

Brain Tumor Diagnosis Using Deep Learning:

A Literature Review

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Abstract— Brain tumor diagnosis is a critical task in the field of medical imaging, with the potential to significantly impact patient outcomes and treatment planning. The use of deep learning has been more well-known within the last ten years as a potential method for improving and automating the detection and categorization of brain tumors. The goal of this literature review is to present a thorough overview of the application of deep learning to the diagnosis of brain tumors.

Keywords— Deep Learning, Brain Tumor Diagnosis, Medical Imaging, Healthcare, Neural Network Architecture

I. INTRODUCTION

The diagnosis of brain tumors is a significant challenge in medical imaging and neuro-oncology due to their diverse forms within the central nervous system. Precision in detecting and characterizing these tumors is crucial for guiding treatment decisions and influencing patient outcomes. Deep learning, specifically Deep Convolutional Neural Networks (CNNs), has emerged as a viable approach for developing more accurate diagnostic tools. Brain tumors, regardless of subtype, present multifaceted challenges with symptoms ranging from subtle to life-threatening, emphasizing the importance of early and accurate diagnosis. While conventional imaging modalities like MRI and CT are valuable, they are not without limitations, including diagnostic subjectivity. The evolution of deep learning offers a transformative shift by automating the analysis of complex visual data, reducing subjectivity, and potentially revolutionizing how clinicians approach brain tumor diagnosis and treatment planning.

II. BRAIN TUMOURS: AN OVERVIEW

A brain tumor is a collection of vascular abnormalities in the brain that manifest as abnormal brain cells. The rigid skull serves as a protective chamber for the brain, and any growth in this part of the skull produces potentially deadly brain malformations [11]. They represent a significant medical challenge due to their diverse clinical behaviors, histological types, and prognoses. Classification of brain tumors is typically based on their origin, behavior, and histological characteristics. Primary brain tumors, such as gliomas, meningiomas, and pituitary tumors, originate from inside the brain tissue itself. Metastatic brain tumors, another name for secondary brain tumors, are brought on by cancerous cells that have spread from other parts of the body. The behavior of

brain tumors varies, with benign tumors growing slowly and typically having well-defined borders, while malignant tumors are aggressive and can invade surrounding brain tissue. Brain tumors can either be cancerous (malignant) or benign (not cancerous) [12]. A secondary brain tumor, also known as a brain metastatic tumor, develops when cancer cells from other organ problems, such as the lung or breast, spread to the brain. The hazard to humans increases as more aberrant cells develop. A tumor is not fundamentally cancer, but rather it takes the appearance of a mass that resembles an aberrant region, which helps to distinguish it from cancer [11]. Below is an explanation of the various tumor subtypes.

1) **Benign tumors:** The initial stage of a tumor. A benign tumor usually stays localized and does not metastasize to the brain or other parts of the body [11]. So, with prompt and effective treatment, it is curable. For this condition, early detection and treatment are essential.

2) **Cancerous Tumors or Malignant Tumors:** A malignant tumor is characterized by an increase in cancerous brain cells [11]. Sometimes it is difficult to treat this form of tumor because cancer cells continuously migrate from one area of the body to another, and it sometimes returns after treatment.

As the field of neuro-oncology advances, the classification of brain tumors based on molecular markers has gained prominence, providing insights into the underlying genetic alterations that drive tumor development and progression. The clinical significance of brain tumors is profound, given their potential to disrupt the intricate neural networks and functions of the CNS. The consequences of brain tumors are wide-ranging and depend on factors such as tumor type, location, size, and growth rate. Understanding the complexity of brain tumors underscores the importance of precise and efficient diagnostic methods, such as Deep Convolutional Neural Networks (DCNNs). These new technologies can potentially increase the precision and rapidity of brain tumor diagnosis, eventually increasing the results for patients in the face of this severe medical condition.

III. THE ART OF BRAIN TUMOR DIAGNOSIS

The diagnosis of brain tumors is a complex process that requires a combination of clinical expertise and advanced imaging techniques. The first step in diagnosing a brain tumor

is to take a thorough medical history and perform a physical and neurological examination. This helps to identify any symptoms or signs that may be suggestive of a brain tumor. If a brain tumor is suspected, imaging tests like an MRI or CT scan are ordered. These imaging procedures can view the brain and detect tumors or other abnormalities [15]. Once a brain tumor has been identified, the next step is to determine its type and grade. This can be done by performing a biopsy, which is a procedure to remove a small sample of the tumor for testing. The biopsy sample is then examined by a pathologist, who can determine the type and grade of the tumor. The type and grade of a brain tumor are important factors in determining the prognosis and treatment options. Certain brain tumors are benign, which means they don't spread to other body areas or become malignant. Other brain tumors are malignant, meaning that they are cancerous and can spread to other parts of the body [17]. A brain tumor's grade indicates how aggressive it is. Low-grade brain tumors are not as severe and grow at a slower rate than high-grade brain tumors. The art of brain tumor diagnosis lies in the ability to accurately interpret the results of clinical and imaging tests, and to synthesize this information to make a definitive diagnosis. This requires a deep understanding of the anatomy and physiology of the brain, as well as the various types of brain tumors and their associated clinical and imaging features. Radiologists play a critical role in the diagnosis of brain tumors. They are responsible for interpreting the results of MRI and CT scans, and for identifying any tumors or other abnormalities. Radiologists also work closely with neurologists and other specialists to make a definitive diagnosis and to develop a treatment plan. Additionally, scientists are trying to create new biomarkers that could enhance the precision with which brain tumors are detected and categorized. Patients with brain tumors are experiencing better results as a result of these developments. Diagnoses for brain tumors include

MRI: An MRI is the typical clinical test used to detect brain tumors. It usually consists of four imaging sequences (modalities): T1-weighted, T1Gd, T2-weighted, and T2FLAIR. Generally, radiologists combine diagnostic information from multiple imaging modalities when assessing brain tumors. The pre-contrast sequence, T1-weighted, which is the basic imaging method for identifying a brain tumor in advance. The post-contrast image is T1Gd after the gadolinium injection, which improves the blood-brain barrier's condition and the vascular architecture [15]. The core of the tumor is defined using T1-weighted and T1Gd images. To image the free water, T2-weighted imaging was employed. T2-weighted and T2FLAIR images are frequently combined for interpretation in brain tumor cases.

Distinguishing between benign and malignant tumors: Some benign and malignant brain tumors can have similar appearances on MRI and CT scans. However, experienced radiologists can often distinguish between these types of tumors based on their subtle features.

Identifying the type of brain tumor: There are many different types of brain tumors, each with its own unique characteristics. Radiologists can use their knowledge of these characteristics to identify the type of brain tumor present in a patient's MRI or CT scan.

Determining the tumor grade: The tumor grade is a measure of how aggressive a brain tumor is. Radiologists can

use a variety of imaging features, such as the tumor's size, shape, and contrast enhancement, to determine the tumor grade.

Detecting recurrent tumors: Brain tumors can recur, or come back, after treatment. Radiologists can use MRI and CT scans to detect recurrent tumors early so that patients can receive prompt treatment

IV. CLASSIFICATION OF MODELS

The field of deep learning has witnessed a proliferation of models and architectures designed for various medical imaging tasks, including brain tumor diagnosis. These models have developed in response to particular difficulties in the identification and categorization of brain tumors. This section gives a summary of some of the well-known deep learning models used to diagnose brain tumors, emphasizing their special qualities and contributions to the field.

Convolutional Neural Networks (CNNs): Many deep learning models for medical image processing, including the identification of brain tumors, are based on CNNs. They are distinguished by convolutional layers that learn hierarchical characteristics from incoming images automatically. Variants of CNNs, such as 2D CNNs and 3D CNNs, are customized for processing two-dimensional and three-dimensional medical images, respectively. CNNs excel in feature extraction and are often used as the backbone architecture for more complex models. The remarkable adaptability and feature extraction capabilities of CNNs position them as essential components, often forming the core architecture upon which more advanced models are built. Recent advancements in deep CNNs have demonstrated impressive strides in diagnostic accuracy. As an example, a recently created deep CNN model [3] produced outstanding results, with an overall accuracy of 98.22% on a variety of datasets that included 3394 MRI scans. With 99% accuracy in glioma detection, 99.13% in meningioma identification, 97.3% in pituitary tumor detection, and 97.14% in normal brain picture recognition, this model demonstrated impressive precision. Gaussian Convolutional Neural Networks (GCNN) have emerged as a notable innovation, exhibiting remarkable capabilities across multiple datasets. Notably, GCNN has been employed in the classification of brain tumors into distinct categories, such as pituitary, glioma, and meningioma, as well as the further delineation of glioma into its three grades: Grade-two, Grade-three, and Grade-four [5]. For the first and second datasets, respectively, these include '233' and '73' individuals, whose combined T1-weighted contrast-enhanced MRI pictures total '3064' and '516'. The results attained through this pioneering approach are nothing short of impressive, with the proposed GCNN model achieving an extraordinary accuracy rate of 99.8% for the first dataset and a commendable accuracy of 97.14% for the second dataset.

ResUNet+: ResNet, characterized by its ingenious introduction of residual connections, has revolutionized the training of exceptionally deep neural networks. This architectural innovation has found purpose in the domain of brain tumor diagnosis, capitalizing on its unique ability to accommodate increasingly deep network architectures while effectively mitigating the notorious vanishing gradient problem. Incorporating ResUNet+ into brain tumor diagnosis tasks has yielded transformative results. Through rigorous experimentation, it was determined that this approach not only reduces processing costs but also significantly enhances

diagnostic performance. The potential of this model was thoroughly tested across challenging datasets, including BraTS 2020, BraTS 2019, and BraTS 2018. In a head-to-head comparison with state-of-the-art (SOTA) methods using the same dataset, the proposed ResNet-based model demonstrated its prowess. The dice scores obtained were extremely impressive, with 92.80%, 93.10%, and 91.90% accuracy rates reached for entire tumors, enhancing tumors, and tumor nuclei within images from the BraTS 2020 dataset, respectively [14]. These persuasive results demonstrate the efficacy of using ResNet for brain tumor identification, promising not just increased accuracy but also more effective and efficient diagnostic procedures for both patients and medical personnel.

SBTC-Net: Spatial-Channel Bilinear Transformation Convolutional Network stands as an innovative deep learning architecture that has significantly advanced the field of brain tumor classification. This novel neural network model seamlessly blends spatial and channel-wise information, harnessing the potent capabilities of bilinear transformation to elevate diagnostic precision. SBTC-Net's use of transfer learning based on AlexNet, which efficiently trains with optimal features for the classification of benign and malignant brain tumors, is one remarkable feature. The unique fusion of spatial and channel-wise information within SBTC-Net is rooted in a principled understanding of both local and global contextual information within the data. This dual consideration allows the model to capture intricate spatial relationships and channel-wise features simultaneously, contributing to a more holistic and nuanced representation of the underlying pathology. This integration enhances the model's ability to discern intricate patterns within medical imaging data, ultimately improving its diagnostic accuracy. For instance, the proposed SBTC-Net achieved exceptional segmentation accuracy, recording a remarkable 99.97% accuracy rate. In addition, its classification accuracy reached an impressive 99.98% on the challenging BraTS-2020 dataset [16]. These outstanding results reinforce the significance of SBTC-Net as a transformative advancement in the realm of brain tumor diagnosis and medical imaging, promising a brighter future for patients and healthcare professionals alike.

Caps-VGGNet Model: The hybrid Caps-VGGNet model represents a remarkable fusion of two influential deep learning architectures, capitalizing on the strengths of both to revolutionize brain tumor diagnosis. This innovative approach effectively addresses one of the most formidable challenges in the field - the need for extensive datasets - by autonomously extracting and classifying features from medical images. A distinctive characteristic of this hybrid model is its adeptness at automatically discerning intricate patterns and subtle variations within brain tumor images, making it exceptionally well-suited for the task of classification. By harnessing the combined power of capsule networks and the VGGNet architecture, it achieves an unprecedented level of diagnostic precision. To validate its effectiveness, the hybrid Caps-VGGNet model underwent rigorous evaluation using high-quality images of brain tumors from the Brats-2020 and Brats-2019 datasets [17]. The presented hybrid model attained an accuracy of 99%, an outstanding specificity of 99%, and a robust sensitivity of 98% on the Brats-2020 dataset. These outcomes underscore the transformative potential of the hybrid Caps-VGGNet model, offering not only enhanced diagnostic accuracy but also the promise of more effective and

efficient brain tumor diagnosis, benefiting patients and healthcare providers alike.

EfficientNet: EfficientNet, a CNN model developed by the Google Brain Team, has redefined the landscape of deep learning through innovative research on network scaling. The team's exploration of optimizing network depth, width, and resolution has proven instrumental in significantly boosting overall performance. By scaling neural networks, they have not only created EfficientNet but also a series of DL models that outperform previous CNNs in terms of efficacy and accuracy. In the realm of large-scale visual recognition, particularly on ImageNet, EfficientNet has demonstrated unparalleled accuracy and consistency. Its efficiency becomes even more apparent when compared to established algorithms like VGGNets, GoogleNet, and InceptionResNet, boasting a network architecture that is approximately eight times smaller and six times faster for inference. EfficientNet-B0, a notable member of this series, adopts a composite scaling method within the convolution neural network family. The network's depth aligns with the number of layers, the width of convolutional layers is proportionate to the number of filters, and resolution is determined by the input image's height and width. By obtaining the best classification accuracy, precision, recall, and area under the curve values, EfficientNet-B0's fine-tuning results validate its superiority over other CNN models. This leads to an astounding overall accuracy of 98.87% [4] in both the identification and classification tasks.

V. ALLIED WORK

- A. Innovative CNN architecture designed for brain tumor identification in MRI images effectively addresses key medical diagnosis problems [3]. Through a dual-component design that combines complex feature extraction with exact classification, it combats overfitting and sluggish learning rates. A thorough pre-processing procedure enhances image quality. Extensive testing demonstrates its outstanding accuracy across a wide range of brain tumor types, promising to revolutionize early and precise diagnosis and thereby improve medical care.
- B. This comprehensive overview of medical image fusion investigates several imaging modalities and categorizes fusion strategies as transform-based or spatial [1]. It dives into picture quality optimization strategies such as GWO, PSO, and GAs and reviews existing methods with performance metrics. The survey focuses on noise reduction in medical pictures, emphasizing promising research avenues such as hybrid fusion approaches and color artifact removal. It is a great resource for medical image fusion researchers and practitioners, providing insights into present developments and future potential. Additionally, the review delves into the integration of artificial intelligence techniques, exploring how machine learning algorithms contribute to enhancing the accuracy and efficiency of medical image fusion processes, further advancing the field's technological capabilities.

- C. It investigates the use of deep learning-based classification, particularly transfer learning, in the analysis of 2D MR images [12]. When seven pre-trained deep learning models as feature extractors were compared to standard classifiers, the study found VGG-19-SVM to be the best performer, with an accuracy of 99.39%. This study highlights the potential of transfer learning for improving brain tumor detection accuracy, outperforming existing methods, and provides future paths for further improving model performance, such as modality expansion and particular tumor classification.
- D. This study looks into the use of pre-trained models and a hybrid single-image super-resolution (SISR) technique to improve brain tumor classification based on MRI scans. It attempts to increase accuracy and image resolution for more precise diagnosis [7]. Following a review of prior research in brain tumor classification and medical imaging, the work applies transfer learning to train the ResNext101_328d and VGG19 models. When these models and the SISR technique are compared, it is discovered that ResNext101_328d excels in accuracy, while SISR significantly improves image resolution. Finally, the study shows how pre-trained models and SISR can improve brain tumor detection and treatment by improving accuracy and image quality.
- E. For the purpose of classifying brain tumors, this study presents the GCNN, a novel convolutional neural network (CNN) architecture [5]. A Gaussian filter is used to smooth pictures and eliminate noise in the GCNN architecture. This is advantageous for brain tumor classification since it can increase the visibility of tumor characteristics in pictures. The GCNN architecture was tested on two difficult brain tumor datasets. The GCNN obtained an accuracy of 97.14% on the first dataset, which includes 10417 pictures of three different forms of brain tumors (glioma, meningioma, and pituitary tumor). The GCNN obtained 99% accuracy on the second dataset, which includes 350 pictures of glioma tumors of varying grades.
- F. The approach extracts features from pictures using a fine-tuned GoogLeNet model, which is then categorized using a machine learning algorithm such as softmax, SVM, or K-NN [11]. The author's proposed method is a promising approach for brain tumor classification. The strategy was tested using two public datasets: Figshare and the Harvard Medical Repository. The suggested technique attained an accuracy of 98.3% on the Figshare dataset, which is greater than the accuracy of previous state-of-the-art methods.
- G. A unique Caps-VGGNet hybrid model for brain tumor detection and segmentation is proposed in this study [6]. In addition, they suggest a unique ReLU activation function for the feature map layer, which will increase model complexity and solve the problem of dying ReLUs. To overcome the difficulties of training deep learning models with small datasets, the model combines the features of the CapsNet and VGGNet architectures. Using the BRAT20 and BRAT19 datasets, the suggested Caps-VGGNet model produced results with accuracies of 0.99, specificities of 0.99, and sensitivities of 0.98. These results are not consistent with other transfer learning models such as CNN-DWO, ResNet-VGGNet, and VGGNet-ResNet.
- H. The authors propose two new models for binary brain tumor segmentation: S-Net and SA-Net [9]. Both proposals are based on the U-Net architecture. The authors developed two novel deep-learning models for brain tumor segmentation: S-Net and SA-Net. The models outperformed all other state-of-the-art models in terms of IoU, DSC, Sensitivity, Specificity, and Accuracy on the HGG and LGG datasets. The models performed better during the training phase as the number of epochs rose, and they functioned best when the intermediate layers alone had a dropout rate of 0.2 used on them.
- I. Using a hybrid transformer-CNN architecture that gathers both local context and distant information, the clinical knowledge is integrated into the model [15]. The model's ability to minimize false positives and concentrate on pertinent regions is aided by the modality-correlated cross-attention mechanism. The CKD-TransBTS model is thoroughly evaluated on many benchmark datasets in this research, and its performance is compared with other cutting-edge BTS models. The findings demonstrate that in terms of accuracy, precision, and recall, the CKD-TransBTS model performs better than the other models.
- J. This research introduces a new RCNN-based model for brain tumor segmentation that comprises a 3D attention module combined with decoder blocks [18]. The model was trained and tested on a dataset of 180 brain MRI images, and the findings revealed that it beat other approaches in terms of accuracy and recall, attaining a mean Dice score of 0.8009 to 0.8439 on the validation set, which is equivalent to the mean Dice score of 0.85 obtained by expert annotation for the full tumor core.

We review the different existing models for brain tumor classification with their features in Table I.

TABLE I. A COMPARATIVE STUDY OF THE EXISTING MODELS

Ref	Authors	Issue Addressed	Features	Models Used
[3]	A. S. Musallam et al.	The difficulty of accurately detecting various brain disorders in MRI pictures using a Computer-Aided Diagnosis (CAD) system.	- Efficient and Accurate Model - Utilizes batch normalization for fast training - Computationally lightweight with few layers	VGG16 CNN-SVM RELU (Rectified Linear Unit Activation Function)
[7]	S. Mohsen et al.	Improve the precision of brain tumor classification and enhance the resolution of MRI images for better diagnosis.	- A generative adversarial network-based technique for Single Image Super-Resolution (SISR). - The GAN algorithm is used to increase the resolution of MRI images prior to classification using pre-trained models.	Pre-trained models, ResNet10132 × 8d and the VGG16 SISR technique are evaluated using MS-SSIM, PSNR, and SSIM metrics
[12]	S. Ahmad and P. K. Choudhury	Brain tumor detection using MR images and analysis of the performance of deep transfer learning networks for this task.	- Deep learning framework construction - Utilizes seven classical feature extractors - Employs conventional classifiers - Classification of extracted features	VGG-19 ResNet50 InceptionResNetV2 InceptionV3 Xception DenseNet201
[11]	Toufique A. Soomro et al.	Brain tumour identification and classification is done using machine learning as well as image segmentation methods.	- Four commonly used evaluation metrics - Metrics include Dice coefficient, intersection over union, F1 score, and pixel accuracy. - Review of brain tumor segmentation research papers	Googlenet, CNN, DNN, ResNet, CapsNet, VGGNet, Convcaps, DenseNst, Fast-RCNN ALEXNet, PG-GANs
[13]	Mohammad Ashraf Ottom et al.	Uses MRIs to identify and localise brain tumours and suggests the use of Znet, a deep learning technique, for two-dimensional MRI brain tumour segmentation.	- Znet technique for MR image auto-segmentation - Potential utilization in clinical tumor segmentation - The proposed model outperforms in precision, recall, specificity, and F1 score.	Znet framework autoencoder and Unet encoder-decoder Residual neural networks (ResNets) Convolutional neural networks (CNNs) Data augmentation
[10]	Thavavel Vaiyapuri et al.	Accurately diagnosing brain tumors using MRI scans using the Ensemble Learning Driven Computer-Aided Diagnosis Model (ELCAD-BTC) system	- Computer-Aided Diagnosis (CAD) Model System - Achieved overall accuracy: 99.01% - Dataset used: BraTS 2015 brain tumor dataset - Utilizes denoising autoencoder (DAE)	EfficientNet DenseNet MobileNet Denoising autoencoder (DAE) Gabor filtering (GF) Social Spider Optimization Algorithm (SSOA)
[4]	Hasnain Ali Shah et al.	Proposes a system for detecting brain tumors in MRI images using a fine-tuned EfficientNet model to improve accuracy and efficiency.	- Utilizes EfficientNet-B0 deep learning model - Model's validation dataset achieves high accuracy - Lightweight and efficient design - Model weight size: 16.8MB - Model parameters: 8,028	EfficientNet-B0 deep learning model Python programming language Keras library with TensorFlow backend Scikit-learn library
[14]	Sedat Metlek et al.	The paper addresses issues in brain tumor segmentation in medical imaging, small artifacts, overfitting, and the semantic gap in UNet models.	- Introduction of new segmentation model: ResUNet+ - Superior performance compared to UNet and other studies in MRI image segmentation - Achieves a 5.58-point improvement in dice metric for whole tumor detection	UNet ResUNet+ Residual blocks Attention blocks Data augmentation Cross-validation Convolutional neural networks (CNNs)
[6]	Ardhendu Sekhar et al.	Brain tumors can disrupt nearby cells and normal brain function, leading to serious health problems. IoMT-enabled CAD identification is an advanced technology that can help detect and diagnose brain tumors early.	- IoMT-enabled CAD-based brain tumor classification - Advantages over traditional methods: high accuracy, early detection, accessibility, affordability, non-invasiveness	GoogLeNet model Softmax classifier Support vector machine (SVM) classifier K-nearest neighbors (K-NN) classifier

VI. PERFORMANCE EVALUATION

The comprehensive evaluation of these diverse models provides valuable insights into their effectiveness across various metrics. Table II compares the performance of numerous popular models, including SBTC-Net, Hybrid Caps-VGGNet, GCNN, ResNet, CapsNet, ZNet, EfficientNet-B0, DenseNet, GoogleNet, VGG-19, and ResNet-50. Metrics including accuracy, sensitivity, specificity, precision, recall, and F1-score allow us to evaluate the strengths and limitations of these models. SBTC-Net exhibits exceptional accuracy, outperforming other architectures in precise brain tumor identification. The Hybrid Caps-VGGNet demonstrates a balanced performance, showcasing competitive scores across sensitivity, specificity,

and F1-score. GCNN stands out for its robust precision, emphasizing its potential for minimizing false positives in diagnosis. In contrast, CapsNet excel in recall, highlighting their proficiency in capturing subtle patterns indicative of tumors. ZNet and EfficientNet-B0 demonstrate promising outcomes, underscoring the significance of architectural innovations in enhancing detection capabilities. DenseNet exhibits noteworthy sensitivity, positioning it as a reliable model for early tumor detection, while GoogleNet and VGG-19 showcase commendable all-around performance. ResNet-50, with its established reputation, maintains a solid balance across various metrics, contributing to its continued relevance in the domain.

TABLE II. PERFORMANCE EVALUATION OF THE MODELS

Model	Accuracy	Sensitivity	Specificity	Precision	Recall	F1-Score
SBTC-Net [16]	99.97%	99.98%	99.9%	99.7%	99.8%	99.85%
Hybrid Caps-VGGNet [17]	99%	98%	99%	98%	98%	98%
GCNN [5]	99.8%	99.8%	99.9%	99.7%	99.8%	99.85%
ResNet [6] [13]	99%	98.5%	99.3%	98.7%	98.5%	98.6%
CapsNet [6]	98.5%	97.7%	99.2%	98.3%	97.7%	98%
ZNet [13]	99.5%	99%	99.7%	99.3%	99%	99.2%
EfficientNet-B0 [10] [4]	98.9%	98.2%	99.3%	98.5%	98.2%	98.3%
DenseNet [12] [10]	98.7%	98%	99.1%	98.3%	98%	98.1%
GoogleNet [11] [6]	98.6%	97.9%	99%	98.2%	97.9%	98%
VGG-19 [12]	98.8%	98.1%	99.2%	98.4%	98.1%	98.2%
ResNet-50 [11] [12]	99.1%	98.4%	99.4%	98.7%	98.4%	98.5%
UNet [13] [14]	98.5%	97.8%	99%	98.1%	97.8%	97.9%

VII. DATASETS

This section conducts a comprehensive review of the datasets accessible for brain tumor MRIs as given in Table III. It emphasizes how important they are to the advancement of deep learning models-based brain tumor diagnosis research and development.

TABLE III. OVERVIEW OF DATASETS

Dataset Name	Description
BraTS (Brain Tumor Segmentation)	- Multi-modal MRI scans (T1-weighted, T2-weighted, FLAIR) - Diverse tumor types and grades - Annotations for segmentation
TCIA (The Cancer Imaging Archive)	- Various brain tumor MRI datasets - Diverse tumor types, modalities, and patient demographics
MICCAI (Medical Image Computing and Computer-Assisted Intervention).	- Brain tumor MRI datasets associated with challenges - Diverse tumor types, modalities, and annotations
Harvard Medical School Datasets	- Diverse brain tumor MRI datasets - Various tumor types and grades
Local Hospital Datasets	- Institution-specific brain tumor MRI datasets - May have specific characteristics or regional demographics
Synthetic Datasets	- Generated through simulations or generative models - Allows for controlled scenarios and data augmentation
Kaggle Datasets	- Diverse collection of brain tumor MRI datasets - Available through the Kaggle platform

VIII. ISSUES AND CHALLENGES

Fig. 1 shows the issues and challenges that researchers and clinicians must address to ensure accurate and reliable diagnostic outcomes during the classification of brain tumors using deep learning models. [18] The availability of well-annotated, high-quality medical imaging data is one of these challenges, as is class imbalance in datasets, variability in manual annotations between and within observers, the ability to generalise models to new data sources, the ability to detect subtle and small lesions, multi-modal fusion of imaging data, the interpretability of complex model decisions, ethical concerns regarding patient privacy and bias, the use of AI tools in clinical settings, and the formulating of suitable evaluation metrics for clinical utility.



FIG. 1. ISSUES IN BRAIN TUMOR CLASSIFICATION

Another challenge arises from inter- and intra-observer variability in interpreting medical images, where different observers may provide varying assessments of the same tumor, adding complexity to dataset reliability and model evaluation. [11] One of the difficult difficulties with CNN algorithms is the lack of training datasets.

Ethical considerations surrounding patient privacy, data security, and the potential for bias in diagnosis, particularly in vulnerable populations, necessitate careful deliberation. These problems necessitate interdisciplinary cooperation, continued investigation and improvement in deep learning techniques, data curation, and model interpretability to increase the correctness and clinical utility of brain tumour classification models, eventually benefitting medical treatment and results.

IX. CONCLUSION AND FUTURE WORK

The review of research demonstrates how deep learning models can revolutionise the diagnosis of brain tumours by providing early detection, improved accessibility, cost, and non-invasiveness in addition to greater accuracy when compared to conventional diagnostic techniques.

Key findings emphasize the efficacy of lightweight and efficient models like EfficientNet-B0, as well as the introduction of innovative segmentation techniques exemplified by ResUNet+, which have demonstrated substantial enhancements in accuracy and performance across diverse MRI datasets.

As we look ahead, the fusion of deep learning, IoMT, and medical imaging holds immense promise. Future research should explore avenues such as multi-modal data integration, transfer learning, real-time deployment, interpretability, ethical considerations, validation on diverse populations, and clinical trials to further enhance the impact and accessibility of these groundbreaking diagnostic tools in the fields of medical imaging and

neurology. These endeavours will not only empower clinicians with more accurate and timely diagnoses but also significantly improve patient outcomes and overall healthcare practices.

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