An Overview of Recent Trends in Brain Tumor Detection using Deep Learning Based Techniques applied on Medical Imaging: A Short Review

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***Abstract*— Brain tumor detection is an important part in biomedical image processing. Brain tumors are one of the primary causes of mortality and disability, and effective treatment depends on early identification. Although to detect these brain tumors, a imaging technique called Magnetic Resonance Imaging (MRI) is frequently used, but it often takes time and is prone to error as it is manually interpreted by radiologist. With the advent of deep learning, there has been a growing interest in using these techniques for brain tumor detection. Deep learning models have shown promising results in detecting brain tumors in MRI scans. This paper presents an in-dept analysis of various deep learning methods available for brain tumor detection and evaluates their performance on publicly available datasets. It discusses the challenges and limitations of existing approaches and outline some of the key research gaps that need to be addressed. The paper concludes with a discussion of the potential impact of deep learning on brain tumor detection and future directions for research in this area.**

***Keywords—brain tumor, image preprocessing, medical imaging , segmentation, deep learning.***

1. INTRODUCTION

Brain tumor is among the most dangerous forms of cancer that affect human beings. It is an abnormal growth of cells within the brain and surrounding tissues. The tumor can be benign or malignant. Benign tumors do not proliferate to other parts of the body whereas with malignant tumors there always the risk of proliferation and invading surrounding tissue. The

type of brain tumor, as well as its location, size, and progression, can all impact the symptoms and prognosis of the disease [1]. Brain tumors can cause a variety of symptoms, such as headache, nausea, and changes in behavior or motor skills. However, these symptoms are often non-specific and can be attributed to a variety of other conditions, making early diagnosis challenging.[2]

The importance of early detection and accurate diagnosis of brain tumors cannot be overstated. Timely and accurate diagnosis allows for prompt treatment, which can improve the patient's prognosis and quality of life. Early detection can allow for the use of less invasive treatment options, such as surgery, which can preserve more of the patient's normal brain function. Medical imaging techniques like CT scans, PET scans and MRI scans are some of the traditional diagnostic approaches for finding brain tumors. These imaging techniques provide detailed images of the brain, which can detect the presence and location of brain tumors [3].

However, traditional diagnostic methods have several limitations. One of the main limitations is the subjectivity of interpreting medical images, as interpreting these images can vary based on the experience and expertise of the radiologist. In addition, medical imaging techniques can produce false negatives, meaning that a brain tumor may not be detected even if it is present. False positives, in which

a brain tumor is detected but is not present, can also occur [4]. Another limitation of traditional diagnostic methods is their lack of efficiency. The process of manually reviewing medical images for the presence of brain tumors can be time-consuming and labor- intensive. In addition, traditional diagnostic methods can be expensive and may not be widely available in certain areas, particularly in resource-limited settings.[5]

The limitations of traditional diagnostic methods for brain tumor detection highlight the need for alternative, more accurate, and efficient methods for detecting brain tumors. Deep learning algorithms, which are a form of artificial intelligence, can significantly increase the precision and effectiveness of brain tumor identification. In addition, deep learning algorithms can analyze large amounts of medical data, including medical images, to identify patterns and features that show brain tumors. This can improve the accuracy of brain tumor detection and reduce the risk of false negatives and false positives [6].

This paper explores the various techniques and approaches used in brain tumor detection using deep learning. It begins by examining the different brain tumors, their characteristics, and the imaging techniques commonly used in detecting them. The paper then explores the different deep learning algorithms, preprocessing techniques involved in brain tumor detection. It further compares the performance and limitations of different deep learning models used in many research papers. It also highlights that each deep learning algorithm has its own strengths and weaknesses and can be applied differently depending on the characteristics of the tumor. The formulation of the below section is section II presents Literature review, that comprises a comprehensive analysis of existing research paper. Section III presents Key Findings which summarize the major models and datasets that are used in the papers. Section IV presents Research Challenges and Future direction, which identifies the gaps and limitations in the existing research and highlights the area where more research is required.

1. LITERATURE REVIEW Convolutional Neutral Network or CNN is a type

of artificial neural network. It basically comprises the fully connected layer, convolution layer, input layer and pooling layer [7]. CNN architecture excels in application relate to computer vision, which includes image classification, image segmentation, object detection in images, among others. [27].

Avigyan Sinha et al. [8] proposes a modified CNN architecture which can be used to classify and detect brain tumors. Under this model, stages like image acquisition, pre-processing, segmentation, feature

extraction and classification of brain tumors are successfully implemented. First, in pre-processing, the brain images are first converted into the Gray Scale image when the data is in 3D. Then, Median Filtering is used to remove noise or signals from the biomedical images. Under the segmentation process, the image is first divided into multiple segments and then an OTSU based thresholding algorithm is applied, which separates the skull of the brain and thus prepares a segmented mask of the tumor region. Then, Classification of the images is done by creating a deep neural network with a convolutional neural network algorithm. For this method, MRI Dataset of 253 Images (from Kaggle Uploaded by Navoneel Chakrabarty) [9] but this is insufficient for deep neural network model. So, with the help of data augmentation, 2530 images were created. This modified approach helped to get a result with an accuracy of 98%.

In [10], the authors have proposed a Hierarchical Deep Learning-Based Model using CNN to classify the Brain Tumors into four primary classes: pituitary, meningioma, glioma, and no-tumor. This model comprises of two stages: training and validation. In the training phase, First the MRI Images from many IoMT devices are collected using the data acquisition method and then sent for pre-processing. In pr-processing, the images are resized, normalized, and augmented to make it ready for CNN. In CNN, the feature is extracted from the data through a mathematical operation called Convolution. These operations are performed by multiple convolutional layers which take data, process it, and classify it into different classes. Then the data is evaluated to check the accuracy and miss rate. If it matches the learning criteria, it gets stored in the Tumor Classifier Cloud Storage. The dataset consisting of 3264 images has been collected from Kaggle. This model has achieved an accuracy of 92.12% and a miss rate of 7.87% which is far better than the existing methods.

VGGNet is a CNN architecture developed for application in the field of Computer Vision. VGG16 and VGG19, the popular models of this architecture were proposed by Simonyan and Zisserman [11]. The reason they are called VGG16 and VGG19 is because they have 16 layers and 19 layers respectively. Thirteen of the 16 layers in the VGG16 are convolutional layers, while three of the 16 layers are fully connected layers. Similar architecture can be found in VGG16 and VGG19, the latter of which has 19 layers, sixteen of which are convolutional, and three of which are fully connected. Four learning techniques which were suggested for testing VGG16 and VGG19 by the authors in [12] are RMSprop, Adadelta, ADAM and SGD optimizers. Each optimizer was tested with the VGG16 network. The test was run ten times, and the best classification performance was achieved by SGD at 97.49%; other

optimizers were able to reach a maximum performance of over 90%. Likewise, each optimizer was tested ten times with VGG19. SGD optimizer provided the best performance in VGG19 (97.93%). With other optimizers, performance was roughly 95%.

Ahmet Çinar and Muhammed Yildirim [13] have worked to improve the accuracy of Resnet50 for deep learning tasks using a variety of hybrid techniques such as F-measure, FPR, FNR, FDR, and accuracy value. To compare the results, they have also worked with other models such as Densenet201, Inceptionv3, and Alexnet. The research has shown that Resnet50 produces better results than any of the other models when the hybrid techniques are applied. Resnet50 is a promising choice as it can deal with previously trained networks and has produced positive outcomes with biomedical data. A genuine dataset made up of two folders were acquired from Kaggle to evaluate the performance of the Resnet50 model [14]. Both folders contain MRI-style images; the first has 98 images without tumors while the second contains 155 images with tumors. A 93.18% accuracy rate was attained after the Resnet50 model was used to train the network. The results obtained suggest that the Resnet50 model is highly accurate for detecting tumors in MRI images. In future studies, the model can be further tested with larger datasets to further improve accuracy.

Heba Mohsena et al. [15] have conducted extensive research using deep learning neural networks (DNN) and compared the results to other models such as K Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA). The comparison was based on several parameters such as accuracy, recall, precision, F-measure, and area under the receiver operating characteristic curve (AUC). Deep Neural Networks (DNNs) is a powerful machine learning technique that has been used to detect and analyze brain tumor images. The use of DNNs can be an effective tool for a variety of predictive and classification tasks. This paper suggests a strategy for distinguishing between normal brains and several tumor kinds, including glioblastoma, sarcoma, and metastatic bronchogenic carcinoma, using brain MRI scans. By leveraging the characteristics of the MRI images, the model can accurately identify the type of tumor and its specific location in the brain. The suggested method trains the DNN classifier for the classification of brain tumors using a set of features retrieved using the discrete wavelet transform (DWT) feature extraction technique from segmented brain MRI images. The dataset comprises of 66 actual MRI images of the human brain, comprising of 22 typical

scans and 44 abnormal scans [16]. As such, the DWT feature extraction approach allows the model to capture and utilize important features present in the MRI images. An innovative strategy has been suggested in this paper to develop a deep neural network (DNN) classifier with good classification results.

Poonguzhali, N et al. [17] have purposed a hybrid technique for prediction of brain tumor. This algorithm is a combination of both RCNN and SVM. The RCNN algorithm has improved the introduction of fast R-CNN, which uses a single network to perform both region proposal and object detection, making the algorithm faster and more accurate. RCNN algorithm generate potential object regions in image and extract features from each region proposal using a CNN algorithm. After that train a support vector machine (SVM) on top of the features extracted from the CNN. The SVM is trained to classify the features as either belonging to an object or not. SVM aims to reduce the generalization error and optimize classification accuracy. Author has taken MRI images of 20 patients that suffering from tumor, converted that image into

.csv file, in the file created number of rows for an image to take the other information. Using these data author build the model using combination of two algorithms (RCNN and SVM) and achieve the more than 95% accuracy.

Islam, M. K et al. [18] have contributed by developing a new K-Means clustering algorithm that uses templates to increase the detection efficiency of human brain tumors across a variety of tumor sizes. Their method involves extracting features from complex magnetic resonance (MR) images that aid in segmenting and identifying malignancies utilizing super pixels and principal component analysis. In comparison to other traditional methods, their experimental results show that the suggested algorithm achieves superior accuracy and faster execution time (in seconds). Similar to the conventional K- means algorithm, which is based on the desired clustering template, the template-based K- means method clusters data. It provides an easy way to categorize a given dataset into predetermined number of clusters and to group figures into k clusters. By merging complex MR images from Kaggle, a complex database was generated to assess the efficacy of the Template-based k-means clustering approach [19]. Tk-means clustering approach was able to achieve an accuracy rate of 95% which shows a clear noticeable improvement for Template-based k-means clustering over the other models.

TABLE I. PERFORMANCE COMPARISON OF LITERATURE REVIEW

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Ref** | **Dataset** | **Model** | **Type of classification** | **Performance** | **Limitations** |
| [20] | BRATS 2021 | 3D model using Enhanced Convolutional Neural Network (BCM- CNN). | Binary Classification | The model performed with an accuracy of 99.98% | Time-consuming due to extra optimization in CNN’s hyperparameters |
| [10] | Kaggle (3264 images) | Hierarchical Deep  Learning-Based Brain Tumor Classifier (CNN) | Multi Classification  (glioma, meningioma, pituitary, and no-tumor.) | Precision of 92.13% is achieved. | MR (Miss Rate) achieved 7.87% |
| [8] | Kaggle (Dataset by Chakraborty) | OTSU based  thresholding and CNN for classification. | Binary Classification | Overall accuracy of 98% is achieved. | Time consuming to process due to extra optimization steps |
| [23] | Figshare (3064 images) | ResNet50, VGG16,  VGG19, and  DenseNet121. | Multi Classification (glioma, meningioma, pituitary, and no-tumor.) | DensetNet121 model achieved an accuracy of 98.91%  ResNet50 model achieved an accuracy of 99.02% | High training time  Large architecture weights |
| [24] | BRATS | VGG16 for  segmentation, feature extraction using Gray Level Cooccurrence  Matric (GLCM) and SVM for classification. | Binary Classification | Proposed model  achieved 25% improvement in terms of PSNR, 10% in SSIM  and 3.83% in accuracy. | Takes more computational time due large architecture weight |
| [18] | Kaggle (Dataset by Chakraborty) | Superpixels and PCA was used to extract features.  K-means clustering was used to segment image. | Binary Classification | The model performed with accuracy and sensitivity of 95% and 97.36% respectively. | Less number of instances used |
| [13] | Kaggle | Resnet50 | Binary Classification | Accuracy of 97% was achieved. | Addition of extra 8 layers  made the model complicated. |
| [25] | Figshare (3064 images) | Residual networks | Multi Classification (glioma, meningioma, pituitary, and no-tumor.) | The model achieved an accuracy of 99% | Augmentation was used which resulted in increased number of parameters. |
| [17] | Dataset source lacking.  Brain MRI of 20 patients was used. | SVM for segmentation R-CNN for classification | Benign and Malignant | The model performed with an accuracy of 95% | No information about source of dataset  Training data was small |
| [26] | Figshare (3064 images) | ELM-LRF-enhanced CNN’s SoftMax and loss function. | Multi Classification (glioma, meningioma, pituitary, and no-tumor.) | 97% accuracy is achieved. | Trivial improvement in terms of accuracy and processing time. |
| [27] | BRATS 2015 and  Radiopedia images | CNN | Binary Classification | The model performed with an accuracy of 97.5% | Uncertainty regarding the modalities being employed (dataset) |
| [28] | Harvard Medical School Brain MRI dataset | Classification was done using DNN.  Fuzzy C-means clustering was employed to segment the image. | Multi Classification (glioma, meningioma, pituitary, and no-tumor.) | 98% accuracy. | Technique deployed was not unique.  Less number of instances used. |
| [22] | Rembrandt | Alexnet with 10 layers and ZFnet with 10 layers | Binary Classification | Both models achieved an accuracy of 97% | No training and testing time mentioned |

1. KEY FINDINGS

Table II exhibits several datasets that are related to MRI scans have been used for research on brain tumor segmentation, detection, and classification. The availability of such large datasets like BRATS, which contains 8,000 MRI scans, has been used in multiple editions of the BRATS challenge, and provides a significant resource for algorithm evaluation in brain tumor segmentation. The existence of various datasets with different sizes and specific uses, such as KAGGLE, HARVARD, REMRANDT, and

RADIOPEDIA, that have been used for research on brain tumors, glioblastoma, and neuroimaging.

1. *Datasets*

TABLE II. PUBLICY AVAILABLE DATASETS

|  |  |  |
| --- | --- | --- |
| **Datasets Name** | **Instances** | **Type of Image** |
| BRATS  [20][24] [27] | 8,000 | MRI |
| FIGSHARE (Brain MRI) [23][25][26] | 3264 | MRI |
| KAGGLE (Brain MRI) [8][10][18][13] | 253 | MRI |
| HARVARD (Brain MRI)  [28] | 66 | MRI |
| REMRANDT [22] | 874 | MRI |
| RADIOPEDIA  [27] | 34 | MRI |

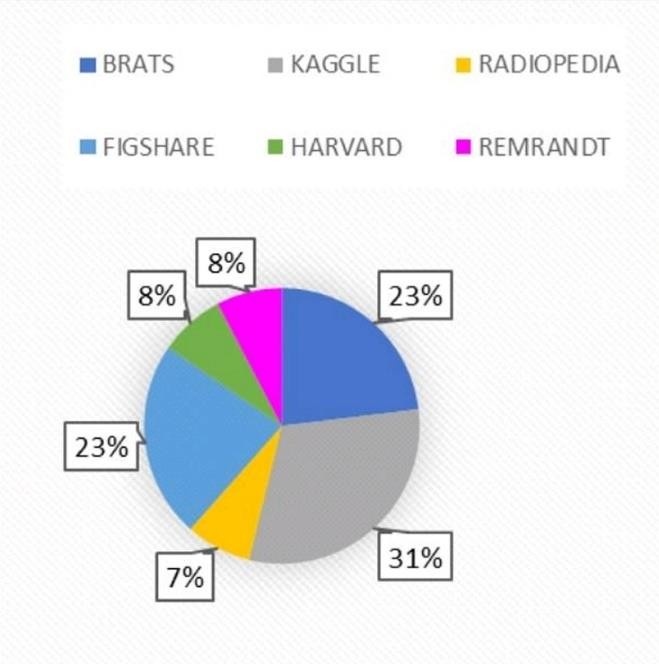


Fig. 1. Dataset Distribution

Fig. 1. Shows the distribution of different sources where brain tumor datasets can be accessed. This

information can be useful for researchers and professionals who are looking on developing deep learning algorithms or other tools for the segmentation and detection of brain tumors. The percentages listed in Fig. 1. Represents the proportion of datasets links that come from each source, but they do not necessarily reflect the size or quality of the datasets themselves. Thus, having access to a variety of brain tumor datasets from different sources can help researchers validate their models and improve the accuracy of brain tumor detection and segmentation.

1. *Usage trends of Deep Learning Models*

The availability of multiple datasets allows for greater flexibility in development of deep learning models. VGGNet is a CNN architecture used for object recognition tasks. The K-means clustering algorithm specializes in extraction of features and compression of data. DNNs are highly effective in solving complex problems, while ResNet known for its residual connections. RCNN is a type of CNN architecture used for object detection tasks, while CNNs are used for image and video processing tasks.

Deep learning models

**6%**

**6%**

**37%**

**16%**

**6%**

**18%**

**6%**

CNN

DNN

DenseNet121

RCNN

VGGNet

ResNet

K-means

Fig. 2. Percentage usage of Deep Learning Models

Fig. 2. lists the percentage usage of different deep learning models with CNN being the most popular at 37%, followed by ResNet at 18%, VGGNet at 16%, RCNN at 6%, DNN at 6%, K-means at 6% and DenseNet121 at 6%. Deep learning modals are widely used in various applications, such as Computer Vision, Natural Language Processing, and Speech Recognition, among others. The percentages listed in the Fig. 2. Represents the popularity of each deep learning model among researchers and practitioners, but the actual usage may vary depending on the

specific use case and problem domain. This information can help developers and data scientists choose the appropriate model for their application and achieve better results.

1. FUTURE DIRECTION AND RESEARCH GAPS
   1. *Research Gaps*

The implementation Deep learning in Brain tumor detection and Its segmentation generates many unique challenges to researcher.

* + 1. *Data scarcity:* A difficult barrier for deep learning techniques is the lack of substantial training datasets. Brain tumor datasets are often small and uneven, with a limited number of examples for certain types of tumors, which can further lead to reduced performance of deep learning model. [29]
    2. *Unlabeled images:* It takes a lot of time and expertise to differentiate between tumor images from non-tumor images . [29]
    3. *Slice-by-slice annotations:* Training deep learning algorithms that conduct tumor segmentation is a challenging and time-consuming process.[30]
    4. *Data quality:* To do tumor detection using deep learning, brain MR images, BRATS dataset are widely used, training a deep learning system using this need extra attention due to modelling uncertainty and noise in standard reference. [30]
    5. *Class imbalance:* Data augmentation technique are used to create more images of lesion of brain tumor by either rotating or scaling the present images, but this may cause class imbalance. [21]
    6. *Loss of useful information*: Researchers have fixed a size for the image to be used in deep learning algorithm, which may lead to loss of useful information after image slicing. [21]

While these are few of many challenges, there is ongoing research to solve these and other limitations and increase the precision and dependability of brain tumor detection using deep learning.

* 1. *Future Directions*

Future direction of brain tumor detection is an active area of research, and there are several future directions that could improve the accuracy and efficiency of diagnosis.

Here are some potential directions:

* + 1. *Integration of multiple imaging modalities:* Brain tumor detection typically uses only one imaging modality such as MRI or CT, but combining data from multiple modalities can enhance the accuracy of diagnosis. The integration of various imaging modalities like MRI, CT, PET, and MRS could be increasingly utilized in the future.
    2. *Use of artificial intelligence (AI):* The potential of AI to enhance the precision and speed of brain tumor detection is significant. By processing vast amounts of data, deep learning algorithms can detect subtle patterns that may go unnoticed by human radiologists. In the coming years, we can expect more progress in developing AI algorithms that are specialized for detecting brain tumors.
    3. *Better access to patient data:* Access to a patient's entire medical history is crucial for enhancing the precision of diagnosis. One potential development for the future is the creation of electronic medical records (EMRs) capable of combining data from various sources, including imaging studies, genetic testing, and clinical notes. By utilizing such integrated information, diagnosis accuracy may be improved and personalized treatment plans can be better formulated by medical professionals.
    4. *Use of molecular biomarkers:* Genetic mutations or protein expression levels are molecular biomarkers that could offer significant insights into a tumor's type and its responsiveness to treatment. Combining such biomarkers with imaging studies may increase the precision of diagnosis in the future.
    5. *Integration of telemedicine:* Telemedicine is a system that enables doctors to offer remote consultation with patients and other healthcare providers. This system is particularly significant for patients residing in distant areas or having trouble in reaching a hospital. In the coming years, we may witness an increase in the integration of telemedicine in the diagnosis and treatment of brain tumors, providing a more accessible and efficient healthcare system.

1. CONCLUSION

In conclusion, deep learning has shown great promise in brain tumor detection, but there are still several challenges that need to be addressed. The availability of large and diverse datasets, transfer learning, integration with other imaging modalities, generalization to unseen imaging protocols, explain- ability and interpretability are some of the key research gaps that need to be addressed. Addressing these challenges will help to improve the accuracy and reliability of deep learning models for brain tumor detection and make them more widely adopted in clinical practice.

Overall, this review paper offers a thorough assessment of the state of art for deep learning-based brain tumor identification, the challenges and limitations of existing approaches, and the key research gaps that need to be addressed. The paper highlights the potential impact of deep learning on

brain tumor detection and provides a roadmap for future research in this area.

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