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An Efficient of Artificial Intelligence based Brain Tumor Diagnosis and Classification: An Advance Medical Diagnosis Approach

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Abstract

As a central regulatory system of the body, the human brain is susceptible to the abnormal proliferation of cells that may cause brain tumors and become a significant threat to health and life. The accurate classification and early identification of these tumors are critical to attaining effective treatment schemes and better prognosis of these patients. Although the traditional diagnostic methods, including biopsies and radiological (CT, PET and MRI) are still good, they have some shortcomings, such as invasive nature, subjective and interpreter's variability. As a solution to these shortcomings, machine learning (ML)-based and deep learning (DL)-based computer-aided diagnostic systems have become potent tools in automated tumor classification, detection and segmentation across different medical imaging modalities. The present review discusses the current trends of ML and DL models, focusing especially on MRI-based segmentation and classification. It compares the conventional ML systems, which include Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forests, and Extreme Learning Machines, with the contemporary DL systems, which include Convolutional Neural Networks (CNNs), ResNet, and transformer-based systems. Moreover, it discusses popular datasets, metrics of evaluation, and segmentation, starting with simple thresholding and clustering to more sophisticated DL-based architectures. The paper makes a comparative evaluation of these methodologies, research gaps and emphasizes the increasing significance of 3D modeling techniques and attention mechanisms in enhancing diagnostic performance. The results showed that DL-based methods especially CNN-based models are always better at tumor detection and segmentation than traditional ML methods and provide more reliable, efficient, and clinically useful solutions to brain tumor diagnosis.

Keywords: Brain tumors, Deep learning, medical image analysis, Machine learning, CNN, Healthcare, Brain tumor detection, Brain tumor classification.

INTRODUCTION

The human brain serves as the main control system over the whole mechanism as it regulates various physiological functions and it enables human beings to adapt to diverse environmental conditions [1]. It allows human beings to interact, to think and show their emotions. The brain consists of three major tissue types that include cerebrospinal fluid (CSF), white matter (WM), and grey matter (GM). The gray matter of the brain that comprises the neurons and the glial cells play a vital role in the regulation of neural functions. The brain has axons myelinated in the white matter that enable different parts to communicate via neural pathways. The corpus callosum is a very important part of the white matter that connects the two sides of the brain leaving them to coordinate their operations [2].The uncontrolled or excessive multiplication of brain cells is known as brain tumor. The fixed and closed shape of the skull may result in abnormal development of some parts that may interfere with normal operations of the brain. These tumors may even spread in some cases affecting other parts of the body causing further deterioration of important functions [3]. Scheduling of treatment requires the early diagnosis of cancer, which is very important in enhancing the patient outcomes [4].

When the disease has reached another location, chances of its effective treatment are reduced significantly. Good and readily available diagnostic tools may possibly save numerous lives by allowing early diagnosis. There are two primary modes through which brain tumors can be diagnosed and these include invasive and noninvasive. Biopsy studies such as the surgical tissue sampling involve microscopic analysis by the pathologists to detect the existence of cancerous cells. Biopsies are considered the gold standard in cancer diagnosis yet they have risks of surgical-related complications and longer recovery period. Non-invasive methods of diagnosis like physical examination and medical imaging are more safe. Such imaging technologies as computed tomography (CT) and magnetic resonance imaging (MRI) are common because of their speediness and accuracy. These imaging procedures are applied by radiologists to identify abnormalities and track the development of diseases and create treatment strategies. These scans can be interpreted in different ways because the quality of the diagnosis of the radiologist can be related in many cases to the experience and the ability [5].

The introduction of CAD systems has been suggested to assist radiological tests and overcome such challenges. CAD systems enhance the stability of diagnosis and efficiency because they offer automated interpretation in order to supplement human expertise. Artificial intelligence is a technique of machine learning and deep learning that is increasingly being applied to brain tissues and the detection of tumors in medical images [7]. Segmentation is another activity of this area which demands that the area of interest in an image has to be isolated so that to determine whether and where irregularities are present. The brain tumors are difficult to segment based on the MRI data because of such factors as image noise, low image contrast, blurred edges, changing intensities, and different tissue compositions. Precise identification and classification of tumors that are usually irregular in form and differing in sizes requires application of advanced computation tools. Automatic and semi-automatic segmentation tools that use AI have become more useful in this regard. Clinicians need to determine the location and extent of the tumor before they can start any form of intervention in the form of surgery, chemotherapy, or radiation.

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_1 - \bar{Y})^2} \qquad \text{Eq (1)}$$

It finds that AI-based algorithms make a big contribution to the detection and division of brain tumors and can be trusted in the modern medical diagnosis. A brain tumor can be described as an unregulated and abnormal increase of brain tissue that causes a force inside the skull that interferes with the normal functioning of the brain.

There are two broad categories of these tumors namely benign (non-cancerous) and malignant (cancerous). Brain malignant tumors are known to develop at a rapid rate destroying un-cancerous tissue and may spread to other organs in the body [8], [9], [10]. Brain tumors are further classified into four groups depending on the aggressiveness and behavior:

- **Grade 1:** These tumors are slow growing and uncommon spreaders. They are also usually linked to a better prognosis and can in most instances be virtually eliminated by surgery. An example of this grade is pilocytic astrocytoma.
- **Grade 2:** These tumors develop with the course of time and might grow and invade the nearby tissues or even evolve into the higher grades. Though they could be treated, such tumors are relatively persistent. This grade is known as oligodendroglioma.
- **Grade 3:** The growth rate of the tumors that are of Grade 3 is higher than the Grade 2 tumors, and they can also extend to the surrounding tissues. Surgical treatment is not always sufficient, and it requires further chemotherapy or radiotherapy. A case in point is the anaplastic astrocytoma.
- **Grade 4:** These are the most malignant and aggressive types of tumors and these tumors have a high propensity to proliferate and invade the blood vessels making them grow faster. Glioblastoma multiforme is a standard Grade 4 tumor [11], [12], [13].

Early detection and proper diagnosis of brain tumors are crucial towards provision of proper treatment and the survival of patients. The brain tumor detection task is extremely difficult as it is affected by the variability of tumor shape, size, location, imaging parameters, and modalities [14]. In order to overcome these hurdles, both the conventional and smart methods have been used. Traditional methods including Leksell Gamma Knife and radioactive beam therapies help to diagnose the lesions but require critical intervention of a human and are time-consuming [15]. In the detection of brain tumors, a number of medical imaging modalities have been employed and these modalities are: Computed tomography (CT), Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET).

MRI is one of them and this is a non-invasive imaging technique that employs the magnetization and microwave pulses to visualize the internal structures. Chemical Exchange Saturation Transfer (CEST) is a special MRI method that is used to image substances at sufficiently low concentrations that are too small to be seen with standard MRI contrast or can be seen with Magnetic Resonance Spectroscopy with standard resolutions. MRI patterns, which are usually used in diagnostics of brain tumors, include Fluid Attenuated Inversion Recovery (FLAIR), T1-weighted and T2-weighted.

The identification and specific detection of the regions affected by tumor is a critical and challenging task that is made difficult with the help of MRI. The human vision system is not that powerful to see the subtle differences due to the complexity of MRI data. Computer-aided diagnostic (CAD) systems are designed to aid radiologists to increase the accuracy of the diagnosis [15]. Regardless of the effectiveness of such techniques, such problems as brain necrosis make it difficult to diagnose and it is necessary to develop effective machine learning solutions.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \qquad \text{Eq (2)}$$

A solution that is proposed combines a random forest classifier and a voxel clustering algorithm to enhance the accuracy of classification [16]. The other form of semi-automatic uses an unsupervised Fuzzy C-Means (FCM) clustering algorithm to subdivide lesion volumes [17]. Also, an algorithm based upon a mixture of algorithms K-means, Fuzzy K-means, Gaussian Mixture Model (GMM) and Gaussian Hidden Markov Random Field (GHMRF) has been presented to tumor segmentation [18]. Another two-step algorithm that involved FCM was suggested to remove necrosis automatically without the need of multispectral MRI images. Although machine learning methods have proven to be effective in processing MRI images in the identification of tumors, the increased accessibility of large and difficult datasets and an increase in computational resources has increased the use of deep learning models to attain better performance.

The diagnosis of brain tumor is a memorable field of Study and implementation in the Medical field because these tumors are extremely debilitating to the health of patients. The intracranial tumors can be classified into primary and secondary, with the first occurring within the tissues of the brain and its associated types can be benign or malignant, and the latter occurring in other parts of the body and is more likely to be malignant, and about one quarter of the total number of intracranial tumors are malignant. The US has forecasted a figure of 67,440 people who are to be diagnosed with non-malignant primary brain tumors and 26,940 people are going to be diagnosed with malignant brain tumors in the year 2023. Also, secondary brain tumors are diagnosed in between 100,000-200,000 patients per year. Brain tumors have been classified as one of the most Common type of cancer, with one out of every 100 individuals being affected by it. They are very aggressive and they cause almost 100,000 deaths per year. These statistics highlight the extreme vulnerability of inaccurate and delayed diagnosis to enhance the survival rates [19, 20].

$$\mathrm{TDI} = \sqrt{(\Delta \mathrm{C})^2 + (\Delta\sigma)^2} \qquad \text{Eq (3)}$$

To conduct this survey, the articles published in the period of 2018 to 2023 have been used to identify the most recent developments in brain tumor evaluation with the help of artificial intelligence. The focus was made on the articles published in high-impact journals to guarantee the inclusion of the rigorously peer-reviewed articles, as well as, high-profile papers of major conferences to include the most recent research. Articles with less effectiveness or no benefit compared to existing approaches were filtered out in order to keep a focus on the most effective and innovative approaches. Medical imaging is essential in the help of clinicians and radiologists in diagnosing and managing patients, particularly in a procedure known as brain tumor classification (BTc). The growth in the field has been remarkable since it has been significantly boosted with advancements that have been made in machine learning. This survey will give a brief overview of the recent research on the classification of brain tumors and focus on the latest development of the transformer-based models and their efficiency and effectiveness in comparison with conventional neural network (CNNs) in medical image classification problems [21, 22].

$$\mathrm{MCC} = \frac{\mathrm{TP} * \mathrm{TN} - \mathrm{FP} * \mathrm{FN})}{\sqrt{((\mathrm{TP} + \mathrm{FP}) * (\mathrm{TP} + \mathrm{FN}) * (\mathrm{TN} + \mathrm{FP}) * (\mathrm{TN} + \mathrm{FN}))}} \qquad \text{Eq (4)}$$

The introduction part provides the format and the outline of this survey. It starts with an extensive discussion of the various previous surveys that have covered BTc and have assessed machine learning, traditional approaches, and CNNs and transformers [23, 24]. The paper at hand is aimed at continuing these studies and developing them further so that one would be able to have a comprehensive view of the topic. The brain tumor classification surveys section gives the review of the existing literature and modern research that examines the effectiveness of the different supervised machine learning algorithms utilized on BTc. It also emphasizes the development of the industry and the personal input of the authors themselves to the use of machine learning to improve the diagnostic process [23]. In line with this a comparative analysis is made to include much discussion on results achieved by machine learning-based methods versus CNN methodology.

It also compares CNN with transformer-based models, trying to establish the circumstances and parameters, in which each method proves better. The discussion aims at explaining the weaknesses and strengths of these approaches with an aim of enhancing their practical implementation in various BTc situations. Later, the paper provides an analysis of datasets that are popular in the analysis of brain tumors, synthesizing the information on the characteristics of datasets, benefits as well as drawbacks of such well-known datasets like BraTS. Such a thorough analysis should help the reader to choose the right datasets to use when conducting a future research and also to solve the most common problems in the field [26, 27]. The next section addresses the problem of the sophistication of classification errors that were detected in brain tumor datasets, and suggests possible mitigation measures. Findings of this survey can be used to guide researchers and practitioners to enhance the level of classification. In addition, the paper provides future research opportunities to enhance the academic development by defining unexplored but promising opportunities that will eventually lead to the development of brain tumor classification techniques and medical imaging diagnosis.

ELU – E- Linear Unit with 0 < a is

$$f(x) = \begin{cases} \alpha(\exp(x) - 1) & \text{for } x < 0 \\ x \text{ for} & x \geq 0 \end{cases} \quad \text{Eq (5)}$$

Brain Tumor Classification:

The human brain consists of three main components of the cerebrum, cerebellum, and brain stem. The second-largest structure is called the cerebellum; it controls motor functions that include balance, posture, walking, and the general coordination. It is situated at the back of the brain and it is directly linked to the brain stem. The cerebrum and cerebellum are both covered with deep gray matter clusters and internal white matter as well as an outer cortical layer of gray matter. The brain stem is located at the bottom of the brain and connects the brain with the spinal cord and controls the most important functions such as control over the motor activity, processing of sensations, heartbeat, respiration, and reflexes. The brain stem has three large components, which are the medulla oblongata, pons, and midbrain, in a structural manner [28, 29].

A brain tumor is known to be the unnatural growth of brain cells. Researchers classify brain tumors according to their origin (primary or secondary), anatomical distribution and pathological features, such as whether benign or malignant [30]. World Health Organization (WHO) has classified over 120 different types of brain tumors by the cell of origin and biological behavior that includes low-aggressiveness forms to very malignant. Tumor grading varies between Grade I which is the least aggressive tumors like meningiomas and pituitary tumors and Grade IV, which is a highly malignant growth. Although classification can change with respect to the type of tumor, grading is usually a measure of the speed at which the tumor advances [31].

In adults, gliomas are the most prevalently diagnosed tumors of the brain, which are further sub-categorized as low-grade gliomas (LGG) and high-grade gliomas (HGG). The WHO also classifies LGG to Grade 1-2 and HGG to Grade 3-4. A reliable diagnosis of the type of tumor is important both to plan effective treatment and to reduce the risks of diagnostic error. Table 1 gives an overview of the most common categories of brain tumors.

Table 1.
Overview of the most common categories of brain tumors [32]

Tumor Type	Description	Precision%	Recal%
Benign	Less aggressive with slow growth	94.8	90.2
Malignant	Extremely dangerous, and grows rapidly and uncontrollably.	90.3	90.7
Primary Tumor	Appears in the body of the brain itself.	90.6	89.2
Secondary Tumor	Begins in some other organ (lungs or breast) and spreads to the brain.	89.5	90.1
Grade 1	It is typically well structured with slow development.	92.5	89.8
Grade 2	Abnormal cell patterns, but grows slowly.	90.7	88.5
Grade 3	Displays greater proliferation when compared to Grade II tumors.	92.8	93.2
Grade 4	Exhibit rapid growth and high malignancy	94.3	92.7
Stage 0	Malignant but non-invasive to adjacent cells	95.6	91.2
Stage 1–3	Progressive stages of malignancy	92.5	91.1
Stage 4	Highly malignant and rapidly spreading, invading surrounding tissues	90..5	86.8

Imaging Modalities

Medical imaging processes have been used extensively over the years in the detection of abnormality in the brain and they find wide classification into structural and functional modalities. Structural imaging is mainly used to examine tumors, injuries and other neurological diseases whereas functional imaging is characterized by the evaluation of metabolic activities, lesions and patterns of brain activity in a very fine level. The most common techniques used in localization of brain tumors are computed tomography (CT) and magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT), positron emission tomography (PET), functional magnetic resonance imaging (fMRI) and ultrasound (US). Such methods aid in identifying tumor features like size, site and morphology [33].

The most notable among them has been MRI, which is not invasive, and it does not involve the use of harmful ionizing radiations. Rather, it generates detailed images of internal structures in 3D form by taking advantage of radiofrequency (RF) pulses with a strong magnetic field [34]. In the absence of any external magnetic field, the tissues in water molecules are in a natural state of equilibrium. The protons are oriented to the direction of the magnetic field, once the magnetic field is turned on. The alignment is temporarily destroyed by a high-energy RF pulse which causes the protons to spin in the other direction. The pulse is switched off and the protons get back to their aligned position, emitting RF signal. Such emitted signals are picked up by the scanner and converted into visual images [35].

$$\delta_h = 60^{\circ}\begin{cases} 0 + \frac{(\beta_g - \beta_b)}{(m_x - m_n)}, if m_x = \beta_r \\ 2 + \frac{(\beta_b - \beta_r)}{(m_x - m_n)}, if m_x = \beta_g \\ 4 + \frac{(\beta_r - \beta_g)}{(m_x - m_n)}, if m_x = \beta_b \end{cases}$$

Eq (6)

$$\delta_s = \left(\frac{m_x - m_n}{m_n}\right)$$

Eq (7)

The difference between MRI images is related to the composition of the tissues because the RF energy absorbed and released in different parts of the brain is dissimilar. An example is that the white matter (WM) has about 70 percent water, the gray matter (GM) about 80 percent and the cerebral spinal fluid (CSF) has almost 100 percent water. These differences in water content present different MRI signals as depicted in Figure 1 [36].

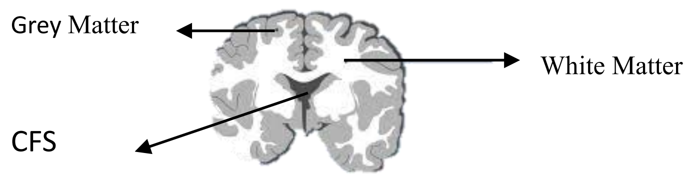

Figure 1.
MRI show Healthy brain image [gray matter (GM) , CSF and white matter (WM).

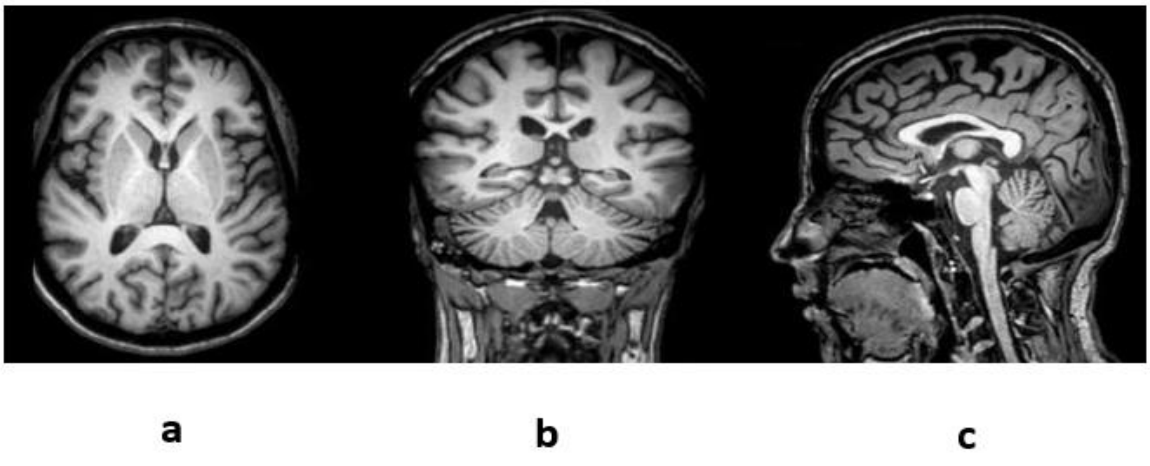

Figure 2.
Fundamental planes of MRI: (a) Image of axial (b) Image of coronal and (c) Image of sagittal

MRI scans are based on 3 main planes that are axial, coronal, and sagittal, where T2-weighted sequence, fluid-attenuated inversion recovery sequences and T1-weighted sequence are used most in imaging the brain. T1-weighted images are good in distinguishing the gray and white matter, but T2-weighted images are affected by the presence of water, and as such, show regions with water as tumors. FLAIR images help in differentiating between the CSF and pathological abnormalities. Normally, tumors will show low to medium gray intensity in T1 weighted images but bright in Image of FLAIR and T2 weighted which helps to identify them (see Figure 3) [37].

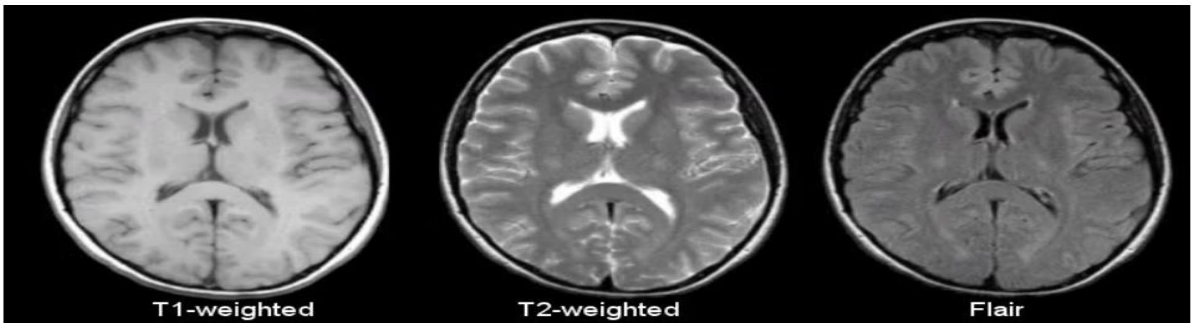

Figure 3.
MRI of brain tumor: (a) Image of T1 (b) Image of T2 (c) Image of FLAIR

Functional MRI is used to measure the changes in blood oxygenation in order to infer brain activity and map the active parts of the brain by comparing the increase in blood flow with mental activity [38]. Computed Tomography (CT) scanners are machines that scan the patients to form detailed images of cross sectional images of their bodies by rotating the X-ray beam and detectors around the patient. The CT images, obtained through the use of algorithms, provide accurate visualisation of bones and tissues that are usually complemented with contrast agents to identify abnormalities. CT is particularly useful where MRI cannot be used, as in patients with implants, where it has a low radiation-risk and is more readily available [38].

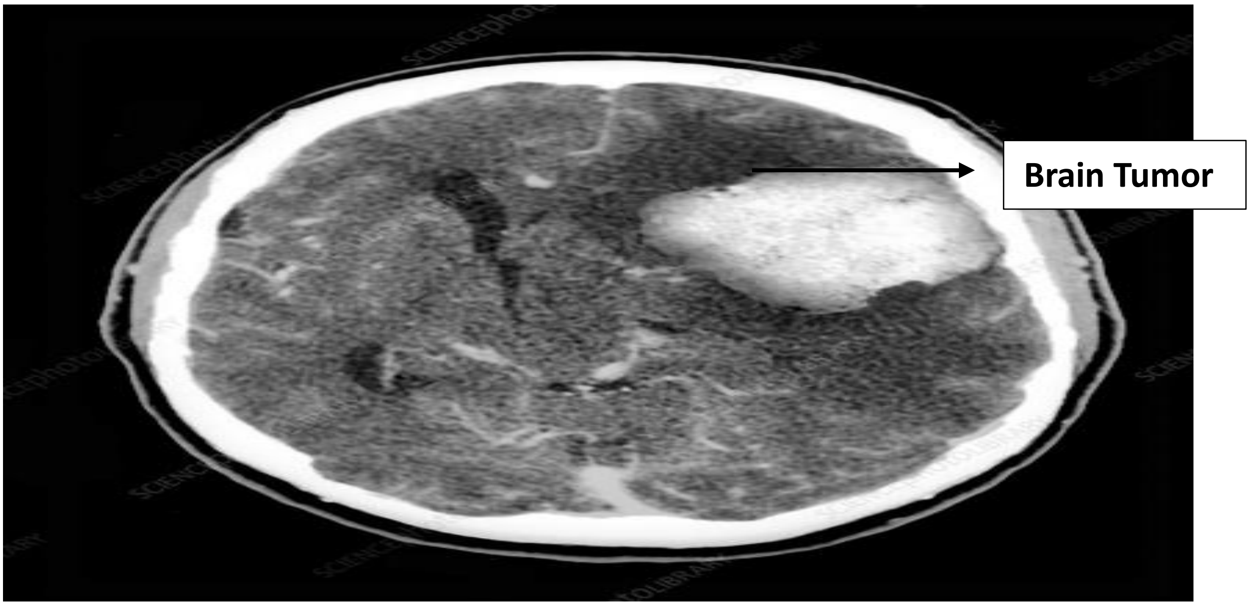

Figure 4.
CT of brain tumor

$$\delta_v = m_x(\beta_r, \beta_g \beta_b,),\ \delta_{sv} = m_n(\beta_r, \beta_g \beta_b,) \quad \text{Eq (8)}$$

$$R(t) = \sum_{i=1}^{n} FI_i(t) * \tau_{ih} + [\tau_h * r_{i-1}] \quad \text{Eq (9)}$$

Positron Emission Tomography (PET):

Pet is a nuclear imaging modality that assesses metabolic activity by tracking radioactive tracers, commonly fluorodeoxyglucose (FDG). PET scans, often combined with MRI or CT , give metabolic information aiding in evaluation of malignancies [39].

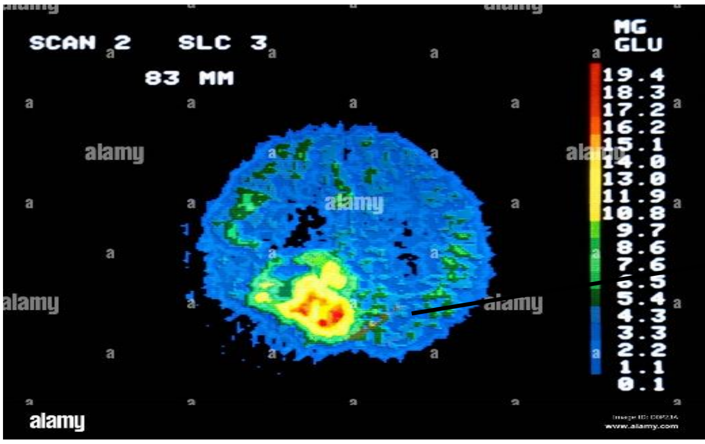

Figure 5.
PET of brain tumor

Single-Photon Emission Computed Tomography is a CT that is used to visualize blood circulation in tissues by combining CT with radiolabeled tracers to provide 3D images of the scanned with gamma-ray emission during the scanning process [40].

Ultrasound (US) is a fast and inexpensive method of imaging where high level sound waves are used to visualize soft tissues. Ultrasound is not as resolute as either MRI or CT, but is commonly utilized as preliminary diagnostic equipment and can be applied to brain tumor resections. Changes in tissue density change the echoes that are recorded, and help distinguish between solid tumors and fluid-filled cysts [41].

Tumor Delineation Methods Classification and Tumor Delineation:

Tumors of the brain continue to be one of the major causes of death in the world. Over the past several years, machine learning (ML), deep learning (DL), and computer vision algorithms started being used more frequently in computer-aided detection and diagnostic (CAD) systems as radiological and pathological images are processed. These systems are geared towards assisting radiologists in the diagnosis of diseases in different body organs such as brain. It has been indicated that AI-based classification and segmentation methods, including both ML- and DL-based models, have been quite successful in the automation of tumor detection-related tasks [42, 43]. Classification is the process of grouping data into categories as a result of having common attributes. A classifier is just a predictive model which classifies input data by identifying its characteristic features. The main purpose of a classification model is to classify the data samples into the right category. ML and DL methods are also extensively used in medical image classification, and the primary distinction between the two approaches is in how the features are extracted in the process of classification [44, 45].

$$Y(t) = \omega[\tau_{ho} * h(t)] \quad \text{Eq (10)}$$

Machine Learning:

Machine learning is an aspect of artificial intelligence that allows the systems to learn data without explicit programming. Medical imaging Post-processing Reclassifying lesions into specific groups of features inputted into the system. Mostly, machine learning algorithms can be divided into unsupervised and supervised learning. Supervised learning relies on the training of models using labeled data whereas unsupervised learning is an attempt to discover patterns and structures in unlabeled data. ML-based imaging analysis has been widely investigated in the context of brain cancer [46]. ML-based classification recognition pipeline often consists of multiple steps, such as image preprocessing, feature extraction, feature selection, and lastly classification, shown in Figure 6 [47].

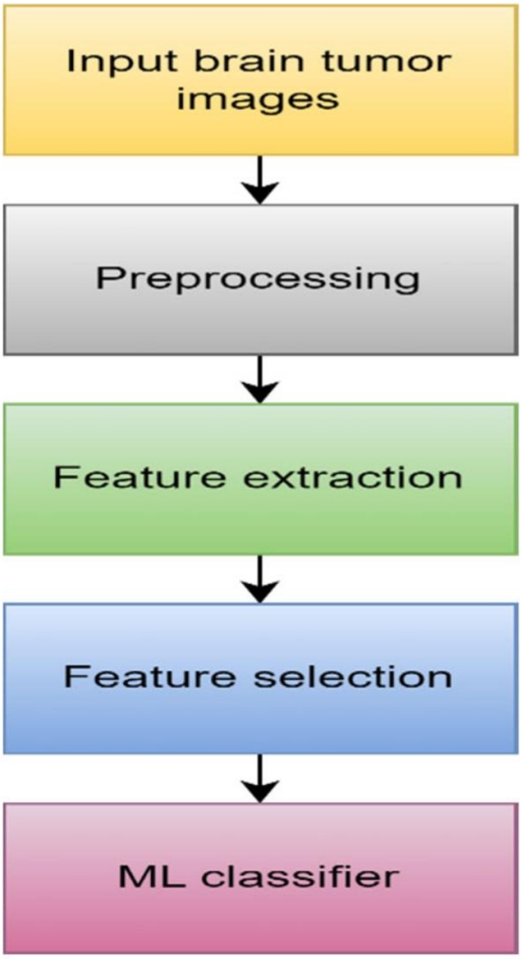

Figure 6.
Flow for Machine Learning

Medical imaging, including MRI, CT, and PET scans are the most commonly used methods of brain cancer data collection and form an important part of identifying tissue abnormalities in the brain. Preprocessing is carried out before analysis in order to enhance image quality and remove noise that can compromise diagnosis. Some of the common preprocessing methods are scaling, cropping, histogram equalization, median filtering and image adjustment. These methods increase the sharpness of the image without eliminating any major areas that could be used to make correct analysis [48, 49].

The feature extraction converts medical images into a pool of representative features which summarize vital characteristic and reduce redundancy thus enhancing classification accuracy and reducing chances of overfitting. Some of the most popular extracted features are texture, contrast, brightness, shape descriptors, gray-level co-occurrence matrix (GLCM), Gabor filters, wavelet-based features, 3D Haralick features, and local binary patterns (LBP) histograms [50, 51].

The next step is feature selection which aims at isolating the most meaningful attributes by eliminating irrelevant or redundant attributes. The most common methods used in this step are principal component analysis (PCA), genetic algorithms (GA) and independent component analysis (ICA) [52, 53].

$$\omega = E_f * \frac{1}{1 + e^{-\theta t_f}}$$

Eq (11)

At last, machine-learning algorithms are used to categorize the processed data on the basis of the detected characteristics. The popular models of supervised learning are k-nearest neighbors (KNN), artificial neural networks (ANN), random forests (RF), and support vectors machines (SVM) [54]. In the training stage, the model is given labeled data that it subsequently uses to predict the category of unknown samples. KNN classifies data based on the distances between the data points, e.g., using Euclidean/Manhattan distance, and SVM separates the classes in the multidimensional space by building an optimally located hyperplane [55, 56].

Extreme Learning Machine (ELM) :

ELM is a more modern machine learning method that has less computational requirements that the traditional neural networks. It relies on the single-layer feed-forward neural network (SLFFNN). ELM assigns weights randomly between the input and hidden layers and uses the MoorePenrose inverse to optimise weights between the hidden and output layers to provide a least squares solution. The technique improves accuracy of classification at a lower complexity of the network, less training and increased speed of learning. ELM networks have three layers that are connected in a fixed-weight between input and hidden layers, which means that only the weights between the hidden and output layers are allowed to be altered throughout training [57, 58].

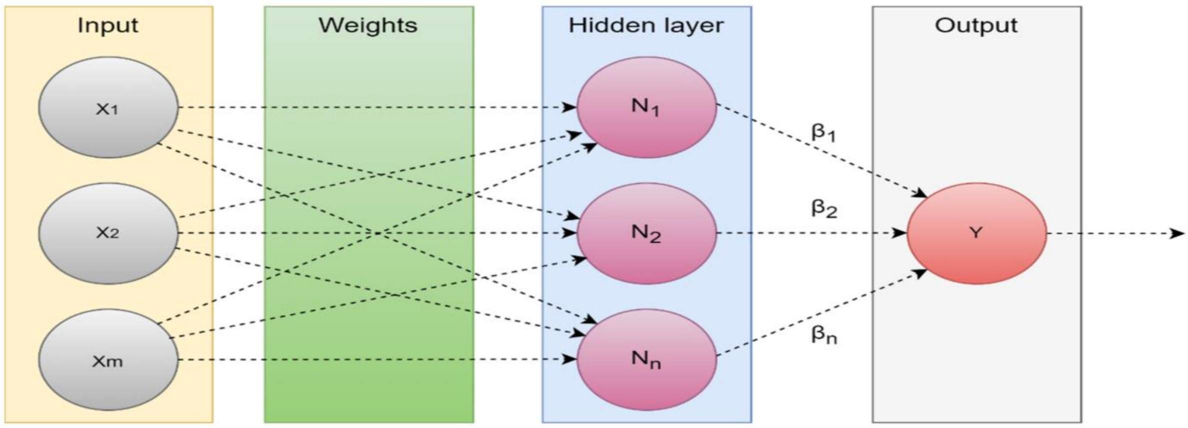

Figure 7.
Extreme learning machine

Deep Learning (DL)

A subdivision of ML (DL), in recent years, has become popular in constructing automated, semi-automated, and hybrid frameworks that are able to detect and segment tumors in a cost-effective manner and quickly. The DL models build the relevant features on the basis of adequately diverse and quality training [59, 60]. In contrast to classic ML, DL combines the feature extraction and feature selection stages of training which lead to better performance. Following the biologically based neural networks, DL models are organized into layers of sequential processes with the output of each layer being weighted sums of the outputs of the preceding layers. By these multi-layered architectures, DL allows the modeling of complex functions, with less dependence on a manual feature engineering [61, 62].

$$\omega = \left\{ \begin{array}{ll} 0; & normal \\ 0 < \omega < 0.25; & Mild \\ 0.25 < \omega, 05; & Moderate \\ 0.5 < \omega < 0.75; & Severe \\ 0.75 < \omega < 1; & Proliferative \end{array} \right\} \quad \text{Eq (12)}$$

Convolutional neural networks (CNNs) are the most common DL models that are utilized in image classification and segmentation. CNNs are hierarchically trained to examine the relation between pixels in space by convoluting the images by learned filters to create feature maps [63]. These convolutional layers preserve both translation and distortion invariance, and they increase the classification robustness (see Figure 8). There are important preprocessing stages, which are resizing, and normalization to make sure that input images are in the correct size according to the fixed-size nature of CNNs. The data augmentation is usually used to address the issue of data imbalance and data scarcity [64, 65].

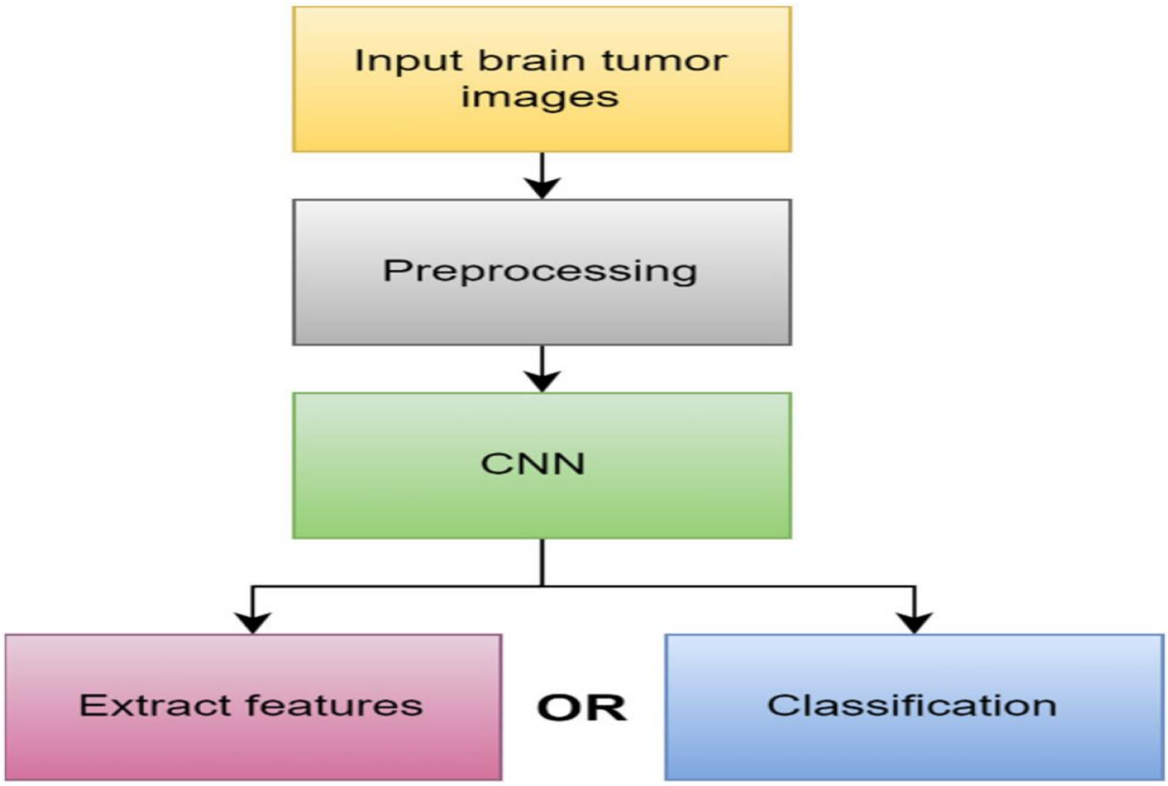

Figure 8.
Block Diagram based on Deep Learning

A typical CNN architecture includes convolutional layers that extract features like edges and boundaries, pooling layers that reduce feature dimensions and computational load, and fully connected layers that serve as classifiers mapping features to predicted labels. CNNs iteratively refine their weights through backpropagation and optimize outputs via functions such as SoftMax. Popular CNN variants include ResNet, AlexNet, and cascade-CNN, each with unique architectural improvements [66, 67].

$$\ln fl_{it}^{+} = \Sigma_{j=0}^{t} \Delta \ln W^{T} x + \quad \overset{+}{b}_{it} = \Sigma_{j=0}^{t} \max(\Delta W^{T}{}_{ij,0}) + \epsilon_{it} \qquad \text{Eq (13)}$$

$$\ln fl_{it}^{+} = \Sigma_{j=1}^{t} \Delta \ln W^{T} x + \quad \overset{+}{b}_{it} = \Sigma_{j=1}^{t} \max(\Delta W^{T}{}_{ij,1}) + \epsilon_{it} \qquad \text{Eq (14)}$$

Segmentation Methods:

Segmentation of brain tumor is essential because it allows proper diagnosis, treatment planning and clinical evaluation. It tries to localize tumor regions of brain scans, which is useful in the representation of features and quantitative analysis of images. Segmentation strategies may be both manual and automated [68]. Manual segmentation is tedious and it has been associated with errors due to image artifacts, irregularity of tumor shapes and blurry delimitations. As a result, different automated segmentation systems have been designed to help clinicians [69, 70].

- **Region-Based Segmentation:**

The method divides images, combining pixels into areas according to homogeneity parameters like texture, shape and intensity. It takes into consideration pixel similarity and spatial proximity with the help of measures of gray-level variance and Euclidean distance. Some of the typical algorithms are the k-means clustering algorithm and the fuzzy c-means clustering algorithm [71, 72].

- **Thresholding Methods:**

Thresholding is a simple method used to divide the images in terms of intensity measures. It is difficult to determine a best threshold particularly when there is low contrast in the image. The global thresholding works well in the case of uniform object and background intensities. Techniques such as Gaussian distribution modeling and Otsu thresholding are very common in determining threshold values [73, 74].

- **Watershed Techniques:**

Watershed algorithms are utilized to examine the image intensity to outline areas such as topological watershed, marker-based watershed, and image-based image foresting transform watershed [75, 76].

- **Morphological-Based Techniques:**

These techniques make use of morphological operations like dilation and erosion to extract image feature in terms of shape. Dilation increases image structures and erosion decreases image structures [77, 78].

$$\ln fl_{it}^{+} = \sum_{j=2}^{t} \Delta \ln W^{T} x + \quad b_{it}^{+} = \sum_{j=2}^{t} \max(\Delta W^{T}{}_{ij,2}) + \epsilon_{it} \qquad \text{Eq (15)}$$

$$J_i^{(b,t)} = \beta^{(b)}(S_i^{(b,t)}) \qquad \text{Eq (16)}$$

- **Edge-Based Methods:**

The edges are defined using edge detection where the intensity of the image starts and ends suddenly. They are Sobel, Roberts, Prewitt and Canny operators. Increased edge detection technique involves automated thresholding and classical edge operators to achieve better tumor segmentation [79].

- **Neural Networks-Based Methodologies:**

Segmentation using neural networks uses models that are made of interconnected neurons and are weighted. The methods are, self-organizing maps, Hopfield neural networks, multilayer perceptron, SVM-based segmentation, and backpropagation learning algorithms. [80].

- **Deep Learning-Based Segmentation:**

Deep learning methods subject input images to layers of a deep neural network to divide tumors with acquired features. The models of semantic segmentation divide pixels according to classes producing dense pixelwise segmentation maps [81, 82].

To ensure the accuracy of a model in medical diagnosis it is important to evaluate the performance of the classification and segmentation. This analysis usually takes into account precision, calculational intricacy and execution time. The performance analysis is based on four basic metrics, such as the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In this case, TP and TN are used to denote the accurate identification of the positive and negative cases whereas FP and FN are used to denote the false identifications [83, 84].

Based on these values, some performance indicators are obtained such as accuracy (ACC), sensitivity (SEN), specificity (SPE), precision (PR), and the F1-score, which is a measure of balancing between precision and sensitivity. Jaccard Index or Intersection over Union (IoU) is a metric used to measure the amount of overlap between predicted segmentation and the ground truth. Likewise, the Dice Similarity Coefficient (DSC) is used to estimate spatial overlap and its values range between zero (no overlap) and one (perfect overlap). The one beneath the receiver operating characteristic curve (AUC) shows the discriminative power of a classifier. Furthermore, similarity index (SI) measures the similarity between expert set of annotations and the segmentation results, which can give us an understanding of reliability of the results [85, 86].

LITERATURE REVIEW

Simple image processing methods like thresholding and edge detection were used in the early stages to detect brain tumor in medical images. Though these methods were the basis, it had severe problems with determining the complex boundaries of tumors correctly. These conventional methods were not so dependable due to the complex structure of the brain and the differences in the form and the size of tumors [87, 88].

The emphasis moved to traditional machine learning algorithms as research progressed such as Support Vector Machines (SVM) and Random Forests. In some cases, these models trained on labelled datasets gave good results. Nevertheless, they were not robust enough to deal with varying tumor morphologies and various image qualities thus restricting their generalization capacity [89]. Deep learning techniques in particular Convolutional Neural Networks (CNNs), became the breakthrough that has greatly advanced the medical image analysis. Models such as VGG, ResNet, and Inception have shown to be very effective at extracting hierarchical features automatically and this resulted in enhanced efficiency and accuracy. Nonetheless, difficulties still remained particularly in managing the noise the Magnetic Resonance Imaging (MRI) scans emitted and being able to accommodate the differences between the different MRI machines and scanning guidelines [90, 91].

Efficient Net became an impressive solution because it was efficient and scalable. Efficient Net turned out to be efficient by working with a variety of datasets and finding nuanced elements of medical images with the help of depth, width, and resolution scaling. It was very adaptable and thus suitable to brain tumor detection [92, 93]. This work pays special attention to the EfficientNetB2 variant, which was chosen due to its high capacity to capture complex features and enhance diagnostic accuracy in general. It is through the incorporation of EfficientNetB2 that the current gaps in the robustness, accuracy and generalization of previous methods will be bridged [94, 95].

$$J^{(b,t)} = \beta^{(b)} \times (W^{(b)} \times J^{(b-1,t)} + W^{(b)} \times J^{(b,t-1)}) \quad \text{Eq (17)}$$

Although Efficient Net has been successful in its wide medical imaging use, its effectiveness in brain tumor detection in MRI scanning is not fully explored. Thus, the study is meaningful as it integrates EfficientNetB2 with other sophisticated preprocessing and data augmenting strategies in order to develop a more efficient detection system. The methodology tries to overcome the limitations of the earlier methodologies and proceed to a more valid diagnostic model [96, 97].

Classification of Machine Learning for brain tumor

In this part, we discuss the use of different machine learning methods in the analysis and classification of brain tumors. The discussion includes the various types of the ML approaches, the algorithms that are more common in tumor classification. As the diagnostic imaging continues to improve, the development of these methods is now necessary, since it has greatly improved diagnostic accuracy and aids therapeutic decision-making. Also, this section investigates feature extraction and selection techniques and how various ML models can be used to obtain accurate tumor classification depending on the imaging data. Based on this extensive survey, we want to pinpoint strengths, weaknesses, opportunities, and threats (SWOT) of the application of Machine learning based brain tumor classification.

In the study, A Multiclass Tumor Analysis of High-Grade Malignant Brain Tumors [98, 99], a Computer-Aided Diagnosis system was created to classify the high-grade malignant brain tumors into various categories. The proposed feature selection plan was able to discriminate five subtypes of malignant brain tumors using a wide range of features in six domains; this has maximized the information of the given dataset. To enable appropriate feature selection, a new method was adopted and this is CVM. Three multiclass classifiers were trained and tested in terms of their accuracy in multiclass classification based on the features chosen. Experimental performance proved to be better with the proposed approach showing about 2,3, and 4 percent better results compared to ICA and GA when used with KNN, mSVM, and NN respectively. It is important that the Neural Network classifier showed the best accuracy of 95% which also confirmed the power of the proposed methodology to classify malignant brain tumors [100]. A second CADx system was proposed to stage stomach diseases, such as gastric cancer, gastritis and gastric ulcers [100, 101]. This work has solved the problem of insufficient medical data by using image augmentation methods using Xception CNNs, including depthwise separable convolutions. In an effort to conquer the problem of poor feature visualization in CNNs, Class Activation Maps have been used to identify the regions of interest, whereas lesion areas on abnormal images have been overlaid on normal images to enhance the dataset.

This enhanced CNN training, and results of the training were compared in terms of confusion matrices as well as performance measures, including specificity, sensitivity, F1-score, and AUC. These findings supported that CAM-based augmentation was indeed very effective in improving the dataset and in performance based of the classification as a whole [102, 103].

In [104, 105], a hybrid ML framework has also been proposed, combining feature extraction by using a MAP-based firefly optimization algorithm with the use of intensity and shape-based features and texture. This process gave an accuracy of 99.2 percent in the case of brain stroke and 88.3 percent in case of brain tumor. This system had the capability of detecting three individual tumor regions and the MRI images of strokes and brain tumors were classified into four. The highest results were obtained with Hybrid Support Vector based Random Forest Classifier (HSVFC) with F-score 0.91 and False positive rate of 0.06 in the brain tumor classification and F-score 0.99 and false positive rate of 0.0 in the brain stroke classification.

The HSVFC was performing better than ResNet-18, SVM, DC,KNN and FFNN with mean classification rates of 76.55 percent to brain tumors, and 98.17 percent to brain strokes [106]. Another research took advantage of hyperspectral imaging to improve tumor localization with firefly algorithm to optimize the clustering process. This work placed an emphasis on the significance of detailed dataset information, the comparison with other localization approaches, the analysis of the data on various datasets, and the meaning of the findings. The suggested solution showed significant enhancement with accurate 96.47, sensitivity 96.32 and specificity 98.24 that was better than the previous ones [107, 108].

Likewise, a brain tumor classification (BTc) framework was also suggested in [109] based on pre-trained deep neural networks and using MRI. The three best features learnt were used to create an ensemble, which was again tested with several ML classifiers. The research used three publicly available brain MRI datasets, but it also identified several research gaps, such as the absence of comparisons with the specialized DL models of medical imaging, a lack of descriptions of the datasets, and a lack of better interpretability and explainability of the ensemble model. Although the experimental data indicated positive improvements in performance, the lack of accuracy in measuring the results and overall comparisons hindered the general evaluation of the suggested methodology [110].

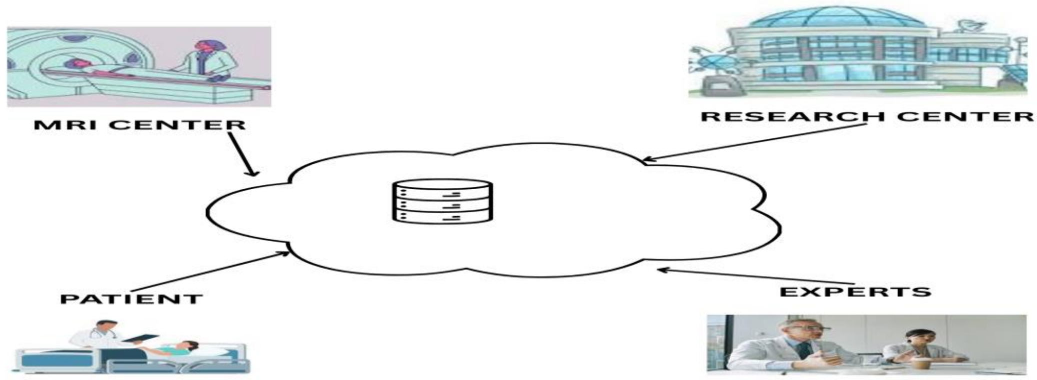

Figure 9.
A pictorial representation illustrating the real-world healthcare and medical industry methodology for distinguishing and classifying real and virtual brain tumors, utilizing both traditional and AI-based approaches.

Classification of CNNs for brain Tumor:

The overview of the use of Convolutional Neural Networks to Examine brain tumors. The architectures and methods of different CNNs applied to classify brain tumors are discussed, and the Method of how they have developed in the field of medical and why they are important in making a better diagnosis and helping treat the disease are discussed. Special emphasis is placed on feature extraction and selection procedures in Convolutional neural network, and the role of various Convolutional neural network in the accurate classification of brain tumors on the basis of imaging data. With the help of this review, we will describe the benefits, constraints, and perspectives of future research related to Convolutional neural network brain tumor classification [111, 112].

The paper in [113] presents a new method to classify brain MRI, which uses unlabeled data to learn useful features without human labels, thus overcoming the problem of small labeled data. The self-supervised learning system exploits data augmentation and model training to extract features and then the classifier, which has been pre-trained, is used as an encoder in supervised classification. The paper examines how contrastive loss-based pre-training, diversity of the datasets and augmentation techniques enhance performance. Nevertheless, they have weaknesses, such as inadequate information of the unlabeled dataset employed, as well as not much discussion of the augmentation strategy, pre-training configurations, and hyperparameter optimization. Experimental findings indicate that contrastive loss based pretraining is superior to both random and ImageNet pretraining, and image diversity and augmentation techniques have a strong correlation to classification accuracy [114, 115].

In [116], the multi-modal MRI data, which has missing modalities, is used to segment brain tumors. The proposed Dual Disentanglement Network has modality specific and tumor-specific information in its MD-Stage and TD-Stage. Although the approach better results on the BRATS 2018 dataset than other methods in the presence of missing modalities, one of the weaknesses is that there is a lack of ablation studies, comparisons to state of the art methods, and the analysis of performance under different degrees of missing data. However, the technique is reliable and accurate in terms of segmentation because it proves to be effective in capturing correlations between modalities and tumor regions as supplemented with affinity-guided dense tumor-region information [116, 117].

$$S_i^{(b,t)} = \sum_{z=1}^{E} p_{iz}^{(b)} J_z^{(b-1,t)} + \sum_{i'}^{y} x_{ii'}^{(b)} J_{i'}^{(b,t-1)}$$ Eq (18)

$$B_{m,n}(q+1)\left(1 - \frac{1 - X(0,1) - X(-1,1)}{1 - c_{m,n} \times f_{mn}(q)}\right) = X(0,1) \times R_{s,n}$$ Eq (19)

Table 2.
Comparative analysis of different methods with a discussion on the advantages and disadvantages of Machine Learning, CNN, and Transformer-based techniques.

Approach	Main Contributions	Advantages	Disadvantages	Ref
CNNs	Suggested a Dual Disentanglement Network to segment brain tumors from multi-modal MRI data	Delivered more precise and dependable segmentation outputs	Absence of comparative results with other approaches	[118]
Machine Learning	Proposed a new framework for multi-class categorization of malignant brain tumors	Provided high recognition rates, reaching up to 95.86%	Dependent on manually crafted features	[119]
CNNs	Explored deep transfer learning approaches for detecting brain tumors in 2D MRI images	Achieved superior accuracy and F1 performance compared to prior models	Missing thorough details about dataset specifications	[120]
Machine Learning	Hybrid system combining techniques for MRI-based detection of brain anomalies	Showed reliable classification for both tumors and strokes	Needs more comparative studies with other frameworks	[121]
CNNs	Introduced Time Distributed CNN-LSTM hybrid approach using 3D MRI data	Attained classification accuracy as high as 98.90%	Limited comparative analysis with advanced deep learning approaches	[122]
Machine Learning	Improved CADx system for gastric disorder recognition using image augmentation	Demonstrated enhanced AUC and F1-score performance	Dataset information was insufficient	[123]
Machine Learning	Enhanced clustering optimization for localizing tumors in brain scans with hyperspectral imaging	Achieved better specificity and higher accuracy	Tested on limited datasets without diverse evaluation	[124]
CNNs	Implemented self-supervised pretraining with contrastive loss for MRI classification	Reached validation and test accuracies beyond 97%	Not thoroughly compared with already established techniques	[125]

Different research uses three BRATS datasets to evaluate a TD-CNN-LSTM network with k-fold cross validation as a measure of generalizability. Findings show that the TD-CNN-LSTM has a test accuracy rate of 98.90 which is higher than that of the 3D CNN baseline. Nonetheless, the research lacks comparisons with other sophisticated deep learning structures and the impact of alternative design and changes of hyperparameters. In spite of these restrictions, the results demonstrate the potential of TD-CNN-LSTM to concurrently analyze all four sequences of the MRI in the classification of brain tumors, which has potential applications in clinical settings [126].

In [127] the authors consider the transfer learning-based deep learning architectures, such as InceptionResNetV2, Xception, InceptionV3, ResNet50, DenseNet201, to detect brain tumors. The study explores the best setups in detecting tumors at an early stage by using seven deep learning architectures together with traditional classifiers.

An experimental analysis shows that the most successful model has a cross-validation accuracy of 10-fold of 99.39, and different combinations of feature extractors and classifiers perform well on different evaluation measures. The learning curves in the study offer some useful information on training behavior, which can be used to identify the most effective methods in tumor detection [128].

The study at [129] suggests the fine-tuning of DenseNet201 using deep transfer learning on skewed data. The average pooling layer is then sampled to generate features, and 2 feature selection algorithms are tested: EKbHFV and MGA. Although the method has more than 95 percent accuracy on BRATS2018 and BRATS 2019 datasets, the paper lacks adequate information regarding dataset characteristics, preprocess procedures, and experiment settings. To measure the discriminative strength of the feature selection procedures, test how threshold differences and hyperparameters change the outcome, and determine how the model is resilient to foreign data, additional research is required in the future. However, the research highlights the importance of how this method is more effective and useful in the classification of multiclass brain tumours compared to other neural networks [130].

In [131], Machine learning models can be used to identify brain tumors with special attention to the uncontrollable increase in the number of tumor cells as one of the primary markers. A review of previous studies in the field of ML-based tumor classification and provide their own experiments with the RESNet 5.0 network with the transfer learning method. Though there is no clearly defined research gap in the work, the model proposed yields 96% precision in the classification of meningioma, pituitary tumors and glioma. Also, it works better on the same data than six other machine learning models, which reinforces its use in tumor grading [132].

In [133], research is conducted on the detection of early brain tumor by use of two-dimensional MR images. The paper uses classification methods based on deep learning and fails to articulate the gap in the research. The main difficulty consists in deciding the most appropriate ratios of deep learning feature extractors and classifiers to increase the efficiency of detection. Findings show that the highest-performing model yields a 10-fold cross-validation accuracy of 99.39, which points to considerable prospects of early diagnosis of tumor. Combines the Internet of Medical Things (IoMT) and deep learning to create a CAD system to classify tumors into glioma, meningioma, and pituitary. The system is tested on accuracy, specificity, and F1-score using transfer learning and MRI scans using GoogleNet. The proposed model outperforms the current ones in terms of accuracy of 96.9, specificity of 96.6, and F1-score of 0.969 because it fills gaps in early tumor detection and classification [134, 135].

$$B = \{B_1, B_2, \ldots, B_k, \ldots, B_l\} \qquad \text{Eq (20)}$$

$$E_c = \frac{1}{K} \times \sum_{g=1}^{k} J_v^{b,t} - k_v \qquad \text{Eq (21)}$$

CNN's and Machine Learning: Comparative Perspective of Classification in Brain Tumor:

Two of the well-known methodologies that are used in various fields such as brain tumor classification are Machine Learning (ML) and Convolutional Neural Networks (CNNs). Both methods are aimed at improving the quality of diagnostics and shaping the treatment plans, however, they are dissimilar in terms of their principles, abilities, and activities. This comparative paper identifies strengths, weaknesses, and future possibilities of ML and CNNs in the context of brain tumor analysis [136].

Feature Extraction and Representation:

The first step, which is known as Feature Representation and Extraction, involves the construction of features (data) that are useful in differentiating various objects (entities) that could exist in the image.

Table 3:
Comparative analysis of Machine Learning, CNNs, and Transformer-based approaches in brain tumor assessment.

Ref	ML	CNN	Transformers	Dataset	Accuracy	Description	Research Gap
[137]	✓	✓		BRATS-2021, BRATS-2019	94%	Introduces CNNs with data augmentation techniques	Limited exploration of model interpretability and dataset robustness
[138]		✓		MRI SCAN	92%	Proposes a CNN architect-ture for tumor clas-sification	More research needed into ensemble strategies for better accuracy
[139]	✓	✓		BRATS-2021, BRATS-2019	Varies	Surveys CNN architectures for tumor detection	Requires evaluation on small datasets and adaptation methods for generalization
[140]	✓	✓		MRI SCANS	93%	Integrates both ML and CNN approaches	Further study on interpretability and clinical reliability of predictions
[141]	✓			BRATS-2021, BRATS-2019	85%	Compares SVM, KNN, and Decision Trees for tumor detection	Deeper analysis into CNN extensions for improved tumor localization
[142]			✓	MULTIGRADE	90%	Incorporates attention mechanisms into transformer models	Need to explore multi-modal fusion for higher accuracy
[143]		✓		AANLIB	87%	Utilizes transformer mechanisms for tumor classification	Requires additional investigation of hyperparameter settings for stability
[144]			✓	MULTIGRADE	89%	Proposes transformer models for tumor segmentation	More benchmarking needed for generalization across datasets
[145]	✓			MRI SCANS	88%	Evaluates SVM, Random Forest, Decision Tree for segmentation	Limited cross-dataset robustness analysis
[146]	✓			MRI SCANS	Varies	Reviews multiple ML techniques for tumor dete-ction and classification	Standardized metrics and benchmark datasets still lacking
[147]		✓		MRI SCANS, MULTIGRADE	87%	Applies RL techniques for tumor segmentation	Exploration of multi-task frameworks to enhance segmentation
[148]		✓	✓	BRATS-2019	96%	Utilizes attention mechanisms in CNNs	Deeper investigation into explainability and

							identifying key features
[149]		✓		MRI SCAN	85%	Adopts GCNs for tumor graph classification	Research into integrating rep-resentation learning methods for performance gains
[150]		✓		MULTIGRADE, AANLIB	91%	Explores transfer learning with pre-trained CNNs	Studies on adapting transfer learning for diverse imaging conditions
[151]		✓		BRATS	92%	Applies transfer learning with genetic algorithms	Deeper exploration of interpretability and clinical feasibility
[152]			✓	MULTIGRADE	85%	uncertainty estimation in CNN-based segmentation	Research on calibration methods for reliable outputs
[153]		✓	✓	BRATS	90%	Incorporates adversarial training for robustness	Investigation into defenses against adversarial challenges in imaging
[154]		✓		MRI SCANS	85%	Utilizes GANs for tumor synthesis and classification	Needs broader evaluation of augmentation strategies on varied datasets
[155]	✓			MRI SCANS	86%	Uses sparse coding techniques for subtype classification	More exploration of semi-supervised methods for better accuracy
[156]		✓		AANLIB	91%	Adopts capsule networks for tumor classification	Further development of capsule-based architectures for scalability
[157]		✓		BRATS-2019	88%	Explores self-supervised learning with contrastive methods	Need more research into pre-training strategies for initialization
[158]	✓			MRI SCANS	Varies	Investigates ensemble techniques for classification	Greater analysis of diversity strategies in ensembles
[159]			✓	AANLIB, MULTIGRADE	84%	Utilizes fuzzy logic for severity classification	Stronger focus required on ensemble robustness for clinical use
[160]	✓			BRATS-2021, BRATS-2019	89%	Addresses limited annota-tion challenges with semi-supervised learning	Further study on active learning strategies to reduce annotation workload
[161]		✓		MRI SCANS	90%	Investigates adversarial attacks on segmentation models	Need for deeper evaluation of defenses against adversarial perturbations
[162]			✓	MRI SCAN	90%	Incorporates attention mechanisms in GNNs for segmentation	Research on graph-based data augmentation strategies for generalization
[163]		✓		MRI SCANS, MULTIGRADE	87%	Utilizes VAEs and GANs for tumor segmentation	Work needed on uncertainty quantification to strengthen reliability

[164]	✓		MRI SCANS, MULTIGRADE	87%	Explores metric learning for tumor segmentation	Better analysis of loss functions for performance consistency
[165]		✓	MRI SCANS	86%	Explores meta-learning techniques for few-shot learning scenarios	More studies into robustness of meta-learning across varied datasets
[166]	✓		BRATS-2019	89%	Integrates SVM and Decision Trees for tumor detection	Research on feature selection strategies to optimize efficiency

Conventional ML methods are based on manual feature extraction, wherein domain knowledge is needed to create features that are best aligned to the underlying data. Such features which are manually engineered are then inputted into machine learning algorithms [167]. Contrary to that, CNNs learn the hierarchical features representation automatically using the raw data. Convolutional, pooling, and activation layers help CNNs to find the complicated spatial and temporal arrangements, and, therefore, are highly effective in image classification efforts, including medical imaging [168]. ML methods can be applied to various data types, but tend to be poorly scaled to high-dimensional data as in MRI scans because of dimensionality curse. In addition, manual feature engineering may be time-consuming and needs much domain knowledge.

CNNs are extremely scalable and capable of handling high-dimensional data such as MRIs without purposely designed features. They are flexible and therefore applicable to large and diverse medical data [169]. ML models tend to be more readable and understandable than CNNs due to their explicit nature as they are defined by the expert. This explicability would come in handy especially in medical decision-making where explainability is crucial [170]. CNNs have been criticized as being black-boxes because they are not very transparent with their decision-making processes. Although methods like activation maps and gradient-based methods offer partial information, CNNs do not offer interpretability [171] comparable to the traditional ML models. ML models rely on the quality of hand-written features and the choice of classifier to a great extent. Even though they may be highly accurate in the optimized settings, ML models tend to perform badly in situations that involve complex and high-dimensional data [172].

CNNs have continually demonstrated state-of-the-art image classification (including brain tumor analysis) [173]. CNNs are also effective at identifying the complex features of the medical images and hence are better in terms of accuracy over ML approaches due to their automatic learning of the multi-level representations [174]. The classic methods of ML typically need extensive amounts of labelled data to perform optimally, and overfitting may obstruct the generalization of these data to unobserved data [96]. CNNs have better generalization performance even on support of limited labeled data as they have data-efficient learning processes. Transfer learning also boosts their performance by capitalizing on the already trained models of similar data sets [175].

METHODS & MATERIALS

Although significant progress has been achieved in the assessment of brain tumors with the help of Machine Learning (ML), Convolutional Neural Networks (CNNs), and Transformer-based models, there are several significant issues that make these solutions still unavailable in clinical practice. A significant issue is that medical imaging data is quite varied and heterogeneous, and this factor largely affects the performance of the models. The difference in acquisition protocols, type of scanners used, resolutions of images and demographics of patients among various institutions usually creates inconsistencies. Consequently, models, which are trained on a certain dataset, might not be able to be generalized in a variety of clinical settings, which restricts their application in the real world.The second urgent need is that of large, high quality annotated datasets. The process is usually time-consuming and expensive, and needs the expertise of a radiologist or pathologist to be annotated. Deep learning models are black box, which further complicates them. Although CNNs and Transformers can reach state-of-the-art accuracy, the mechanisms behind their decision-making are not always transparent and explainable, which can lead to a lack of trust in these systems by clinicians who require interpretable and explainable outcomes to aid in medical decision-making. This is still one of the biggest obstacles to clinical implementation. The robustness of the models is also a major concern. The deep learning systems may be susceptible to noise, artifacts, and even adversarial attack, which may cause a wrong classification in high stakes settings. Since clinical implications of brain tumor diagnosis are severe enough, resiliency against these vulnerabilities is most crucial. The other new problem is the incorporation of multi-modal information.

Although integrating MRI, CT, histopathological imagery, and even clinical records can offer a more detailed insight and a more comprehensive evaluation, it also creates the problem of data preprocessing, alignment, fusion policies, and computational demands. Also, computational and infrastructure limitations are still a major issue, especially in low-resource medical care facilities where high-quality GPUs and high-performance computing platforms are not necessarily accessible. This brings up issues on the scale and equal distribution of AI-based solutions worldwide. Lastly, there are ethical and regulatory factors that require non-technical attention, including patient data privacy, datasets bias, and meeting medical standards, to which no less priority is assigned, until AI-based brain tumor diagnostic tools can be relied on in clinics.

Dataset Preprocessing and analysis

The classification of brain tumors mainly depends on the dataset that is available and of good quality to train and test machine learning models. These datasets are multisensory imaging including MRI, CT and histopathological images, which are fundamental in training precise and effective classification algorithms. The section gives an overview of some of the most significant brain tumor classification data, highlighting their features, advantages, and disadvantages, and the general impact on the medical imaging development. This sub-section serves as a reminder of publicly available datasets frequently referred in the literature on the topic of brain tumor studies.

BRATS-2021

Based on previous versions, BRATS-2021 is a new and comprehensive dataset of multimodal MRI scans used to segment brain tumors. The version includes the development of imaging technologies and standards of annotations that present more powerful and varied data to characterize tumors correctly.

Harvard (AANLIB) Dataset

Anticipated to be included in the database is the Whole Brain Atlas (AANLIB) which is a web-based repository of central nervous system MRI scans. It has over 13,000 MRIs on 30 cases representing a wide spectrum of disease such as tumors, strokes, gliomas, Alzheimer disease, and infectious diseases. It is a great source of comparative studies in classification activities due to its variety. Regarding (2), The data are used in this research is in line with the Multigrade Brain Tumor Dataset, augmented with data donations of, BRATS-2021 [176], Harvard (AANLIB) [177, 178].

Analysis

Effectively capturing the non-linearity of the data is one of the key problems in brain tumor classification. Machine learning algorithms, especially traditional models, are not always capable of capturing complex relationships as found in medical imaging because they are linear models. This deficiency reduces their ability to differentiate the tumor characteristics accurately. This has been partially solved using Convolutional Neural Networks (CNNs) which exploit several interconnected layers to learn non-linearities. The optimization and design of CNN architectures that are capable of fully leveraging these non-linear features is however still under active research. The other major issue is the fact that two-dimensional (2D) images are used in order to study three-dimensional (3D) structures such as brain tumors. Conventional imaging methods tend to result in 2D cuts that can be insensitive to depth-based data that are important in accurate diagnosis. This limitation can be overcome by either devising sophisticated means of deriving depth information out of 2D images or by using modalities like volumetric MRI and CT scans which inherently give 3D representations.

Another difficulty is that the current classification methods do not have multidimensional representations. Although 2D imaging can provide useful information, it is not able to completely represent complicating spatial, temporal, and morphological features of tumours. The addition of multidimensional insights, like time-series recordings of dynamic imaging studies or spatial differences of multi-sequence MRI scans, carries a considerable challenge in the form of the increased complexity of the data processing and analysis.

Table 4.
Comparative Analysis of original Image sets and Augmented Image Sets (Brats-21)

Tested parameters	Original image sets			Augmented image sets		
	SGDM	RMSProp	ADAM	SGDM	RMSProp	ADAM
Batch size	7	10	7	10	10	8
Maximum epochs	6	5	8	6	6	7
InitialLearnRate	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04
Training time (min/s)	36:45	38:40	34:15	46:31	62:41	51:31
Accuracy	95.9	96.5	95.9	99.04	99.04	98.56

Also, the combination of attention mechanisms is an opportunity and a challenge in the classification of brain tumor. Attention modules have also been shown to help a model to focus on the most relevant parts of the input data and have been shown to improve feature extraction and classification. But they can be successfully incorporated into CNNs or Transformer-based systems only when they are carefully experimented to find the best strategies. Moreover, it is important to consider the way the attention mechanisms can be interoperable with other parts of the classification pipeline and adapt their behavior in ways that are modifiable and useful in clinical practice.

Addressing the above challenges of non-linearity, dimensionality, depth representation and use of attention mechanisms in brain tumor classification would render the methodologies more precise and reliable and eventually lead to better diagnostic results and patient care.

Table 5
Comparative Analysis of original Image sets and Augmented Image Sets (AANLIB)

Tested parameters	Original image sets			Augmented image sets		
	SGDM	RMSProp	ADAM	SGDM	RMSProp	ADAM
Batch size	10	10	10	10	10	10
Maximum epochs	5	6	8	5	6	6
InitialLearnRate	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04
Training time (min/s)	51:51	56:37	58:39	95:31	110:13	111:58
Accuracy	93.53	90	95.88	96.65	98.09	97.13

Table 6.
Comparative Analysis of original Image sets and Augmented Image Sets (Squeezenet)

Tested parameters	Original image sets			Augmented image sets		
	SGDM	RMSProp	ADAM	SGDM	RMSProp	ADAM
Batch size	10	8	10	10	10	10
Maximum epochs	7	6	5	6	7	6
InitialLearnRate	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04
Training time (min/s)	25:54	27:59	28:8	62:42	58:44	63:5
Accuracy	93.53	90	93.53	98.56	96.17	96.65

Table 7.
Comparative Analysis of original Image sets and Augmented Image Sets (Resnet50)

Tested parameters	Original image sets			Augmented image sets		
	SGDM	RMSProp	ADAM	SGDM	RMSProp	ADAM
Batch size	10	10	7	10	10	10
Maximum epochs	6	7	6	6	6	6
InitialLearnRate	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04	1.00E−04
Training time (min/s)	26:49	30:50	30:33	57:10	61:50	57:18
Accuracy	94.71	97.06	85.29	90.91	95.69	94.74

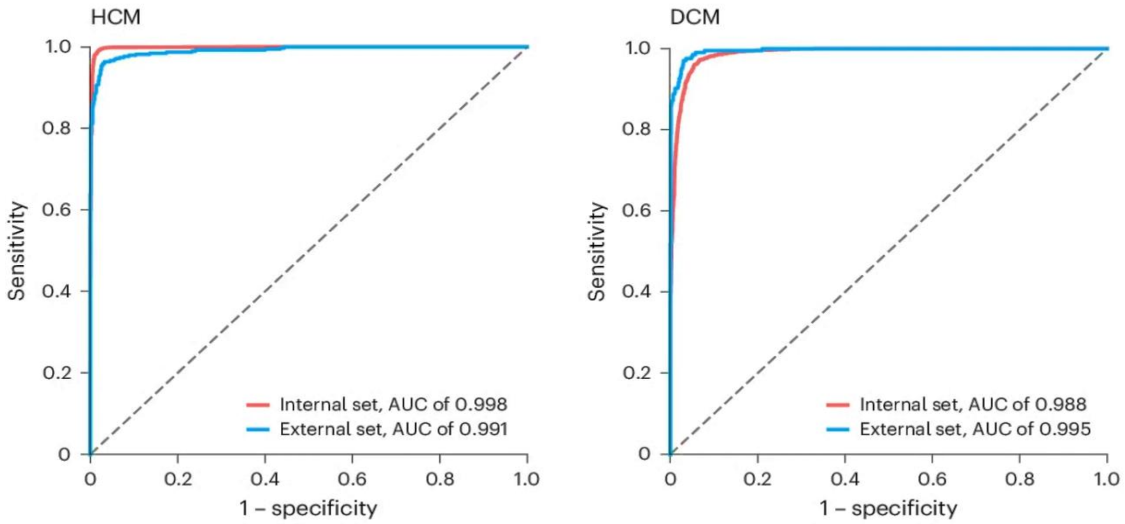

Figure 10.
Sensitivity vs specificity

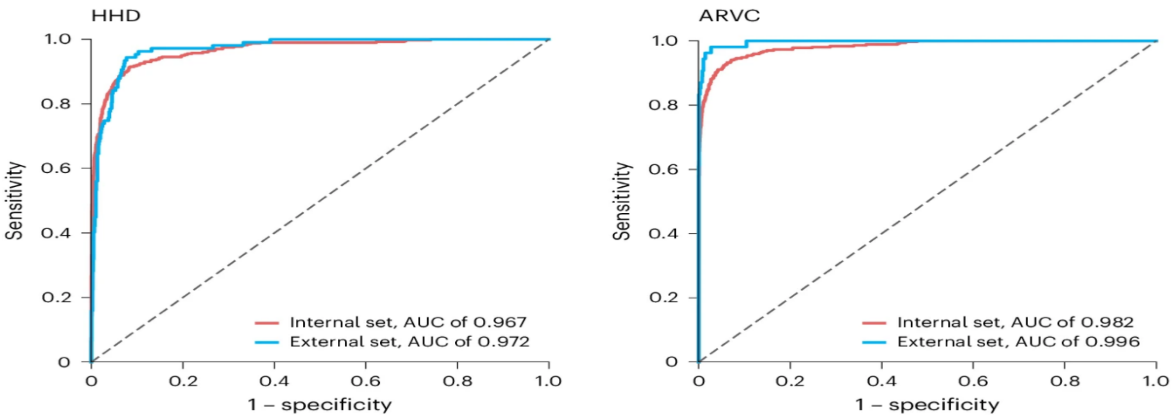

Figure 11.
Sensitivity vs specificity for HHD and ARVC

CONCLUSION

In this Paper, we discoveries in the development of brain tumor classification methods, with a focus on the shift between older methods involving machine learning to more recent deep learning models like Convolutional Neural Networks. The traditional techniques though essential in setting the base were usually constrained in their ability to deal with the non-linearity and Challenge of medical imaging data. The response to some of these challenges in CNNs was automated feature extraction and hierarchical learning, and Transformers still developed the field further by proposing more contextual knowledge and the ability to capture dependencies over a long range. Comparative analysis of these methods has given an understanding that there is no universal method that is superior. They both possess their own advantages and drawbacks, and the methods should be selected based on the needs of the diagnosis and the availability of the data as well as the clinical background. Similarly, the importance of the datasets like BRATS and Harvard AANLIB has been highlighted because they are used as a benchmark to evaluate the progress and are still influencing further developments in automated tumor classification. Irrespective of these developments, issues like heterogeneity of datasets, interpretability requirement, and multimodal data integration have been becoming urgent problems.

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