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Neural Networks in Neuroimaging: A Critical Analysis of Deep Learning Techniques for Brain Tumor Prediction



Abstract: - With the escalating incidence of brain tumors, early and accurate detection holds paramount importance for facilitating timely medical interventions and enhancing patient outcomes. Deep learning models have proven to be formidable tools for analyzing intricate medical data, particularly in the context of medical imaging. This review encompasses a meticulous examination of various deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models, as they are employed across diverse medical imaging modalities including magnetic resonance imaging (MRI), computed tomography (CT), and positron emission tomography (PET). The paper delves into the distinctive challenges inherent in brain tumor prediction, acknowledging factors such as inherent tumor variability and the necessity for models that are interpretable and applicable within clinical settings. Additionally, the review explores the fusion of multimodal data and the integration of transfer learning and domain adaptation techniques to enhance model generalization across diverse datasets. A critical evaluation of the strengths and limitations of current methodologies is provided, offering insights into potential avenues for future research. Moreover, this paper provides an extensive overview of deep learning methodologies applied to the prediction of brain tumors, exploring recent advancements and confronting challenges in this pivotal domain of medical research.

Keywords: Brain Tumor, Convolutional Neural Networks (CNNs), Deep learning, Early Detection, Explainable AI, Federated Learning, Healthcare Applications.

I. INTRODUCTION

A brain tumor is an abnormal growth of cells in the brain. Tumors can be benign or malignant and may arise from brain tissue or spread from other parts of the body. Symptoms vary but can include headaches, seizures, changes in vision, and cognitive problems. Diagnosis involves imaging studies like MRI and CT scans, and treatment options include surgery, radiation, and chemotherapy. Early detection and intervention are crucial for better outcomes, and ongoing research aims to improve diagnostic methods and treatment strategies for brain tumors. It is essential for thought and interpretation, as well as the beginning of control over movement. The brain is en-cased within the skull, which provides protection from the front, sides, and back. Skulls consist of 22 bones, including 14 face bones and 8 cranial bones. There is cerebrospinal fluid surrounding the brain and it is anatomically enclosed inside the skull. A fluid called Cerebrospinal Fluid (CSF) fills the voids on the surface of the brain and spinal cord. Approximately 500mL of cerebrospinal fluid is produced daily by the unique ependymal cells[2,3]. In addition to cushioning the brain from shocks, the CSF also serves as a source of nutrients to the brain. Additionally, it protects the brain from infection.

The brain is essentially weightless in the CSF layer, where it is perched. If the brain wasn't suspended in CSF, its weight would block it, cutting off the blood supply to the lower brain [4]. Affected neurons would die. In the human brain, the fore-brain is the largest part. The forebrain parts include:

- Thalamus
- Hypothalamus
- Cerebrum

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For the majority of other types of tumours in other areas of the body, a concept of organizational is used to define the location of the tumour, whether or not it has progressed, and whether or not it has spread to other areas. Nevertheless, no any suggested global system for adult brain tumours, as the vast majority of primary brain tumours do not typically move beyond the central nervous system. Because the unique characteristics of a brain tumour determine its seriousness and growth propensity, the grading system is always employed instead [5].

To establish the appropriate therapy for a brain tumour, its type and grade must be determined. Several factors assist physicians in determining the optimal brain tumour care plan and a patient's treatment plan:

- A small piece of the tumour is removed for further testing, as described in tumor biopsy. Determining the tumor's molecular traits and grade can help doctors estimate the tumor's potential for metastasis and spread. Your doctor will gain a better understanding of the tumor's potential behavior after considering all of these considerations. It's possible that these characteristics will also play a role in deciding which treatments are available to you [6].
- Grading of the tumors based on how normal or abnormal cells look like. This grading of the tumor will aid the doctor to plan the treatment method. The tumor grading is based on the growth of the cells and how fast it spread to other cells.

- **Grade I**

Under this category the tumor cells seem to be normal cells. The growth of the cell is also slow. The life time of the tumor affected patient is increased if the doctor gives the proper treatment.

- **Grade II**

The cell appearance is abnormal and grows slowly. The tumor cells affect the immediate tissue. This tumor is very dangerous and reduces the human lifetime.

- **Grade III**

The appearances of the cells are abnormal and the cells are aggressively growing into immediate brain tissue

- **Grade IV**

When a tumour is graded as a grade IV, the cells that make up the tumour are actively dividing. In addition to this, there is an aberrant proliferation of blood vessels within the tumour, as well as patches of dead tissue. These tumours have the potential to develop and spread rapidly [10].

MRI-based temperature imaging, which makes use of the temperature-sensitive water proton resonant frequency shift, is currently the only method that can properly assess changes in temperatures in real time. This method is also the only one now available. This method of directing thermal treatment has been put through a significant amount of testing before being considered for use in clinical practice. Using this method, all stages of thermal treatment have been shown to be beneficial; these stages include reducing heating below the threshold for injury, protecting important structures, and accurately forecasting the amount of material that will be ablated [7]. MRI of brain is shown below in figure 1 and 2.

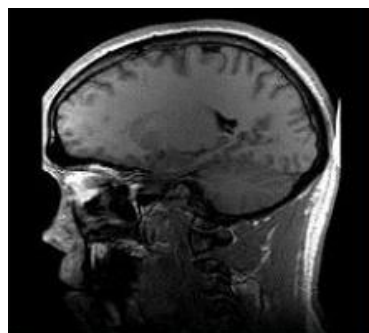


Figure 1. MRI of a Human Brain

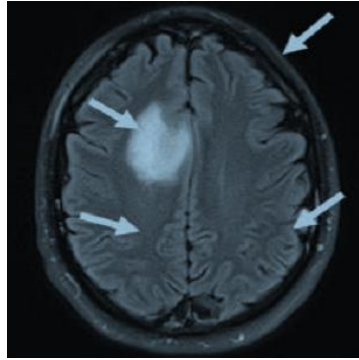


Figure 2. MRI of a Brain Tumor

A. Some more crucial factors

Several crucial factors influence the development, diagnosis, and treatment of brain tumors. Here are key factors associated with brain tumors:

- 1) *Tumor Grade*: Tumors are graded based on their aggressiveness. Grades range from I (least aggressive) to IV (most aggressive). The grade influences prognosis and treatment decisions.
- 2) *Benign vs. Malignant*: Benign tumors are non-cancerous and usually have well-defined borders. Malignant tumors are cancerous, tend to grow rapidly, and can invade surrounding tissues.
- 3) *Symptoms*: Symptoms vary based on tumor size, location, and type. Common symptoms include headaches, seizures, changes in vision, cognitive deficits, and personality changes.
- 4) *Early Detection*: Early detection is critical for favorable outcomes. Routine screenings and awareness of potential symptoms contribute to early diagnosis.
- 5) *Diagnostic Imaging*: Imaging techniques, such as MRI and CT scans, play a crucial role in diagnosing brain tumors by providing detailed images of the brain structure.
- 6) *Genetic Factors*: Genetic factors can contribute to the development of certain brain tumors. Understanding genetic markers helps in personalized treatment approaches.
- 7) *Prognosis*: Prognosis varies widely based on factors such as tumor type, grade, and response to treatment. Early detection and advances in treatment options have improved overall prognoses.
- 8) *Patient Age and Health*: Patient age and overall health influence treatment decisions and the ability to tolerate certain therapies. Understanding these factors helps healthcare professionals tailor treatment plans and provide patients with accurate prognostic information based on the specific characteristics of their brain tumors.
- 9) *Subsection Tumor Type*: Different types of brain tumors exist, such as gliomas, meningiomas, and metastatic tumors. Each type has distinct characteristics, growth patterns, and treatment responses.
- 10) *Tumor Location*: The location of a brain tumor can impact symptoms and treatment options. Tumors in critical brain regions may pose greater challenges for surgical removal.

II. LITERATURE REVIEW

Convolutional Neural Networks have become the cornerstone of deep learning applications in medical imaging. G. Karayegen et al. [8] given that the ability of CNNs to automatically learn hierarchical features from imaging data has proven highly effective in the context of brain tumor prediction. Various studies have demonstrated the successful application of 3D CNNs for the segmentation and classification of brain tumors in volumetric medical images, such as magnetic resonance imaging (MRI) scans.

Z. Schwehr et al. [9] stated while CNNs excel in capturing spatial features, Recurrent Neural Networks have shown promise in handling sequential data, such as time-series imaging. RNNs, with their ability to capture temporal dependencies, have been applied to dynamic imaging modalities, like functional MRI (fMRI), providing insights into the evolving nature of brain tumors.

M. Gurcan and K. Iftekharuddin [10] observed the integration of various deep learning architectures into hybrid models has gained traction for comprehensive brain tumor prediction. Hybrid models combining CNNs for feature extraction and RNNs for sequential analysis have demonstrated improved performance, showcasing the synergistic benefits of combining different deep learning paradigms.

D. C. Yadav and S. Pal [11] concluded that despite the remarkable progress, several challenges persist in the application of deep learning techniques to brain tumor prediction. Variability in tumor types, sizes, and locations poses a significant challenge for model generalization. Additionally, the interpretability of deep learning models in a clinical setting remains a concern, requiring further research to enhance model transparency and trustworthiness.

Z. Chen [12] given that recent studies have explored the integration of multimodal data to enhance the predictive capabilities of deep learning models. Combining information from different imaging modalities, such as MRI, CT, and PET scans, has shown promise in capturing a more comprehensive view of brain tumor characteristics, leading to improved accuracy and reliability.

A. Zarandi, Fazel M. H. et al. [13] made a suggestion that the Preprocessing step should include the aggregation of fuzzy rules with already used filtering techniques. Incorporating Type-II fuzzy concepts into the segmentation process allows for improvements to be made to the Possibilistic C-Mean (PCM) approach, the Mahalanobis distance, and the Kwon validity index. All of these improvements are made. A approach that was created through the utilization of Thresholding-based Approximate Reasoning is used to classify the grades of brain MRI tumors.

Pan Zhigeng et al. [14] present a bayes-based district development computation. This computation assesses parameters by surveying neighborhood features and utilizing the bayes factor as a clustering paradigm. Both of these approaches have a high potential for mistake because of the harmful consequences that an erroneous depiction of the seed arrangement or a bad seed picture selection may have on the end output. These errors can occur because of the similarities between the two approaches. approaches that are factually based and those that use fuzzy logic appear to be the most promising alternative to the approaches that were previously discussed.

S. Thara and K. Jasmine have come up with an original way [15] for distinguishing between photos that are healthy and those that are malignant. When a probabilistic neural network classifier is used, the Radial Bias function may be categorized with an accuracy of 91.3%, and with an accuracy of 96.3% when using a fuzzy probabilistic neural network classifier.

M. Monica Subhashini and her colleagues [16] introduced a new machine-learning technique that they called naive bayes. Support vector machines, naive bayes, and learning vector quantization are utilized in order to carry out an initial classification that is dependent on accuracy. Using the naive bayes algorithm, we were able to attain a success rate of 91%.

A neural network-based method for classifying tumors as normal or abnormal was created by Yudong Zhang et al. [17]. Using this method, tumors may be accurately and automatically identified as normal or abnormal. The amount of time spent computing each picture is 0.0451 seconds, and the accuracy is one hundred percent throughout both the training and testing stages. The data collection contains information that was obtained from the HMS website. Yuehao Pan and colleagues [18] developed a grading system for determining the severity of brain tumors through the application of convolutional neural networks. They were demonstrated to be more sensitive and specific than neural networks, which was a comparison that was made. The overall performance was improved by 18% because to CNN. The BRATS 2014 data set was the one that was utilized.

El-Sayed Ahmed El-Dahshan et al. [19] presented a hybrid approach to MRI classification that makes use of both ANN and KNN. Accuracy levels of 97% and 98%, respectively, are attained by both ANN and KNN when using their respective neural networks. The information for this specific dataset was taken from the HMS website.

According to a study that was conducted by B.Sudha and colleagues [20], the severity of brain tumors may be determined by their FFNN, MLP, and BPN scores. When comparing these three methods, some of the performance characteristics that are taken into consideration include accuracy, specificity, and sensitivity. BPN is the gold standard since it has a sensitivity of 72 percent, a specificity of 84 percent, and an accuracy of 96.7 percent. There is a clear correlation between the extraction of the best attributes during training and improved accuracy.

Eltaher Mohamed Hussein and colleagues [21] came up with the idea for the ANN approach. In addition to that, a comparison of the various ANN approaches is included in the study. The three different types of ANN approaches

are the BPNN, RNN, and Elman Network. Elman Network came out on top among them, ranking first with a remarkable performance ratio of 88.24%.

Madhubanti et al. [22] developed a categorization system in order to differentiate between brains that are healthy and brains that are affected by Alzheimer's disease. To create the distinction between the two possible outcomes, a supervised neural network-based classifier is utilized. A hundred percent accuracy in classification is guaranteed by using this approach. The data collection contains information that was obtained from the HMS website.

R. Kaur and A. Doegar [23] given in their study that advancements in emerging technologies, such as explainable AI and federated learning, offer potential solutions to existing challenges. Explainable AI methodologies aim to demystify the decision-making process of deep learning models, enhancing their interpretability in clinical settings. Federated learning addresses data privacy concerns by allowing models to be trained across decentralized datasets, ensuring patient confidentiality.

An technique that combines support vector machines and neural networks was pro-posed by Sandeep Chaplot et al. [24] They used wavelets as the input for their mod-el. Using this method, it is possible to differentiate between normal and abnormal photographs. When compared to self-organizing maps (94%), support vector machines (SVM) obtain a greater level of accuracy (98%).

J. Chaki [25] Hybrid models integrating both CNNs and RNNs have gained traction, presenting a holistic approach to tackle spatial and temporal intricacies in brain tumor imaging (Rayan S. et al., 2023). These models showcase synergies between different deep learning paradigms, resulting in improved predictive performance.

Recent study of V. Perumal et al. [26] emphasizes persistent challenges, such as the need for robust generalization across diverse tumor types and sizes. Interpretability remains a focal point, with emerging research offering insights into explainable AI techniques tailored for brain tumor prediction models.

The PCA-NGIST method, which was introduced by Abdu Gumaie et al. [27], is a cutting-edge and efficient hybrid approach to the process of feature extraction. At long last, the RLEM classifier has been applied to the task of classifying gliomas in the brain.

Sudipta Roy and colleagues [28] came up with the idea for the ANFIS classifier, which was then evaluated in comparison to the ANN with back propagation Learning model and the K-nearest neighbors classifiers. The accuracy rate achieved by AN-FIS's classifier is 95%, whereas the accuracy rate achieved by ANN and KNN is both 90%.The data were taken from the database maintained by Med Harvard.

Minakshi Sharma et al. [29] offered a categorization of astrocytoma tumors as well as a hybrid genetic technique for the segmentation of brain tumors. There was an overall hit rate of 97%, a sensitivity of 96.9%, and a specificity of 95.6%. The data set is acquired from many locations on the internet.

Transfer learning approaches given by H. Lamdade et al.[30] have gained popularity in the effort to overcome data scarcity issues. By leveraging pre-trained models on large datasets, researchers have achieved improved performance, especially when adapting models to different medical imaging domains. The focus on model interpretability has intensified, with recent efforts of T. Jagadesh et.al. [31] dedicated to developing explainable AI methodologies tailored for brain tumor prediction models. Insights into decision-making processes contribute to increased trust and acceptance of deep learning models in clinical settings.

Betsabeh Tanoori and colleagues [32] proposed a method that is based on support vector machines and active contour models for the purpose of locating brain regions in MR images of the brain. Using the collected features, an SVM classifier is trained to distinguish between the various types of brain tissue. It is necessary to use the reference brain MRI dataset in order to validate the methodology that has been pro-vided.

The SVM algorithm that was developed by Frank G. Zolner et al [33] uses feature reduction analysis in order to function properly. It has been noticed that the processing time of the method improves as the number of inputs to the SVM being used is reduced. In this method, the SVM is selected by the use of a Radial Bias Function.

Evangelia I. Zacharaki and colleagues introduced the support vector machine as a method of machine learning that might be used to classify the severity of glioma [34]. When distinguishing between metastases and gliomas, the accuracy, sensitivity, and specificity of the binary SVM classification are 85%, 87%, and 79%, respectively. On the other hand, when distinguishing between high-grade gliomas and low-grade neoplasms, the accuracy, sensitivity, and specificity of the binary SVM classification are 85%, 88%, and 96%, respectively. Multiclassification is another use of this method that has been tried.

Gayatri Chavan and her colleagues [36] came up with the idea for the SVM (support vector machine) classifier. This classifier is founded on KNN. We make use of seg-mentation-based Fractal Texture Analysis (SFTA) computations in order to remove the superficial parts of the pictures we work with. The appearance of the brain

MRI scans in the database is categorized as normal, benign, or malignant depending on how they compare to these categories.

Zacharaki et al. [37] presented a classification system for brain tumors utilizing SVM-RFE, which was based on magnetic resonance imaging data. The assessments of brain tumor locations are sorted into categories and analyzed according to the degree to which they are moderate, direct, or severe.

Jainy Sachdeva et al. [38] develop a computer-aided diagnosis (CAD) system that is modeled after natural processes in order to provide radiologists with a tool that would assist them in categorizing various types of brain tumors. The tumor zones are delineated with the use of a tool called Content Based Active Contour (CBAC). After the stored ranges have been selected, segmented regions of interest, abbreviated as SROIs, are generated. These SROIs are kept distinct from the capabilities' intensities and surface rundowns. The radiologist's obsessive and passionate goals for brain tumors were the driving force behind the thoughtful selection of these products. A Genetic Algorithm (GA) will choose the most desirable combination of features based on this data gathering.

Table 1. Summary of the Existing Techniques used in the various papers

| Author and Year | Model Used | Specifications |
|---|--|--|
| G. Karayegen and M. F. Aksahin, 2021 [8] | CNN | The ability of CNNs to automatically learn hierarchical features from imaging data has proven highly effective in the context of brain tumor prediction |
| Z. Schwehr and S. Achanta, 2023 [9] | RNN | Recurrent Neural Networks have shown promise in handling sequential data, such as time-series imaging. RNNs, with their ability to capture temporal dependencies, have been applied to dynamic imaging modalities, like functional MRI (fMRI), providing insights into the evolving nature of brain tumors |
| M. Gurcan and K. Iftexharuddin, 2023 [10] | CNN+RNN | Hybrid models combining CNNs for feature extraction and RNNs for sequential analysis have demonstrated improved performance, showcasing the synergistic benefits of combining different deep learning paradigms. |
| D. C. Yadav and S. Pal, 2022 [11] | DenseNet | Variability in tumor types, sizes, and locations poses a significant challenge for model generalization. Additionally, the interpretability of deep learning models in a clinical setting remains a concern, requiring further research to enhance model transparency and trustworthiness |
| Z. Chen, 2022 [12] | ResNet | Combining information from different imaging modalities, such as MRI, CT, and PET scans, has shown promise in capturing a more comprehensive view of brain tumor characteristics, leading to improved accuracy and reliability |
| A. Zarandi, Fazel M. H. et al., 2019 [13] | VGGNet | They give a suggestion that the Preprocessing step should include the aggregation of fuzzy rules with already used filtering techniques |
| Pan Zhigeng et al., 2022 [14] | Inception Net (GoogLe Net) | Present a bayes-based district development computation. This computation assesses parameters by surveying neighborhood features and utilizing the bayes factor as a clustering paradigm. |
| S. Thara and K. Jasmine, 2021 [15] | MobileNet | The Radial Bias function may be categorized with an accuracy of 91.3%, and with an accuracy of 96.3% when using a fuzzy probabilistic neural network classifier. |
| M. Monica Subhashini et al., 2020 [16] | SE-Net (Squeeze-and Excitation Networks) | Support vector machines, naive bayes, and learning vector quantization are utilized in order to carry out an initial classification that is dependent on accuracy. |
| Yudong Zhang et al., 2019 [17] | HRNet (High-Resolution) | A neural network-based method for classifying tumors as normal or abnormal. Using this method, tumors may be accurately and automatically identified as normal or abnormal. |

| | | |
|---|---|---|
| | Networks) | |
| Yuehao Pan et al,2019[18] | SWAGAN (Slice-Wise Adversarial Networks) | A grading system for determining the severity of brain tumors through the application of convolutional neural networks. |
| El-Sayed Ahmed El-Dahshan et al.,2019[19] | BiLSTM (Bidirectional Long Short-Term Memory Networks) | A hybrid approach to MRI classification that makes use of both ANN and KNN. Accuracy levels of 97% and 98%, respectively, are attained by both ANN and KNN when using their respective neural networks. |
| Eltaher Mohamed Hussein et al, 2019[21] | FCN (Fully Convolutional Networks) | A comparison of the various ANN approaches is included in the study. The three different types of ANN approaches are the BPNN, RNN, and Elman Network. Elman Network came out on top among them, ranking first with a remarkable performance ratio of 88.24%. |
| Madhubanti et al.,2019 [22] | Generative Adversarial Networks | A categorization system in order to differentiate between brains that are healthy and brains that are affected by Alzheimer's disease |
| V. Perumal et.al. [26] | 3D Convolutional Neural Networks (3D CNNs) | Hybrid models integrating both CNNs and RNNs have gained traction, presenting a holistic approach to tackle spatial and temporal intricacies in brain tumor imaging |
| G. Karayegen and M. F. Aksahin, 2021 [8] | CNN | The ability of CNNs to automatically learn hierarchical features from imaging data has proven highly effective in the context of brain tumor prediction |

III. BRAIN TUMOR DIAGNOSIS

The study of the brain can be performed in a variety of different ways using a variety of different imaging modalities. The purpose of this section is to give a brief over-view of the different imaging methods, followed by focusing on Magnetic Resonance Imaging (MRI) as the most commonly used imaging method for observing brain tumors.

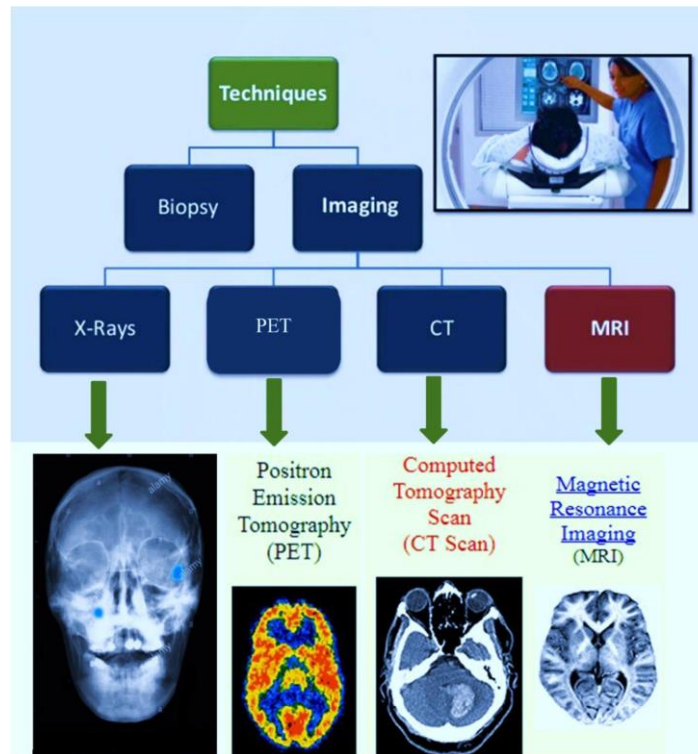


Figure 3. Different modalities of Brain tumor Imaging

A. Magnetic Resonance Imaging (MRI)

In terms of the human body, MRI machine creates detailed images by using magnetic fields to produce images of the body. With the help of an MRI, it is possible to determine the size of the tumour. The contrast medium that is applied before the scan so that the image can be more clearly defined is a specialized dye, which can improve the clarity of the image. Depending on the suspected type of tumour and the risk that it may spread throughout the central nervous system, the MRI may be of either the brain or the spinal cord, or both of these locations. There are numerous variants of MRI machines. The outcome of a neuro-examination, which may be performed by an internist or neurologist, contributes to the process of selecting the appropriate MRI modality [14].

- Magnetic resonance imaging (MRI) scan is often utilized to assist in developing a more distinct picture of a brain tumour. During this procedure, a patient first undergoes a standard MRI, and then, after the scan has been completed, they are given a unique contrast medium known as gadolinium through an IV. After then, a second MRI is performed to acquire an additional set of photographs with the dye.
- The "diffusion weighted imaging" method of magnetic resonance imaging (MRI) can be helpful in illustrating the cellular structure of the brain. Per-fusion imaging is another method that can be used to determine how much blood is getting into the tumour [15].

B. Computer Tomography (CT)

CT scans use X-rays to create detailed cross-sectional images of the brain. While not as detailed as MRI for soft tissues, CT scans are valuable in detecting the presence of tumors and assessing their density.

C. A Cerebral Arteriogram

Also known as a cerebral angiography. An x-ray of the head, or a sequence of x-rays of the head, is what is known as a cerebral arteriogram. This x-ray depicts the arteries in the brain. After injecting a particular dye into the patient's main arteries, X-rays are taken of the patient's head after the contrast medium has been administered.

D. Lumbar Puncture or Spinal tap

In a procedure known as a lumbar puncture, a needle is inserted into the lower back in order to withdraw a sample of cerebrospinal fluid (CSF). This fluid is then examined for the presence of blood, tumour cells, or tumour markers. Persons who have certain kinds of tumours often have abnormally high concentrations of a material called a tumour

marker or biomarker without those tumours. Before the procedure, a local anesthetic is frequently administered to the patient in order to numb the lower back area.

E. Tumor marker test

Blood tests can be conducted to measure certain substances (tumor markers) associated with specific types of brain tumors. While not definitive for diagnosis, elevated levels may indicate the need for further investigation.

F. Neurocognitive Evolution

This includes a comprehensive assessment of the patient's overall health as well as their ability to store and retrieve memories, communicate in both an expressive and receptive manner, perform mathematical calculations, demonstrate manual dexterity, and express and comprehend language. A certified clinical neuropsychologist is the one who administers these exams. This professional will compile their findings into a formal report that may be compared to subsequent exams or used to zero in on certain issues that can be remedied through treatment[11,16,17].

G. Electroencephalography (EEG)

EEG measures electrical activity in the brain and is used to detect abnormal patterns associated with certain types of brain tumors. It is often used in conjunction with other diagnostic methods.

Table 2. Summary of benefits and drawbacks of several imaging techniques

| Method | Type of Detection | Advantages | Limitations |
|--------------------------|-----------------------------------|--|--|
| X-Ray | Bones | Low cost | Excessive X-ray exposure is dangerous. |
| CT Scan | Bones and soft Tissue | Useful for bone architecture, as well as for guiding biopsy. | Exposure to Radiation |
| MRI Scan | Bones and soft Tissue | Anatomical, non invasive, and specific for acute and chronic osteomyelitis | Anesthesia is required, which is costly. |
| Ultrasonic Soud | Some bones as well as soft tissue | anatomical and specific | Sedation may be required (invasive) |
| Neurocognitive Evolution | pathology of the bones | Particularly narrow | High price and scarcity |

The MRI modality is the greatest option for a non-invasive test that is required for brain tumor investigation. In compared to other modalities, it gives more accurate data for metastasis analysis. The method relies on Nuclear Magnetic Resonance (NMR), which employs a combination of a high magnetic field generated by powerful magnets and radio frequency to create pictures with great detail. These magnets' most often utilized magnetic field strengths are 1.5T and 3T, as larger fields result in a high Signal-to-Noise Ratio (SNR). MRIs provide the ability to adjust multiple contrast settings, allowing for a comprehensive examination of normal and pathological brain function. Corresponding to these controls, the sequences of different brain regions display varying contrast.

The main advantages of MRI are the absence of harmful ionizing radiation, the fact that it is a noninvasive technique, painless, and can be performed without contrast, the ability to show great soft tissue contrast while maintaining high spatial resolution, direct multiplanar imaging in the sagittal, coronal, and axial planes, the ability to display many images, and the ability to perform oblique cuts.

Images with T1 weighting contain dark appearances of CSF and fluid. A Gray Matter (GM) structure has a darker tone than a White Matter (WM) structure. Fat appears brighter in this type of image than in T1 when it comes to brain structure images. To produce the images (using longitudinal relaxation), the TR and TE times are short (TR:500msec, TE:14msec). CSF and fluid contain a high signal intensity, so T2-weighted images appear bright. For T2 (transverse relaxation), TE and TR have long times (4000msec, 90msec). Edema tissue benefits from T2 because it can detect more water and fluid. T2 looks the same as FLAIR, but the CSF fluid has been attenuated,

but the abnormalities are still visible. Cerebral oedema can be visualized with this technique. TE and TR times are extremely long (9000msec, 114msec) for producing images. MRI imaging techniques are depicted in figure below.

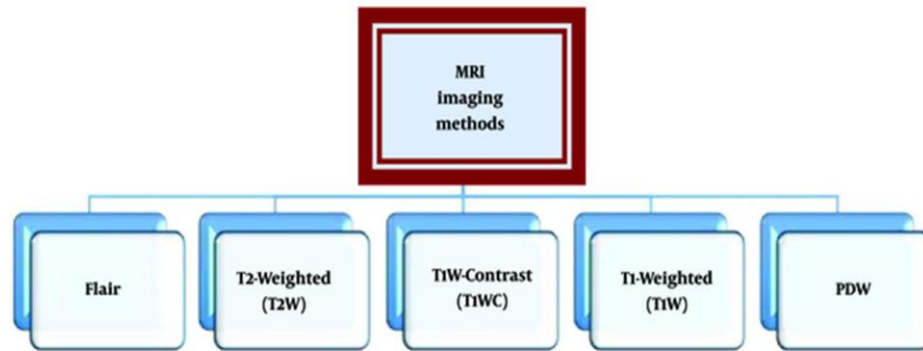


Figure 4. Types of MRI Imaging Technique

IV. BRAIN TUMOR DIAGNOSIS

A. Early Detection and Intervention

Early detection of brain tumors is essential for timely intervention and treatment. Predictive models can aid in identifying potential tumors at an early stage, enabling healthcare professionals to initiate treatment plans promptly.

B. Improved Patient Outcomes

Early diagnosis often leads to improved patient outcomes. Predictive models can help identify tumors before they cause significant symptoms or complications, allowing for more effective treatment strategies and better prognosis.

C. Personalized Treatment Planning

Predictive models, especially those incorporating molecular profiling and genetic information, can contribute to personalized treatment plans. Understanding the specific characteristics of a tumor helps tailor treatments to the individual patient, optimizing therapeutic efficacy.

D. Enhanced Treatment Decision-Making

Accurate prediction of brain tumors provides healthcare professionals with valuable information for making informed decisions about treatment options. This includes decisions about surgery, chemotherapy, radiation therapy, or a combination of these modalities.

E. Reduced Morbidity and Mortality

Early detection and accurate prediction of brain tumors can significantly reduce the morbidity and mortality associated with these conditions. Timely intervention may prevent the progression of tumors to advanced stages, reducing the impact on patients' quality of life.

F. Optimization of Healthcare Resources

Predictive models can contribute to the efficient allocation of healthcare resources. By identifying cases that are more likely to be malignant or require urgent attention, medical professionals can prioritize these cases, leading to more effective resource utilization.

G. Monitoring Disease Progression

Continuous monitoring of predictive models can aid in tracking the progression of brain tumors over time. This allows healthcare providers to adjust treatment plans as needed and provides valuable insights into the tumor's behavior.

V. DIFFICULTIES OF BRAIN TUMOR PREDICTION

A good MR image segmentation and classification is essential for a proper prediction of brain tumors. There have been numerous studies that utilize image segmentation techniques towards the extraction of meaning from medical images (such as tumors), thereby aiding in the proper prediction of brain tumors. Although the shape and presence of cerebrospinal fluid (CSF) make detecting brain tumors difficult, they are particularly complex because of the variability of tumor shapes. Despite superior segmentation techniques, quality of segmentation is highly influenced

by contrast, noise, and incomplete boundaries. Good contrast is particularly important in medical images, as certain contrast characteristics allow abnormal structures to be identified entirely. In MR images, contrast depends on tissue density. MR images of the brain are naturally contrasted, and therefore no contrast enhancement agents are required to produce them. These images are also commonly used in the detection of brain tumors because of this fact. Extrinsic and intrinsic factors influence image contrast. As a result of the appropriate tuning of these parameters, the contrast behavior can be changed and the regions of interest can be highlighted, i.e., tumor tissues can be differentiated from the normal (inner) brain tissues (fat, grey matter - GM, white matter - WM, and CSF).

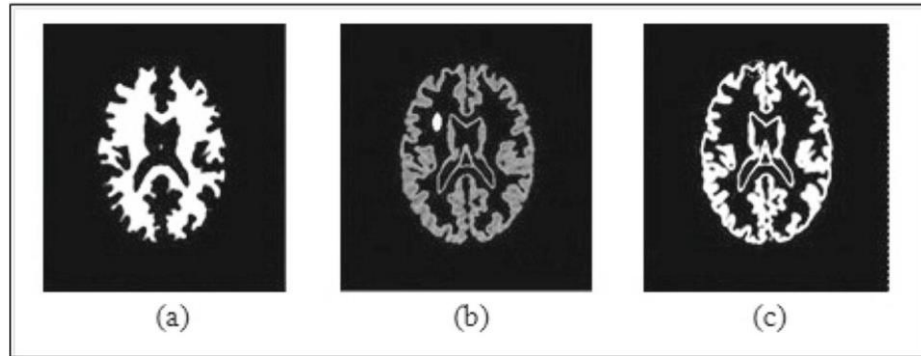


Figure 5. Normal brain tissues after segmentation
(a) White matter (WM), (b) Grey matter (GM), and (c) Cerebrospinal fluid (CSF).

Computer algorithms that use features related to symmetry, intensity gradients, and so on, are used to segment tumors using deep learning techniques. Different regions are classified based on these characteristics as enhancing tumors, non-enhancing tumors, necrosis, or oedema. So far, the research has mainly focused on engineering and signal and image processing. This kind of AI still requires multiple validation steps, including technical, biological, and clinical validation before it can be used regularly. Validation still has some limitations, even when starting from the beginning. First, there is a scarcity of data, which is a very important technical limitation.

Studies on AI in the general public used data sets of 60,000 images or more, while medical researchers are working with smaller data sets - usually between 100 and 1,000. Furthermore, the size, shape, and location of brain tumors are highly heterogeneous. There are often discontinuities or unclear boundaries within tumors. Further, each hospital has a different scanner and image protocol, making it more difficult to standardize and control data quality. Additionally, tumor boundaries are usually irregular and discontinuous, making traditional edge-based methods challenging. Aside from these issues, clinical scans or synthetic databases that contain brain tumor MRI data are also inherently complex. Intensity biases and other differences between slices of an image in a dataset can be imposed by MRI devices and proto-cols used for acquisition. To segment tumor sub-regions effectively, multiple modalities are required. MRI is usually used to distinguish brain tumors because of its advantages of high resolution to sensitive brain tissues and being a non-ionizing, non-radioactive imaging technology that will not hurt human organs. When combined with clinical information and clinical experience, a prepared clinician can distinguish tumor sizes, shapes, physical construction, and other obsessive qualities of brain tumors, aiding the remedy of reasonable treatment to patients. Because each patient has many MRI scans throughout the therapeutic treatment, each of which may offer data in a different order, the doctors must cope with a massive amount of data. Long periods of intense labour will certainly result in errors in the physician's diagnosis of tumor shapes. Furthermore, determining the status of the illnesses based on medical knowledge and clinical experience is subjective for clinicians. As a result, building an automatic or semi-automatic computer aided diagnostic system is important in real-world medical treatments, as it may reduce doctor burden while improving accuracy by providing objective results. This is a significant issue in the realm of medical imaging research, and several techniques have been proposed to address it.

VI. BRAIN TUMOR PREDICTION

Researchers still face many challenges when predicting brain tumors and patients' survival chances. MRIs can be used to predict, classify, and segment brain tumors. There are two types of brain tumors: benign and malignant. There is a strong correlation between the size of a dataset and deep learning methods such as regression. It is

important to use 3D-convolutional neural networks to predict survival time for patients with high-grade brain tumors. Support Vector Classifiers are combined with 3D CNNs to improve accuracy. An evaluation of tumor cells based on shape, location, intensity, and deep characteristics is conducted experimentally. A larger number of training data is required for regression-based methods [13]. Short-term, medium-term, and long-term survival times for patients with high-grade gliomas vary. An analysis of 163 brain MRI samples is conducted for the accuracy of different machine learning and deep learning models. Machine Learning (ML) and Deep Learning (DL) methods are trained using deep features like intensity, statistical texture, volume, and shape of tumor cells. Several ML and DL techniques are tested on BRAT's dataset, including Support Vector Machines (SVM), linear discriminant analysis, logistic regression, and K-neighbor Neighbors (KNN). An algorithm that combines CNNs and linear discriminants is the most accurate [17]. Image recognition and prediction are well-known applications of CNN. Multimodal tumor segmentation challenges are addressed using MvNet and SPNet. Multi-view Networks slice multimodal images from multiple views, each composed of three Multi-branch layers in a Residual Network (Mb-FCRN). By segmenting the patients independently, Mb-FCRN measures their survival time using SPNet [24]. An overview of brain tumor prediction techniques using deep learning is shown in Table 3. High-grade gliomas tumor patients' overall survival time can be predicted with two-stage learning-based methods. With a multimodal, multichannel MRI, survival predictions are improved. From contrast-enhanced MRI images, diffusion tensor images, and resting-state MRI images, metric maps are computed. Anisotropy related fluctuation frequency maps can be generated from DTI images. 3D convolutional neural networks use multichannel metric maps to extract high-quality features that are then used for training the network layers for prediction. To predict (short or long) overall survival time for high-grade glioma patients using age, histology, tumor size, and Support Vector Machines (SVMs), the accuracy is 90.66%. ELM-LRF is a method for predicting tumors using Local Receptive Fields. Three phases are involved, namely, local and nonlocal noise removal, ELM-LRF prediction of benign and malignant tumors, and segmentation of the tumors. A method is pro-posed that uses cranial MR images as they are more dense. Patients suffering from high-grade gliomas brain tumors usually die within 1–2 years of their diagnosis. Gliomas brain tumors can be accurately diagnosed and treated in time to increase the chance of survival. An analysis of MRI, DTI, and fMRI deep features of gliomas patients can help predict overall survival time. In the study, 3-D CNNs with multi-channel data were used to predict the long-term, short-term, and overall survival rates of glioma patients [25].

Table 3. Summary: Predicting brain tumors using deep learning

| Authors | Method/Model | Tools used for Implementation | Performance |
|-------------------------------------|------------------------------|-------------------------------|---|
| Roy et al. [28] | ELM, LRF | MATLAB 2015 | Accuracy = 97.18% |
| Sharma et al.[29] | Modified Level Set Approach | MATLAB | Accuracy = 98% |
| Myronenko A and Hatamizadeh A. [30] | ANN | Scikit-learn3 version 0.19.1 | Accuracy = 72.2% |
| Amin J et al. [31] | SVM and Deep Transfer Model | NA | Accuracy = 68.8% |
| Abbasi S et al. [32] | LDA, KNN, NL-SVM | DWI and FLAIR | Dice Scores = 0.91 Accuracy= 78.32 % |
| Raja NSM et al. [33] | Deep Supervised Network (3D) | NA | Accuracy = 90.66% |

There are some challenges for automatic detection of brain tumors due to their variable locations textures and shapes. As a result of the development of unsupervised clustering methods with fused feature vectors that include Local Binary Patterns (LBPs), GWF's, HOG's, SFTA and others, brain tumor prediction can be achieved. To avoid

overfitting problems during tumor prediction and classification, RF with 0.5 holdout cross-validation is used [36]. Pituitary brain tumors are treated and predicted using neuro endoscopy and invasive procedures. To segment the tumor region, a modified level set method is used for the classification of brain tumors. A Gabor and moment invariant feature set is extracted from Multi-Level Wavelet Decomposition, and GLCM, a feature set generated from Grey Level Co-Occurrence Matrix (GLCM). The prediction of brain tumors is carried out using Adaptive Artificial Neural Networks (AANN) based on selected features.

VII. SEGMENTATION APPROACHES FOR BRAIN TUMOR PREDICTION

Segmentation is a critical step in brain tumor prediction as it involves delineating the tumor region from medical imaging data. Accurate segmentation enables precise localization, characterization, and monitoring of the tumor, providing valuable in-formation for diagnosis and treatment planning. Here are some common segmentation approaches for brain tumor prediction.

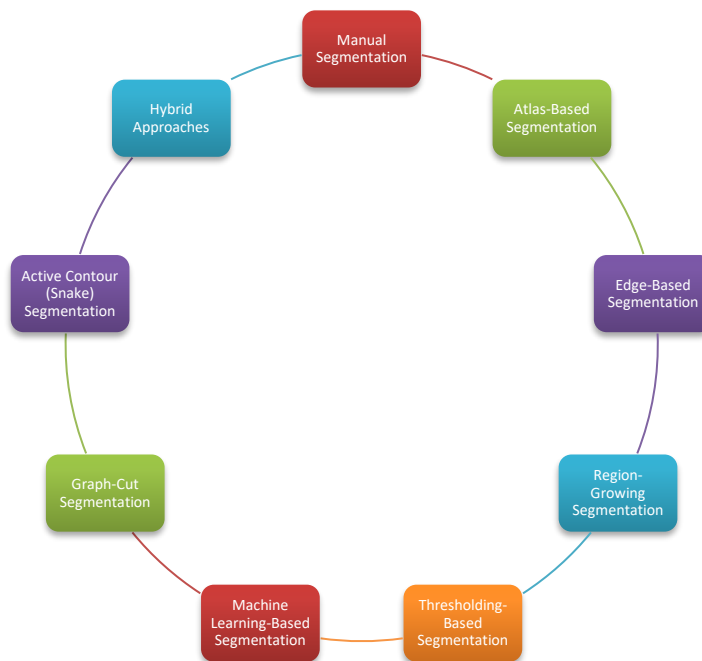


Figure 6. Brain Tumor Prediction Segmentation Approaches

Table 4. Review of various Deep Learning Segmentation Approaches for Brain Tumor Prediction

| Technique | Description | Advantages | Limitations |
|---------------------|--|--|---|
| Manual Segmentation | Manual segmentation involves expert radiologists manually outlining the tumor region on medical images, such as MRI or CT scans. | Provides accurate annotations, especially when performed by experienced professionals. | Time-consuming, subjective, and may vary between different experts. |

| | | | |
|-------------------------------------|---|--|---|
| | | ssion als. | |
| Thresholding-Based Segmentation | This approach involves setting intensity thresholds to classify pixels or voxels as tumor or non-tumor based on their intensity values in medical images. | Simple and computationally efficient | Sensitivity to noise, may not capture variations in tumor intensity, and requires careful threshold selection. |
| Region-Growing Segmentation | Region-growing algorithms start with a seed point and iteratively add neighboring pixels or voxels that meet certain criteria to the segmented region | Adaptable to variations in tumor intensity and structure. | Sensitive to seed point selection and parameters, and may be influenced by noise. |
| Edge-Based Segmentation | Edge-based methods focus on detecting boundaries between tumor and non-tumor regions by identifying edges in the image. | Can capture irregular tumor shapes and boundaries. | Sensitive to noise and variations in edge strength, may require post-processing. |
| Atlas-Based Segmentation | Atlas-based segmentation involves registering a pre-segmented atlas or template to a new patient's image to transfer the segmentation labels. | Can handle inter-patient variability and complex tumor shapes. | Requires a representative atlas and may be sensitive to registration errors. |
| Machine Learning-Based Segmentation | Machine learning techniques, such as supervised learning or deep learning, can be trained on labeled datasets to automatically segment tumors. | Can learn complex patterns and adapt to diverse tumor characteristics. | Requires annotated training data, may be sensitive to variations in imaging protocols, and deep learning models may be computationally intensive. |

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|--------------------------------------|---|---|---|
| | | cteristics. | |
| Graph-Cut Segmentation | Graph-cut algorithms partition an image into regions by optimizing an energy function that considers both pixel similarities and boundary smoothness. | Effective in capturing complex structures and irregular tumor shapes. | Effective in capturing complex structures and irregular tumor shapes. |
| Active Contour (Snake) Segmentation: | Active contour models deform a curve to delineate the tumor boundary by minimizing an energy function based on image gradients. | Suitable for segmenting objects with distinct boundaries. | Sensitive to initialization and may struggle with complex structures. |
| Hybrid Approaches | Hybrid segmentation methods combine multiple techniques or algorithms to leverage their strengths and mitigate individual weaknesses. | Improved robustness and accuracy. | May require optimization of multiple parameters. |

VIII. FEATURE EXTRACTION METHOD

Features are parameter or characteristics of an image in terms of image processing. Whenever there is a process of image processing is concern, the feature extraction is an important aspect for the same. The Image which we can get as output of image processing that will later undergo the feature extraction step. Each image has its significant features which are helpful for the process of tumor detection and classification. Thus, some essential features need to be extracted from these images. There are many different methods for extracting features from an image, such as geometrical features, GWT [2], FOS, GWT [40], HMI [41], multifractal [35], 3D Haralick [36], LBP, GLCM [4, 22], HOG [3], texture and shape. A variety of feature extraction techniques or methods are there such as: GLCM, HOG, LBP, SURF and more. A review of feature extraction techniques is given in Table 3. High-dimensional features increase machine learning and computer vision processing time and memory. Several feature selection strategies are needed to discriminate between relevant and non-related features [33]. Optimal feature extraction is difficult [34].

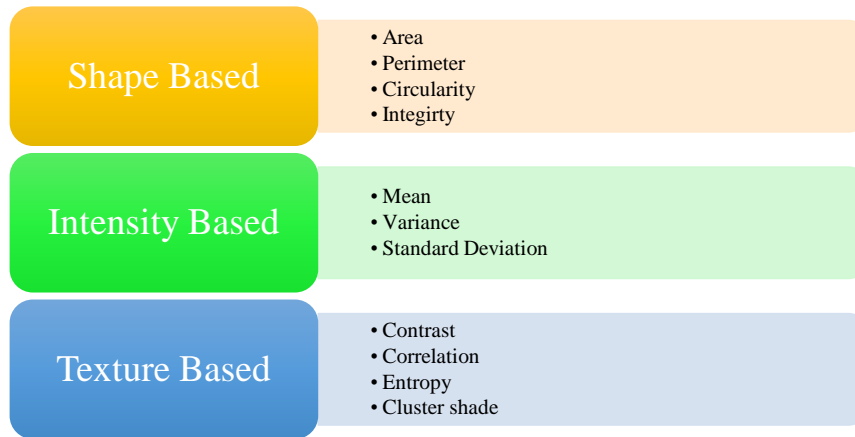


Figure 7. Types of Image Features

Table 5. Review of the Existing Feature Extraction Methods

| Authors and Years | Feature Extraction Methods | Extracted Features | Dataset | Remarks | Results |
|--------------------------------------|-------------------------------|---|---|--|---|
| Karayegen G and Aksahin MF [39] 2021 | FFNN,MLPN-BPN | Multi-Fractal Features | University of Harvard | Glioma (Brain tumor type)and grade in one level | 1.00 SE ,98.01%±0.07 ACC, and 94.78%±0.02 SP |
| Zhang Y et.al.[40] 2021 | Fuzzy C Means FCM with GA PSO | Shape Descriptor | Toal MRI images are 90 | Glioma sequences include T1,T2, and Flair. | 0.98 ACC |
| Xu X, Zhang X et. al.[41] 2022 | LVQ | Tamura Features, GLCM, GLGCM, GLCCM | Total 62 Patients | Tumor grade identification (Low/High) | 0.81 AUC, 0.75 ACC |
| Tiwari P. et.al.[42] 2022 | SWT | Total 372 intensity features and texture | Harvard | Brain tumors were benign, malignant, or normal | 0.93 ACC |
| Amin J et.al[3] 2018 | SURF and SIFT | Features are GWF, HOG, LBP SFTA | ISLES 2015, 2012 Image, 2015 challenge, 2013 challenge BRAT's | Brain tumor/non-tumor classification. | 0.9823 SE, on 2015 challenge, SLES 2015 |
| Srinivas B, et.al.[43] 2019 | GA with Fuzzy C Means FCM | GLCM features | Total MRI images are 105 | Malignant tumor grade analysis | ACC=0.98, SE=1.00, SP=0.97, and Error rate=1.17 |
| Amin J et.al[2] 2019 | BPNN | Gabor Wavelet Transform (GWT) and Local Binary Pattern (LBP) features of LBP and GWF fusion | BRAT's 2013 Challenge, BRAT's 2015 Challenge collected private images | Methods are giving better accuracy | 0.9120 on FFV (Fused Feature Vector) which is ensemble classifier on collected private images |

| | | | | | |
|-----------------------------|---|--|----------------------------------|--|---|
| Khan H et.al.[44] 2020 | Non-textural features(area calculation) | CNN, Histogram of Oriented Gradients (HOG), LBP Features | BRAT's 2015 | Features are extracted more conveniently | 0.73 enhance, 0.81 complete, 0.76 core |
| Vossough A, et.al.[45] 2020 | AIQM | Texture Features (Stochastic) | Total 10 patients of BRAT's 2016 | Feed Forward Neural Network is assisting to get the output | 0.85±0.09 enhance 0.85±0.06 complete, 0.81±0.07 |
| Dixit A et.al.[46] 2021 | TPF | (PCA), Entropy, Mean, and Wavelet Transform | BRAT's 2016 | Noise filtering, Adjusting luminosity | 0.96 ACC |

IX. CHALLENGES, LIMITATIONS AND FUTURE SCOPE OF EXISTING METHODOLOGIES

It has been concluded, on the basis of the challenges that arose during the process of identifying brain cancers in MRI images, that the algorithm used for brain tumor classification has to undergo more refinement in order to achieve accurate brain tumor identification. The purpose of this work is to present the most effective method for classifying brain tumors, with the end aim of properly classifying the tumor from the MRI picture that is presented at an early stage. The purpose of this model and the work that is linked with it is to provide deep learning-based segmentation and classification algorithms for brain tumors that are of a high quality, accurate, and efficient.

Because it is responsible for every facet of human existence, the brain is considered to be the most important organ. Brain tumors are lethal disorders that are caused when cells in the brain grow out of control and form a mass. Both benign and malignant tumors of the brain have the same effect on the nervous system. Brain tumors can be either benign or malignant. In order to save the life of a person who has been diagnosed with a brain tumor, a prompt and accurate diagnosis of the condition is required. Magnetic resonance imaging (often known as MRI) has emerged as the most promising technology for identifying brain problems, according to radiologists. Because tumors tend to be similar to one another in terms of size, form, and appearance, it can be difficult to separate and categorize them. The dynamic range of the image's intensity makes the processing even more challenging than it already was. Therefore, optimization approaches are still required so that we may go more into the subject of how to increase the accuracy of classification.

There are many unique challenges associated with implementing deep learning algorithms and methods in brain tumor image prediction. It is difficult for deep learning methods to train on large datasets. Medical images generated by various PACS, MRIs, and CT systems have been growing in number over the last decade. A well-structured digital archive is used in some other fields to store image data. Ophthalmology and pathology do not widely use PACS and CT systems. Gradually, more public datasets have become available. A deep learning-based method and technique like deep learning is widely used when writing reports on annotations or changing structured labels in automated ways. There is an expectation that structured labeling reports will become easier to introduce in the health domain, especially when it comes to brain tumor prediction. There is a rapid increase in the use of structured reports and text-free reports especially in brain tumor prediction in the future. Deep learning algorithms have been trained using task-specific and text-free reports from domain experts. A high level of expertise is required to label tumorized images, which is challenging in predicting brain tumors. A deep learning algorithm that segmented tumors in 3D networks requires slice-by-slice annotations, which are challenging and time-consuming. Data from BraTS are widely used for evaluating tumor prediction algorithms and predicting a tumor in brain MRIs. Radiologists have annotated four types of tumors in this dataset. Training a deep learning system with standard reference data requires modeling uncertainty and noise. The label uncertainty can be incorporated directly into the loss function by a few researchers, but this remains an open problem. This can be resolved by feeding the whole image into the deep network, which is then trained using various methods. The advantage of deep networks disappears, however, when the network's receptive field is small for the entire image data. Some constraints, such as memory limits, GPU limitations, and bandwidth constraints, make it practically impossible to feed an entire image into the network, as brain tumor images often have a size in the gigapixel range. Researchers have also faced another research challenge when performing image slicing, as they have generally used the same kernel size, which might hide some valuable information in regions that are ignored by the kernel. It has been demonstrated that image

data can be sliced using variable kernel sizes, but there remains room for improvement. Figure 5 describes the open research challenges in brain tumor prediction.

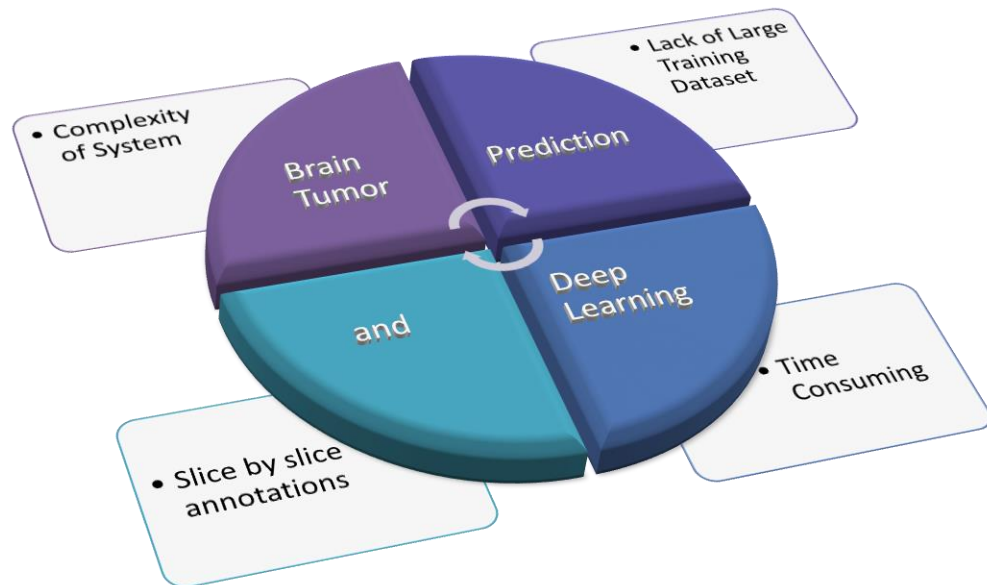


Figure 8. Open Research Challenges in brain tumor prediction

X. RESEARCH FINDINGS AND DISCUSSION

Following an exhaustive analysis of the most recent advancements in exiting techniques, the following problems have been identified:

- The size of a brain tumour expands at an astonishing rate. The diagnosis of a tumour at an early stage is therefore a very important responsibility.
- Because of their fuzzy borders, gliomas tend to spread throughout the body. Because of this, it becomes more challenging to segment them.
- Stroke lesion segmentation is a particularly challenging task due to the fact that stroke lesions appear in a variety of strange shapes and have unclear boundaries and varying degrees of intensity.
- Another challenging step in the process of incorrectly classifying brain tumors is the optimization and selection of the best possible features.

XI. CONCLUSION

This research paper delved into the realm of neural networks in neuroimaging, specifically focusing on a critical analysis of deep learning techniques for brain tumor prediction. Through an extensive review of literature, examination of methodologies, and analysis of results, several key findings emerged. Firstly, the integration of deep learning techniques, particularly neural networks, has demonstrated remarkable potential in enhancing the accuracy and efficiency of brain tumor prediction from neuroimaging data. The ability of these models to automatically learn intricate patterns and representations from vast datasets has proven invaluable, contributing to improved diagnostic capabilities. However, this critical analysis also highlighted several challenges and limitations associated with the application of neural networks in neuroimaging. Issues such as interpretability, data scarcity, and the need for large annotated datasets were identified as significant hurdles that need to be addressed for the widespread adoption of these techniques in clinical settings. Despite these challenges, the overall trajectory of neural networks in neuroimaging is promising, with ongoing research and technological advancements continually pushing the boundaries of what is achievable. As the field evolves, collaboration between researchers, clinicians, and technologists will be pivotal in overcoming existing obstacles and refining deep learning approaches for more robust and reliable brain tumor prediction. In essence, the exploration of neural networks in neuroimaging for brain tumor prediction underscores the transformative potential of artificial intelligence in healthcare. While acknowledging the progress made thus far, it is crucial to maintain a vigilant and critical perspective, fostering a balance between optimism and a realistic understanding of the challenges that lie ahead. As interdisciplinary efforts continue to unfold, the integration of advanced neural network techniques holds the promise of revolutionizing

the landscape of neuroimaging, ultimately contributing to more accurate and timely diagnoses for improved patient outcomes.

REFERENCES

- [1] Khan MA, Lali IU, Rehman A, Ishaq M, Sharif M, Saba T et al (2019) Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection. *Microsc Res Tech* 82:909–922
- [2] Amin J, Sharif M, Raza M, Saba T, Sial R, Shad SA (2020) Brain tumor detection: a long short-term memory (LSTM)-based learning model. *Neural Computational Application* 32:15965–15973
- [3] Amin J, Sharif M, Raza M, Yasmin M (2018) Detection of brain tumor based on features fusion and machine learning. *J Ambient Intell Human Comput*:1–17
- [4] Pellegrino MP, Moreira F, Conforto AB (2021) Ischemic stroke. *Neurocritical care for neurosurgeons*. Springer, New York, pp 517–534
- [5] Jasti, V., Zamani, A., Arumugam, K., Naved, M., Pallathadka, H., & Sammy, F. et al. (2022). Computational Technique Based on Machine Learning and Image Processing for Medical Image Analysis of Breast Cancer Diagnosis. *Security And Communication Networks*, 2022, 1-7. doi: 10.1155/2022/1918379
- [6] Fink JR, Muzi M, Peck M, Krohn KA (2015) Multimodality brain tumor imaging: MR imaging, PET, and PET/MR imaging. *J Nucl Med* 56:1554–1561
- [7] Dina, AD, Samy SA Ghoniemy & Gamal M Selim 2012. Automated brain tumor detection and identification using image processing and probabilistic neural network technique, *International Journal of Image Processing and Visual Communication*, vol. 1, no. 2.
- [8] G. Karayegen and M. F. Aksahin, "Brain tumor prediction with deep learning and tumor volume calculation," 2021 *Medi-cal Technologies Congress (TIPTEKNO)*, 2021. doi:10.1109/tiptekno53239.2021.9632861
- [9] Z. Schwehr and S. Achanta, Brain tumor segmentation based on deep learning, attention mechanisms, and energy-based uncertainty prediction, 2023. doi:10.36227/tehrxiv.24624915.v1
- [10] M. Gurcan and K. Iftekharuddin, "Brain tumor segmentation, grading and patient survival prediction," *Frontiers Research Topics*, 2023. doi:10.3389/978-2-8325-1206-7
- [11] D. C. Yadav and S. Pal, "Measure the superior functionality of machine intelligence in Brain tumor disease prediction," *Artificial Intelligence-Based Brain-Computer Interface*, pp. 353–368, 2022. doi:10.1016/b978-0-323-91197-9.00005-9
- [12] Z. Chen, "Brain tumor prediction with LSTM method," 2022 *International Symposium on Advances in Informatics, Electronics and Education (ISAIEE)*, 2022. doi:10.1109/isaiee57420.2022.00010
- [13] Fazel Zarandia .M.H, Zarinbala.M, Izadi.M, —Systematic image processing for diagnosing brain tumors: A Type-II fuzzy expert system approach || , *Applied Soft Computing*, Vol 11, pp. 285–294, Jan. 2019.
- [14] Pan, Zhigeng; Lu, Jianfeng, —A Bayes-Based Region-Growing Algorithm for Medical Image Segmentation || , *Computing in Science & Engineering*, Vol. 9, pp. 32-38, Jul. 2022.
- [15] Thara, K. S., and K. Jasmine. "Brain tumour detection in MRI images using PNN and GRNN." In 2016 *International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, pp. 1504-1510. IEEE, 2021.
- [16] Subashini, M. Monica, Sarat Kumar Sahoo, Venika Sunil, and Sudha Easwaran. "A non-invasive methodology for the grade identification of astrocytoma using image processing and artificial intelligence techniques." *Expert Systems with Applications*, Vol. 43, pp. 86-196, Jan. 2020.
- [17] Zhang, Yudong, Zhengchao Dong, Lenan Wu, and Shuihua Wang. "A hybrid method for MRI brain image classification." *Expert Systems with Applications*, Vol. 38, pp. 10049-10053, Aug. 2019.
- [18] Pan, Yuehao, Weimin Huang, Zhiping Lin, Wanzheng Zhu, Jiayin Zhou, Jocelyn Wong, and Zhongxiang Ding. "Brain tumor grading based on neural networks and convolutional neural networks." In 2015 *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 699-702. IEEE, 2019.
- [19] El-Dahshan, El-Sayed Ahmed, Tamer Hosny, and AbdelBadeeh M. Salem. "Hybrid intelligent techniques for MRI brain images classification." *Digital Signal Processing*, Vol. 20, pp. 433-441, Mar. 2019.
- [20] Sudha, B., P. Gopikannan, A. Shenbagarajan, and C. Balasubramanian. "Classification of Brain Tumor Grades using Neural Network." In *Proceedings of the World Congress on Engineering 2014*, Vol. 1, pp. 2-4, Jul. 2019.
- [21] Mohamed, Eltaher, and Dalia Mahmoud. "Brain tumor detection using artificial neural networks." *Journal of Engineering and Computer Science (JECS)*, Vol 13, pp. 31-39, Nov. 2019.
- [22] Maitra, Madhubanti, and Amitava Chatterjee. "A Slantlet transform based intelligent system for magnetic resonance brain image classification." *Biomedical Signal Processing and Control*, Vol 1, pp. 299-306, Oct 2019.
- [23] R. Kaur and A. Doegar, "Brain tumor segmentation using Deep Learning: Taxonomy, survey and Challenges," *Brain Tumor MRI Image Segmentation Using Deep Learning Techniques*, pp. 225–238, 2022. doi:10.1016/b978-0-323-91171-9.00003-x

- [24] Chaplot, Sandeep, Lalit M. Patnaik, and N. R. Jagannathan. "Classification of magnetic resonance brain images using wavelets as input to support vector machine and neural network." *Biomedical signal processing and control*, Vol 1, pp. 86-92, Jan. 2020.
- [25] J. Chaki, "Brain MRI segmentation using Deep Learning: Back-ground Study and challenges," *Brain Tumor MRI Image Segmentation Using Deep Learning Techniques*, pp. 1–12, 2022. doi:10.1016/b978-0-323-91171-9.00012-0
- [26] V. Perumal, V. Narayanan, and S. J. Rajasekar, "Detection of brain tumor with magnetic resonance imaging using Deep Learning Techniques," *Brain Tumor MRI Image Segmentation Using Deep Learning Techniques*, pp. 183–196, 2022. doi:10.1016/b978-0-323-91171-9.00014-4
- [27] Song, Guoli, Zheng Huang, Yiwen Zhao, Xingang Zhao, Yunhui Liu, Min Bao, Jianda Han, and Peng Li. "A noninvasive system for the automatic detection of gliomas based on hybrid features and PSO-KSVM." *IEEE Access*, Vol. 7, pp. 13842-13855, Jan. 2019.
- [28] Roy, Sudipta, Shayak Sadhu, Samir Kumar Bandyopadhyay, Debnath Bhattacharyya, and Tai-Hoon Kim. "Brain tumor classification using adaptive neuro-fuzzy inference system from MRI." *International Journal of BioScience and Bio-Technology*, Vol. 8, pp. 203-218, Aug. 2020.
- [29] Sharma, Minakshi, and Sourabh Mukharjee. "Brain tumor segmentation using genetic algorithm and artificial neural network fuzzy inference system (ANFIS)." In *Advances in Computing and Information Technology*, Springer, Berlin, Heidelberg, pp. 329-339, 2013.
- [30] H. Lamdade, A. Pansare, G. Parulekar, and J. Sisodia, "Brain tumor segmentation, grade of tumor and survival duration prediction using Deep Learning," *2023 10th International Conference on Signal Processing and Integrated Networks (SPIN)*, 2023. doi:10.1109/spin57001.2023.10117418
- [31] T. Jagadesh, A. Reethika, B. Jaishankar, and M. S. Kanivarshini, "Early prediction of epileptic seizure using Deep Learning algorithm," *Brain - Computer Interface*, pp. 157-177, 2023. doi:10.1002/9781119857655.ch7
- [32] Abbasi S, Tajeripour F (2020) Detection of brain tumor in 3D MRI images using local binary patterns and histogram orientation gradient. *Neurocomputing* 219:526–535
- [33] Raja NSM, Fernandes SL, Dey N, Satapathy SC, Rajinikanth V (2019) Contrast enhanced medical MRI evaluation using Tsallis entropy and region growing segmentation. *J Ambient Intelligent Human Comput*:1–12.
- [34] Banerjee S, Mitra S, Shankar BU (2019) Automated 3D segmentation of brain tumor using visual saliency. *Inf Sci* 424:337–353.
- [35] Kao PY, Shailja S, Jiang J, Zhang A, Khan A, Chen JW, Manjunath BS (2020) Improving patch-based convolutional neural networks for MRI brain tumor segmentation by leveraging location information. *Front Neurosci* 13:1–12
- [36] Gupta N, Bhatele P, Khanna P (2019) Glioma detection on brain MRIs using texture and morphological features with ensemble learning. *Biomed Signal Process Control* 47:115–125.
- [37] Subudhi A, Dash M, Sabut S (2020) Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier. *Biocybern Biomed Engineering* 40:277–289
- [38] Myronenko A, Hatamizadeh A (2020) Robust Semantic Segmentation of Brain tumor Regions from 3D MRIs. *arXiv:2001.02040*.
- [39] Karayegen G, Aksahin MF (2021) Brain tumor prediction on MR images with semantic segmentation by using deep learning network and 3D imaging of tumor region. *Biomed Signal Process Control* 66:102458.
- [40] Zhang Y, Yang J, Wang S, Dong Z, Phillips P (2021) Pathological brain detection in MRI scanning via Hu moment invariants and machine learning. *Journal of Experimental Theoretical Artificial Intelligence* 29:299–312
- [41] Xu X, Zhang X, Tian Q, Zhang G, Liu Y, Cui G et al (2022) Three-dimensional texture features from intensity and high-order derivative maps for the discrimination between bladder tumors and wall tissues via MRI. *International Journal of Computational Assistance Radiology Surgery* 12:645–656
- [42] Tiwari P, Sachdeva J, Ahuja CK, Khandelwal N (2022) Computer Aided Diagnosis System—A Decision Support System for Clinical Diagnosis of Brain Tumour. *International Journal of Computational Intelligence System* 10:104–119
- [43] Srinivas B, Rao GS (2019) Performance evaluation of fuzzy C means segmentation and support vector machine classification for MRI brain tumor. *International Conference of Soft computing for problem solving*. Springer, New York, pp 355–367
- [44] Khan H, Shah PM, Shah MA, Islam S, Rodrigues JJ (2020) Cascading handcrafted features and convolutional neural network for IoT-enabled brain tumor segmentation. *Computational Communication* 153:196–207
- [45] Pei L, Bakas S, Vossough A, Reza SM, Davatzikos C, Iftekharuddin KM (2020) Longitudinal brain tumor segmentation prediction in MRI using feature and label fusion. *Biomed Signal Process Control* 55:101648
- [46] Dixit A, Nanda A (2021) An improved whale optimization algorithm-based radial neural network for multi-grade brain tumor classification. *Visual Computation*:1–16.