** The major challenge in tumor segmentation is incorrect tumor identification, driven by the diverse nature of tumors and surrounding tissues, noise in imaging techniques, and differences between observers.
- **Insufficient Contrast:** Tumor tissues can be easily confused with non-tumor tissues on medical imaging, making it difficult for an automated tumor detection system to reliably distinguish tumor from non-tumor tissues.
- **Shape and Size Variance:** Tumor morphologies can differ substantially in size and shape, posing challenges for automated tumor-segmentation systems that aim to generate accurate results.
- **Multiple Modalities:** Tumors are often evaluated with multiple imaging modalities (e.g., MRI, CT, PET). However, each imaging technique captures different information, so combining and integrating this information into a single automated tumor segmentation and classification system can be complex and challenging.
- **Subregion Segmentation:** Tumors can consist of subregions with distinct characteristics and behaviors. To accurately segment and classify these tumor subregions, advanced techniques will need to be developed and employed by automated tumor detection systems.
- Tumors often overlap with other anatomic structures, making it challenging to segment or label them correctly.
- Deep learning algorithms currently used for tumor segmentation and classification require large annotated datasets for training. Acquiring a large enough annotated dataset of tumor images is both time-consuming and expensive.
- Expert radiologists manually annotate tumor images used to train medical imaging algorithms; however, there are issues with interoperator agreement and the time required to perform this task.
- Due to differences in imaging devices/protocols, variations in image quality and resolution occur. As a result, developing a universal algorithm for segmenting and classifying tumors is difficult.
- **Computing Capacity:** Computational power is often required to run algorithms for tumor segmentation and classification, and this process can take a long time due to the large volumes of data involved in three-dimensional imaging. Both the high cost of these algorithms and the relatively long time required to complete a process have limited their availability for use in clinical settings.
- **Ability to Generalize to New Tumors:** Most algorithms for tumor segmentation and classification have been developed for specific tumor types. Generalising these types of algorithms to accommodate other tumor types will either require retraining the algorithm or fine-tuning its performance.
- **The Requirement for Real-Time Applications:** In some medical scenarios, it is necessary to segment and classify tumors in real time (e.g., during surgical procedures and radiation treatments). Performing these tasks accurately in real time presents two challenges for the algorithm: speed and accuracy.

4. Proposed Model

The purpose of tumor segmentation and classification is to effectively distinguish and characterize tumors within medical imaging devices using computers. This approach completes the work in several phases. Preprocessing is the initial stage in improving the quality of the original image. After this, a segmentation approach is utilized to split the area containing the tumor(s) from the remainder of the image. Then, characteristics relating to the tumor(s), such as its shape, texture, or intensity, will be gathered through a classification method that uses machine learning models that have been trained with numerous tumor examples with known classifications. Finally, the resultant visual will aid physicians in improving comprehension and evaluation of the tumor(s). Therefore, the efficiency and precision of tumor segmentation and classification have been significantly improved through image processing and machine learning.

4.1. Tumor Segmentation

The voxel obtained from an MRI/CT scan is called the raw scan image. These three-dimensional volumes of the brain comprise different brain regions (gray matter, white matter, cerebrospinal fluid). Acquiring these voxels is only the first step in processing the images. Before any analysis or segmentation can occur, a series of preprocessing steps must be performed to achieve higher quality and accuracy. The most common types of pre-processing performed include: removing intensity variations or bias fields produced by the scanner/equipment or tissue properties through bias field correction; filtering noise using a variety of filtering methods such as Gaussian or median filtering resulting in reduced noise and an improved signal to noise ratio; removing any external non-brain tissue from the image volume through skull stripping/clipping; and ultimately allowing subsequent analysis or segmentation of the brain tissues to occur without uncertainty caused by the presence of exterior non-brain tissues. Once the preprocessing steps are complete, the images are further processed to extract features for tissue segmentation. The tumor segmentation process is shown in Figure 7.

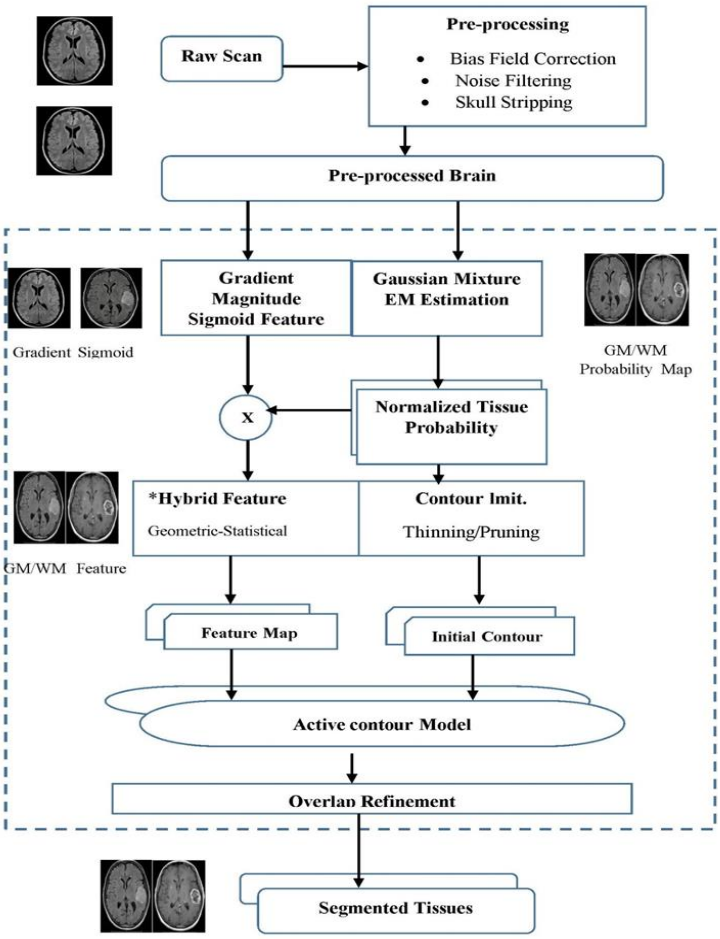

Figure 7: Proposed tumor segmentation

One commonly used feature is the gradient sigmoid, which calculates the gradient magnitude at each voxel (3D pixel) and applies a sigmoid function to convert it into a probabilistic map. The gradient magnitude sigmoid feature is then used to estimate the Gaussian Mixture EM (expectation-maximization) parameters for each tissue type, yielding a GM/WM (gray matter/white matter) probability map. Let's consider the pixel, boundary, and region equations 1:

$$p\left(\varphi_*\middle|B_1,\ldots,B_J\right) \quad (1)$$

Where P indicates the pixels, B_1 is the initial boundary, B_J is the edge of the boundary, and φ is the region of the image:

$$\varphi_j = \beta + \varepsilon_j, \varepsilon_j \sim \eta(0,\tau^2), j = *,1,\ldots,J \quad (2)$$

Where β is the parameter controlling the smoothness of the segmented image, Ɛ is the input or original image, Ƞ is a set of neighboring pixels, and τ is a threshold value for determining the convergence of the iterative algorithm:

$$I_{k=1}, I_k, k = 1,\ldots,K, I_0 = 0 \quad (3)$$

This map assigns a probability to each voxel, indicating the likelihood that it belongs to a particular tissue type:

$$r_{jk}\middle|\lambda_{jk} \sim \text{Poisson}\left(\lambda_{jk}E_{jk}\right), j = 1,\ldots,J; k = 1,\ldots,K \quad (4)$$

Normalized tissue probability maps are created by dividing the GM/WM probability map by the sum of all tissue probabilities:

$$\varphi_{*k}, \varphi_{1k},\ldots,\varphi_{Jk}|\beta_k,\tau_k \sim \eta(\beta_k,\tau_k^2), k = 1,\ldots,K \quad (5)$$

This results in a map where the values at each voxel add up to 1. This stage is vital for obtaining images that reflect the probability of various tissues:

$$\beta_k \sim \eta\left(m_{\beta k}, s_{\beta k}^2\right), k = 1, \ldots, k \quad (6)$$

$$\beta_k \sim \eta(\mu_k, \sigma_k^2), k = 1, \ldots, K \quad (7)$$

$$\beta_k = \eta_{k-1} + \rho_{k-1}, k = 2, \ldots, K \quad (8)$$

The subsequent phase uses the adder (X) to superimpose the GM/WM feature onto the normalised tissue probability map, creating a more reliable and accurate depiction of the tissues:

$$\tau_k \sim \text{half} - \text{normal}(s_{\tau k}) \quad (9)$$

The GM/WM feature also creates a hybrid feature that includes both statistical and geometric features:

$$p\left(\varphi_{*_1}, \ldots, \varphi_{*_K} \middle| r, E\right) \quad (10)$$

With this hybrid feature, it is possible to examine not only the similarity of the voxelised images but also their respective intensities and textures:

$$ESS_{ELIR} = E_\varphi \left\{\frac{i(p(\varphi))}{i_F(\varphi)}\right\} \quad (11)$$

To optimise the segmentation process, a thinning and pruning approach has been employed to limit the contour to exclude small isolated areas that may not be part of the segmented tissues:

$$r_{C*k} | \lambda_{C*k} \sim \text{Poisson}(\lambda_{*k} E_{C*k}), r_{T*k} | \lambda_{T*k} \sim \text{Poisson}\left(\alpha \lambda_{*_k} E_{T*k}\right) \quad (12)$$

Upon creating the feature map, all the previously discussed feature types have now been identified, including the gradient sigmoid, Gaussian Mixture Expectation-Maximization algorithm, GM/WM, and the hybrid feature set:

$$\varphi_{*k} \sim \eta\left(m_{\varphi k}, s_{\varphi k}^2\right) \quad (13)$$

This comprehensive feature map provides the most thorough representation of the brain's anatomy and the tissues that comprise it. Thus, an initial contour will be drawn to provide an approximation to form contour boundaries within the images:

$$E_{jk} = \frac{L_{jk}}{2} \times \left(r_{jk} + c_{jk}\right) + L_{jk} \times \left(n_{jk} - r_{jk} - c_{jk}\right); j = 1, \ldots, 10, k = 1, \ldots, 12 \quad (14)$$

The initial contour of the structure is refined using an active contour model that adjusts the contour based on the image's intensity and gradient information, as described in the background of this paper. The refinement process will also include an overlap-refinement step to ensure that all tissues are properly segmented, with no gaps or overlaps between them. The outcome of the refinement process will be to place represented tissue classes, such as GM, WM, and CSF, into categories for subsequent analysis and quantification of brain tissues:

$$\log\left(\delta(\hat{t}_{i+1})\right) - \log\left(\delta(\hat{t}_i)\right) = 1 - \frac{d_i}{n_i} \quad (15)$$

Using complex Pre-processing and Feature Extraction methods, segmentation of various types of Brain Tissues on the original Scan Images can be performed quickly and accurately by automating the process. This is essential in many neuroimaging studies.

4.2. Tumor Classification

A brain imaging technique that doesn't require surgery is magnetic resonance imaging (MRI). MRI employs powerful magnetic fields and radio frequency radiation to obtain very detailed pictures of your brain. After the image is taken, multiple functional steps are required to obtain useful data from it, and one of those steps is Pre-processing. In pre-processing, Researchers remove any unwanted materials or noise from the Scan Image, including, but not limited to, motion artefacts and magnetic field inhomogeneities:

$$\omega_k = \sum_{i \in c_k} \rho_i \, , \mu_k = \sum_{i \in c_k} i \, . \frac{\rho_i}{\omega_k} \tag{16}$$

An accurate preprocessing stage is vital to ensure that all future implementations deliver accurate and dependable results. Subsequently, a Tetrolet transform is performed on the pre-processed image:

$$\rho_i = \frac{\sigma_i}{\eta}, \rho_i \geq 0, \sum_{i=0}^{l-1} \rho_i = 1 \tag{17}$$

$$k \in \{0,1, \ldots . K-1\} \tag{18}$$

The Tetrolet Transform Decomposes the Image into smaller sub-bands, called tetramino sub-bands:

$$\mu_T = \sum_{i=0}^{L-1} i. \rho_i = \sum_{k=0}^{K-1} \mu_k . \omega_k \tag{19}$$

$$\propto_B^2 = \sum_{k=0}^{K-1} \omega_k . (\mu_k - \mu_T)^2 \tag{20}$$

These tetramino sub-bands, or smaller sub-bands, when combined, produce a more efficient way of representing the Original Image and all its frequency components as individual sub-bands of the tetramino. The Process of tumour classification is shown in Figure 8.

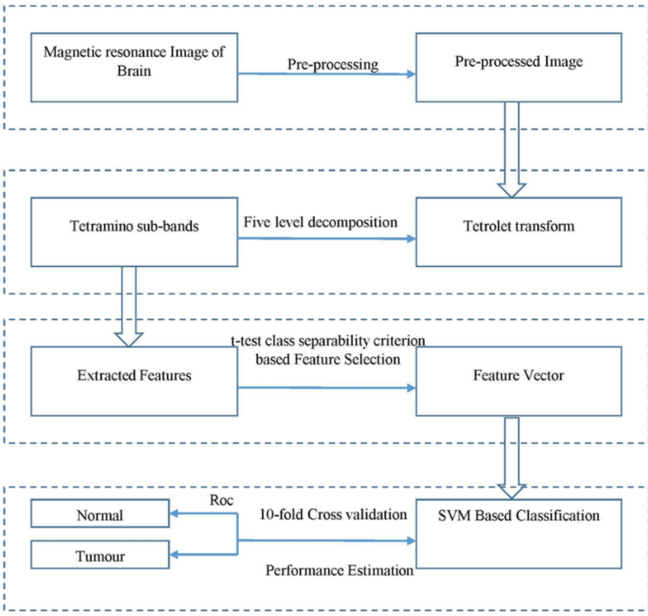

Figure 8: Proposed tumor classification

The Tetrolet transform is applied to pre-processed images at 5 Different Decomposition Levels. At each level, the Frequency Components are decomposed into increasingly smaller sub-bands, allowing for a comprehensive Analysis of the Original Image:

$$\{t_0^*, t_1^*, t_2^*, \ldots, t_{k-2}^*\} = \operatorname{argmax}_{0 \leq t_0 < \ldots < t_{k-2} < L-1} \{\propto_B^2 (t_0, t_1, \ldots, t_{k-2})\} \tag{21}$$

$$LBP_{P,R} = \sum_{i=0}^{P-1} s(g_i - g_c) 2^i \tag{22}$$

After Each Level of Decomposition, Extracted Features are compared to features extracted from deconstructed Images. Not only do the extracted features provide specific characteristics of the Image, but they also provide important information about the Underlying Tissues and Structures in Relation to Detecting Tumours. To Select the Best Feature Subsets, the T-Test is Utilised:

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{23}$$

$$|G(i,j)| = \sqrt{\left(G_x(i,j)\right)^2 + \left(G_y(i,j)\right)^2} \tag{24}$$

This statistical analysis (test) examines how different standard/tumor class features differ between the two and, therefore, selects only those with a high level of repeatability to perform the analysis. Once the high-repeatability features have been selected, they are combined into a feature vector that describes the image's distinguishing characteristics. This feature vector is then used to train a Support Vector Machine (SVM) classifier. The '10-fold cross-validation strategy' is used to develop the SVM classification; all the data is split into 10 subsets: each is used as a test set, and the remaining subsets are used to train the model. This approach maximizes training on all available data while ensuring the final model can accurately classify new data. The classification model's accuracy is assessed using Receiver Operating Characteristic (ROC) curves. ROC curves provide a visual representation of the model's performance at different threshold values during training and enable evaluation of the model's positive rate and its ability to classify negative or normal cases. The dataset pictures have been reliably categorized as "normal" or "tumor" using ROC curves and the trained model; tumor identification in MRI images can thus be performed repeatedly with an efficient, automated process.

4.3. Proposed Algorithm

Tumor segmentation algorithms provide an automated means of detecting and outlining tumors in medical images (MRIs, CT scans). The algorithms fundamentally employ pattern recognition techniques and machine learning. By this, they can accurately locate tumor tissue and distinctly separate it from healthy tissue; for example, algorithms may use shape, intensity, and texture of the tumor to segment it from surrounding normal tissue. Tumor classification algorithms, on the other hand, take the segmented tumor and further assess its characteristics, including type, size, and stage of development. The algorithms that classify tumors generally employ a combination of medical knowledge and computer vision techniques to extract information from tumors that can be correlated with a range of features, and then classify them into one or more categories, including malignant, benign, aggressive, etc. Classification algorithms may help determine tumor aggressiveness and formulate an appropriate treatment plan. Tumor segmentation and classification algorithms work together to provide a thorough analysis of a tumor, helping ensure an accurate diagnosis and enabling appropriate treatment.

4.3.1. Tumor Segmentation

The input to the computer simulation is a collection of MRI scans. MRI scans are used in medicine and healthcare; they enable the diagnosis and monitoring of many medical conditions. MRI scans allow for detailed viewing of the inside structures of our bodies, including determining where any abnormality is located, how extensive it is, and how far it has progressed. After completing the scan, the recorded data are processed using the scan software's user interface. It uses the MRI Input function to store the scanned MRI images in computer memory, converting them to standard digital image formats for later steps. The exp development process takes the converted metameric scans and increases their clarity, allowing better differentiation between healthy tissue and any abnormalities. After this step, the exp scan images will serve as input to a program that creates finite element models. The FES_IND(N) program creates finite element nodes (FENs) based on user-provided input and exp images stored in memory. The following code demonstrates an algorithm created specifically for the stated purposes.

Algorithm 1: Tumor Segmentation	
Input: MRI Images;	
Output: SEGMENT_Images;	
//Initialization	
Step 1.	READ_IMG = MRI_Input ( );
Step.2.	IMG = exp (IMG);
Step.3.	GENERATE = FES_IND (N);
Step 4.	CURRENT_Population = 100;
Step.5.	COMPARE_Mean (IMG (IND a)) for every a = N
Step.6.	EXECUTE_Until TC ( );
Step.7.	for a = 1 to N
//Region Selection	
Step.8.	SELECT_FROM_Current.Population (N1, N2,..Nx)
//Crossover	
Step.9.	A(N1), A(N2),...,A(Nx) = Croossover.Probability (N1, N2,..Nx)

//Mutation	
Step.10.	A(N1) = MUTATE (N1);
Step.11.	A(N2) = MUTATE (N2);
Step.12.	A(Nx) = MUTATE (Nx);
//Segmentation	
Step.13.	SEGMENT_mean (IMG (N1));
Step.14.	SEGMENT_mean (IMG (N2));
Step.15.	SEGMENT_mean (IMG (Nx));
Step.16.	New_Population = New(N1), New(N2), New (Nx);
Step.17.	end for

FEN are points within the images that represent the boundaries of different regions or structures. The size and complexity determine the number of generated nodes; N. Node N is evaluated as a potential Segmentation Area in future processing. Once N has been established, a population of 100 individuals (CURRENT_Population) is generated, and the programmer compares their mean pixel values with the mean pixel value from the original image (COMPARE_Mean). This means comparing individuals provides an estimate of ROI, where potential abnormalities may occur. Selective segmentation of regions is achieved using SELECT_FROM_Current.Population(N1, N2, ... Nx) process, which provides a means of determining which individuals have produced the best mean pixel values when analysed together. The next step is to introduce 'genetic diversity' using the crossover probability function (Crossover. Probability). This function enables individuals to combine their code through genetic reproduction to create new individuals, which in turn increases the amount of variety within the population, and improvements in segmentation quality may be achieved through population variation. The MUTATE(N) function introduces new mutations to an individual's genes, generated randomly according to a probability distribution. The result is the creation of new gene variations with differing probabilities. The newly generated individuals are then used to segment MRI scans. Using the SEGMENT_mean function, this process is completed, with each individual having an associated average intensity reading to help determine which part of the scanned image to segment. Each time an average detection is obtained for each scanned individual, a new population of mutated and segmented members is added to the divided scanned population. Once the new population is accumulated, segmentation is processed again until TC is met, which may include the number of successive iterations to perform or the acceptance level.

4.3.2. Tumor Classification

First, researchers need to obtain MRI images to provide initial input to the classification algorithm and define N, the total number of individuals in the genetic population. After this step is complete, researchers will need to read the MRI images into variables. This step is crucial because researchers will use these variables in later processing stages. After reading the images into variables, the final step in this process is to create the foundation for the genetic algorithm by creating variables and setting parameters for the genetic algorithm that researchers are writing. The following list contains the functions of the proposed genetic classification algorithm.

Algorithm 2: Tumor Classification	
Input: MRI Images;	
Population Size = N;	
Output: Classification Results;	
Step 1.	Initialize the process.
Step.2.	READ_IMG = MRI_Input.IMG ( );
Step.3.	Do {
Step 4.	for a = 1 to N {
Step.5.	CALC_FITNESS (f);
Step.6.	if f > PP(B)
Step.7.	then SET_it in NEW_BEST( );
Step.8.	}
Step.9.	PP(G) = Best.fitness_CURRENT_POPULATION (G);
Step.10.	For i = 1 to N {
Step.11.	CALC_New.VELOCITY ( );
Step.12.	UPDATE_TUMOR_Position ( );
Step.13.	}

To complete this, the fitness function must be established; The range of potential solutions must be defined; and the criteria for selection and reproduction must be defined. After establishing these factors, the algorithm will enter a loop of size N, where N is the population size. Each member of the population will then have their fitness evaluated by calling the CALC_FITNESS procedure (i.e., through the criteria established in the fitness function). As each individual is evaluated, it will receive a ranking value based on its fitness score. When the fitness score for an individual exceeds the value defined in the PP(B) variable, that individual is deemed superior and is recorded as the best result in the NEW_BEST list. This evaluation of individuals continues until all individuals have been evaluated. Once all individuals in the population have been evaluated, the current best solution is updated by assigning the entire population's fitness to the variable PP(G). By using this value as a reference, the algorithm can determine how to improve upon the current best solution; thus, each successive iteration is determined. The final component of the loop includes determining new velocities for every member of the population and then repositioning each member within the searchable region. This portion of the algorithm plays an essential role, ensuring that new candidate solutions are explored and that the algorithm continuously improves as new velocities are calculated for each candidate solution. The new positions of the members within the population will be evaluated in the following iteration, and the loop will continue until a pre-set stopping condition is satisfied. The final design of the algorithm for MRI image classification involves evaluating the fitness values of population members, selecting the best-fitting individuals, and continuously updating their positions until an acceptable solution for classifying the unique MRI scans is found.

4.4. State of the Art for the Review

Tumor segmentation and classification are crucial components of medical image analysis. Tumor Classification classifies (and explains) each ROI by looking at its Assuming Anatomy, Tumor Type, the tumor's anatomical position, and its size. Segmentation separates MR images into Regions of Interest (ROI) based on their anatomy or pathology. Current State-of-the-Art tumor segmentation and classification techniques utilise manual (time-consuming, requiring human input, and highly variable between observers) and automatic (computerised, requiring less effort) approaches; each method. Automated segmentation methods are more accurate and efficient than manual segmentation methods, allowing health professionals to spend less time on tedious tasks. Region-based active contour segmentation is an automated segmentation method that uses a combination of image gradients and statistics to automatically designate a 'target' area in an image. Additionally, image segmentation can be performed using methods that minimize energy to achieve the most accurate segmentation results. Moreover, using Machine Learning (ML), images can be segmented automatically from training sets of labelled images, enabling the algorithm to learn features that allow it to discriminate between normal and abnormal tissue. Recent advancements in ML have focused on the design of Deep Learning (DL) systems for image segmentation and classification.

Large medical image libraries are used to train DL algorithms so they can learn to recognize and extract features that yield good segmentation and classification outcomes. It has been demonstrated that using DL models significantly increases segmentation speed and accuracy when compared to conventional picture segmentation techniques. Further, several researchers currently combine various imaging modalities (MRI, CT, PET) to get enhanced segmentation and classification outcomes. This multimodal method improves patient diagnosis and treatment planning by providing a broader spectrum of cancer and its features. Despite progress in Tumour Segmentation and Classification using Deep Learning Approaches, challenges persist. Many obstacles must be overcome, such as the requirement for high sample sizes for a deep learning model to train efficiently; the necessity to make up for the varying classes of data within the dataset; and the need for more generalised algorithms capable of yielding successful results across different tumour types, imaging modalities, etc. Currently, successful workflow practices for segmentation and classification have relied on a combination of manual and automated techniques, integrating elements of both to achieve the desired results. Utilising both deep learning and multimodal imaging has produced impressive results in detecting and classifying a variety of Tumour Types; however, further investigation is needed to continue enhancing the effectiveness of these approaches, as described above.

5. Conclusion

The segmentation and categorization of tumors are important elements of medical imaging analysis, particularly for improving the likelihood of detecting cancer early and providing appropriate treatment options. Tumor segmentation and classification have made significant strides in recent years, driven by advances in machine learning and greater access to high-quality medical imaging databases. The primary goal of tumor segmentation is to localize the area of interest, which can be done manually by an expert or using automated methods (e.g., thresholding, region growing, and clustering). Once the region of interest is determined, the following step is to designate the tumor from the adjacent tissue. This task has proven very challenging because the intensity and texture of the tumor and adjacent tissue can be quite similar. For this reason, recent advances have employed segmentation techniques such as active contours (AC), level sets, and deep learning-based methods (DNN). Another major hurdle in tumor segmentation is dealing with the various imaging modalities, each of which has its own distinct characteristics and noise. For example, although magnetic resonance imaging (MRI) exhibits excellent soft-tissue contrast, it can be adversely affected by artifacts such as bias field and motion blur, compared to computed tomography (CT). Thus, to generate the most accurate and detailed segmentation results, the segmentation technique must be tailored specifically to each imaging modality.

After segmenting the tumor, classification typically occurs by putting a label on segmented tumors, such as “benign” or “malignant,” etc.

Tumor classification is typically performed by extracting features that uniquely characterize the tumor using either handcrafted features (e.g., shape, texture, intensity) or innovative machine learning techniques (such as deep learning) that may directly create useful feature representations to classify segmented pictures by learning intricate and nonlinear relationships between features from raw image data. In recent years, deep learning approaches (based on convolutional neural networks, CNNs) have been shown to produce good results in tumor segmentation and classification and to learn from large amounts of data. Because CNNs simultaneously learn informative features and perform classification without requiring manual feature extraction, they have emerged as the preferred framework for both tasks, using an end-to-end training strategy. The application of transfer learning approaches has boosted the performance of CNNs trained to categorize medical images when only limited annotated medical image data is available. A CNN may be pre-trained on large benchmark datasets, such as ImageNet, and then refined on a limited set of medical images using transfer learning.

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