International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

BRAIN TUMOR DETECTION USING DEEP LEARNING

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ABSTRACT

An illness known as a brain tumor is brought on by the expansion of aberrant brain cells. Brain tumors fall into two primary categories: benign brain tumors, which are non-cancerous, and malignant brain tumors, which are cancerous. Given the rarity and variety of brain tumors, it is challenging to forecast the survival rate of a patient who is tumor prone. According to UK cancer study, 15 out of every 100 patients with brain cancer will be able to live for ten years or longer following their diagnosis. The kind of brain tumor, the degree of cellular abnormality, the location of the tumor inside the brain, and other variables all affect the course of treatment. Deep learning models are used to diagnose problems as artificial intelligence advances.Images from magnetic resonance imaging are utilized to train deep learning models for brain tumor diagnosis. An example of a scanning technique is magnetic resonance imaging (MRI), which creates detailed images of the inside body by combining radio waves and strong magneticfields. Convolutional neural network (CNN) model which is constructed from scratch, are example of deep learning model used in this research project that are used to identify tumor regions in scanned brain pictures. 253 patients' brain MRI pictures were taken into consideration; 155 of these images showed tumors, and the remaining 98 did not.

1. INTRODUCTION

The diagnosis of brain tumors presents a significant problem in the field of medical diagnostics because of its intricacy and potentially catastrophic outcomes. A branch of artificial intelligence called deep learning—inspired by the neural networks seen in the human brain—has shown great promise in revolutionizing the way we identify and treat brain cancer. In the past, medical imaging methods like computed tomography (CT) scans and magnetic resonance imaging (MRI) have been crucial in the diagnosis of brain malignancies. Even though these techniques are quite successful, they frequently need the interpretation of the pictures by highly qualified radiologists, which can be laborious and prone to human error. Deep learning is a novel technique that trains computers to identify patterns in medical images, automating the detection process. Deep neural networks can be trained to discriminate with astonishing accuracy between different types of cancers and normal brain tissue by feeding massive volumes of labelled MRI and CT scan data into these systems. Deep learning's primary benefit is its capacity to extract finely detailed elements from photos that the human eye would not be able to recognize. A particular kind of deep learning architecture called convolutional neural networks (CNNs) is quite good at this task. They do this by successively applying learnt filters to find hierarchical patterns in the data.Because of this capabilities, CNNs can detect minor irregularities that point to cancers, even at an early stage when human detection would be difficult.Furthermore, image analysis isn't the only way that deep learning is used in brain tumor identification. Scholars are currently investigating its capacity to include many forms of medical data, including genetic data and patient medical history, in order to generate complete diagnostic models. These models not only support early identification but also forecast the behaviour of tumors and optimize patient-specifictreatmentplans.

Deep learning integration has far-reaching consequences for healthcare practice. This technology has the potential to greatly improve patient outcomes and expedite the delivery of healthcare by decreasing delays in diagnosis and increasing accuracy. The future holds even more advanced deep learning models that can address more complex problems in neuroimaging and personalized medicine as research progresses.To sum up, deep learning has a revolutionary effect on brain tumor identification that cannot be denied, even though there are obstacles on the path from research to widespread clinical application. The advancement of artificial intelligence is bringing us one step closer to a time when the battle against brain tumors will truly be won, with early diagnosis and focused treatment becoming attainable goals.

1.1 Overview

The dataset under consideration comprises 253 patients' MRI scan images, of whom 155 have tumors and 98 do not. The study that is being presented tries to create a detection model that can identify a tumor in a patient's MRI scan image. In general, the detection model is expressed as follows:

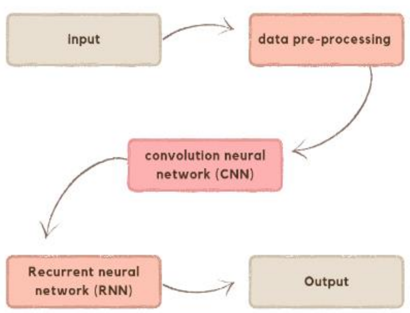

FIG 1.1 Simple Flowchart For General Brain Tumor Detection Model.

1.2Objectives

1.2.1 Improving Diagnostic Accuracy: The main objective is to show how Convolutional Neural Networks (CNNs) may greatly increase the accuracy of MRI scan-based brain tumor identification. We want to attain high sensitivity and specificity in recognizing many kinds of brain malignancies, including gliomas, meningiomas, and pituitary adenomas, by training these models on a wide dataset of annotated MRI images.

1.2.2 Cut Down on Diagnosis Time:

We want to draw attention to the efficiency improvements that automated tumor detection systems can achieve when contrasted with conventional techniques that depend on radiologists' manual interpretation. Our goal is to expedite access to vital diagnostic data so that treatment planning and medical intervention can happen sooner by using deep learning to automate the detection and classification process.

1.2.3 Enhancing Healthcare Efficiency: By putting forth a method that automatically divides and classifies brain tumors, our paper aims to improve the effectiveness of healthcare delivery. These chores can be automated to maximize healthcare resources, lessen the workload for radiologists, and enhance diagnostic imaging departments' overall workflow efficiency.

1.2.4 Validation and Comparative Analysis: We will use conventional evaluation measures to thoroughly test our proposed deep learning-based system's performance against current approaches in this work. By comparing our method to existing diagnostic procedures, comparative analysis will show how much better it is in terms of accuracy, dependability, and scalability.

1.2.5 Research and Practice Contribution:

We hope that by disseminating our findings, we will augment the expanding corpus of knowledge regarding medical image analysis and deep learning applications in the field of medicine. By exchanging ideas, techniques, and experimental findings, we can drive additional research in this vital field of medical imaging and improve automated brain tumor diagnostic systems in the future.

2. RELATED WORK

The development of sophisticated imaging methods and the use of machine learning (ML) and deep learning (DL) approaches have led to a substantial evolution in the field of brain tumor diagnosis.[2]This section gives a summary of the state-of-the-art approaches now in use, covering ML techniques, recent developments in DL, classic approaches, and current constraints.

2.1 Traditional Approaches

Magnetic resonance imaging (MRI) and computed tomography (CT) scans are the maintains of traditional approaches for the detection of brain tumors.[6]The intricate anatomical details on brain anatomy and pathology are provided by these imaging techniques. Radiologists use visual analysis of these pictures to determine the location, size, form, and enhancing patterns of tumors and to classify them. The process of manually segmenting tumors from MRI scans requires drawing boundaries around the tumor, which might be arbitrary and subject to variation across interpreters. Conventional procedures, although widely employed, are laborious, necessitate specialist knowledge, and may not be sensitive enough to identify subtle or tiny tumors.

2.2 Deep Learning Advancements

Recently, deep learning has become a valuable method for improving and automating the identification of brain tumors from medical pictures. This is especially true with Convolutional Neural Networks (CNNs). CNNs may recognize complicated patterns suggestive of malignancies because they are excellent at immediately learning hierarchical representations from raw pixel data. Research, for example, has shown that CNNs are highly efficient and accurate at separating malignancies from MRI scan data.[8]Utilizing learnt features, transfer learning further enhances performance by applying CNN models that have already been pre-trained on big datasets (like ImageNet) and are optimized for medical imaging tasks.

2.3 Machine Learning Methods

In addition to CNNs, other conventional machine learning algorithms have been used for brain tumor classification, including Support Vector Machines (SVMs), Random Forests, and clustering techniques. In order to distinguish between distinct tumor types, these algorithms usually require human feature extraction from imaging data. Features including texture, shape, and intensity statistics are used in this process. For instance, SVMs have outperformed deep learning techniques in the classification of brain cancers using features that were extracted.

2.4 Brain MRI

The advantages of magnetic resonance imaging (MRI) in helping medical professionals identify physical issues in the brain are widely known. Using MR imaging, a sequence of two-dimensional images can be used to visualize the volume of the brain in three dimensions. Different MRI techniques are used to aid in the diagnosis, such as gadolinium contrast enhancement.

2.5 MRI database accessible

For the purpose of identifying brain infections such as schizophrenia, Alzheimer's disease, and chemical imbalance of the cerebral damage, the Section of Biomedical Image Analysis (SBIA) develops PC-based picture evaluation methodologies. A comparison between a quantitative record and a reality model should be used to approve each plan in order to determine its effectiveness. Experts in the field regularly create reality models. Through the use of engineered pictures, physicians and radiologists can evaluate new approaches.

2.6 Identification of a Brain Tumor

In recent years, a great deal of progress has been made by medical tomography professionals in identifying brain cancers using both completely automatic and semi-automatic methods. The clinical acceptability of diagnostic techniques is based on how simple they are to calculate and how much monitoring they require. brain tumor recognition can be divided into three steps, tumor detection, differentiation, and classification, which have all been clarified in depth in this section. The provided technology was used to explain the extra unique performance.

2.7 Current Limitations

There are still a number of obstacles in the way of brain tumor identification despite the advances. Large annotated datasets are crucial to the training of deep learning models, but they might not always fully capture the range of tumor changes among various patient populations and imaging modalities. Variability in MRI acquisition parameters (such as image sequences and field strength) can have an impact on the consistency and generalizability of the model. Additionally, in clinical situations, the interpretability of deep learning models is still a challenge because doctors need to know exactly how automated diagnoses are made.

Moreover, deep learning models can be computationally demanding to train and implement, which restricts their broader use, particularly in healthcare settings with limited resources. Furthermore, there are real difficulties in integrating automated technologies with clinical operations because of issues with data protection, regulatory and approval by medical experts.

3. METHODOLOGY

3.1 Data Set

153 patients' brain MRI scans, including both normal and brain tumor patients who were referred to imaging centers due to headaches, are included in the data set images used in this work. Following the physician's assessment and diagnosis, 80 healthy patients' brain scans were among the images gathered. Include 1321 photos, of which 515 are for the train set and 56 are for the testing set. 73 cancers in patients Include 571 photos, of which 1151 are for the train data and 170 are for the test data. Aged between 8 and 66, 86 of the 364 patients with brain tumor illness were female and 68 were male. 1892 photos overall from 153 patients were gathered, 226 photos were used as test images and 1666 images as train data. The gathered photos were initially 512 × 512 in size.

3.2 Data Collection and Pre-processing

Pre-processing data refers to the process of using pre-processing procedures to transform raw data into meaningful data. The following are the pre-processing methods we have employed:

3.2.1: Adding libraries

Imported libraries include Tensor Flow, NumPy, pandas, matplotlib, OS, and scikit-learn, among others.

3.2.2: Enhancement of Data

Image data-augmentation refers to the practice of adding more images to the dataset by modifying individual photos through various approaches such as rotation. The photos are produced by the Image Data Generator class. There were 155 cancerous and 98 non-tumorous photos prior to augmentation, and there are now 1085 cancerous and 980 non-tumorous images following augmentation. In the below fig 3.2.1.

3.2.3:Import the updated information.

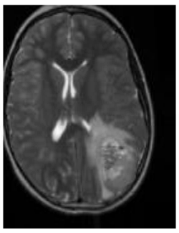

FIG 3.2.1:Original Image

3.2.4: Apply a gray scale conversion to the photos.

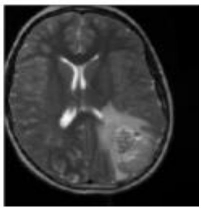

FIG 3.2.2: Original Image Converted to Gray scale

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

3.2.5:Eliminating noise and refining the image. Several erosions and dilations are used to reduce noise. Pixels along the image's edges are removed during erosion. Dilation is the opposite of erosion in that it adds pixels to the image's edges. The Gaussian blur technique is used to smooth the image. When using Gaussian blur, the image is convolved using the Gaussian filter. The high frequency components in the image are eliminated by the low pass Gaussian filter. Consequently, the image is smoothed.

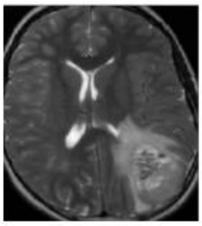

FIG 3.2.3: Image After Applying Gaussian Blur And Eliminating Of Noise.

3.2.6: Grasp the largest shape.
An object's perimeter or outline is referred to as its contour.

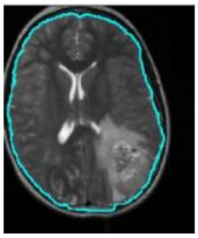

FIG 3.2.4: Find The Largest Contour.

3.2.7: Determine which contoured image's extreme points are.

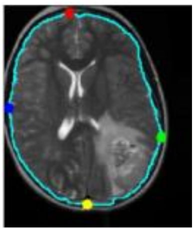

FIG 3.2.5: Extreme Points Of Contoured Image

3.2.8: Shrink the picture.
Because each picture had a different size prior to pre-processing, all of the enhanced photos had to be reduced to 240 by 240 pixels in order to use CNN.

3.2.9: Utilizing the extreme points, crop the photos. The pictures were cropped at their extremities.

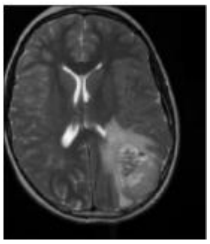

FIG 3.2.6: Cropped Image

3.2.10: Dataset splitting: There are three distinct sets of data in the dataset.

1.They are training information:

- Number of pictures: 1445
- 758 tumorous photos in total
- There are 687 non-tumorous photos.

2.Examining information

- 310 pictures in total
- 175 tumorous pictures in total.
- 135 non-tumultuous pictures in total

3.Information for validation:

- 310 pictures in total
- 152 tumorous picture numbers
- 158 non-tumultuous picture numbers

4. MODEL ARCHITECTURE

Two major architectures have shown notable effectiveness in the field of deep learning-based brain tumor detection: Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). The architecture is designed to accurately segment and detect brain tumors from MRI scans, capturing both local and contextual information.

4.1 Convolutional Neural Networks (CNNs): Because CNNs can automatically extract hierarchical information from images, they are essential for medical image analysis.

CNNs are particularly good at identifying discriminative features including tumor boundaries, textures, and spatial correlations when it comes to MRI scan-based brain tumor detection. Classification and segmentation tasks are well-suited for them since they usually comprise of numerous convolutional layers followed by pooling layers that extract and summarize information gradually.

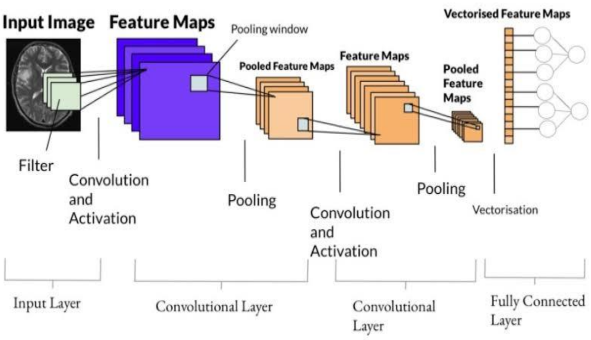

FIG 4.1.1: CNN Architecture

4.2 Recurrent Neural Networks (RNNs): RNNs have been modified for applications involving temporal features of medical data, including longitudinal MRI scans, and are particularly useful for sequential dataprocessing. When it comes to brain tumor diagnosis, RNNs can follow changes in tumor characteristics over time by analyzing MRI slice sequences. This helps with early tumor detection and tumor progression tracking. They are useful for the interpretation of dynamic medical imaging data because they can integrate information across several time steps and identify temporal dependencies.

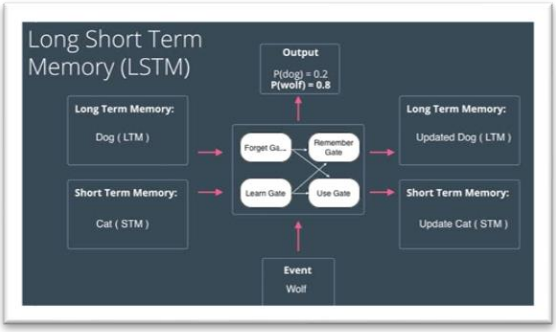

FIG 7: RNN Architecture

5. RESULT AND DISCUSSION

5.1 Result

Brain tumors continue to be a prevalent problem in the field of medical imaging. An extensive overview of the most recent technologies available for brain tumor diagnosis is provided by this study. MRI scans are used in tumor identification to determine whether brain tumors are present or absent. Additional analysis utilizing tumor segmentation and classification techniques is necessary for several images. To classify a tumor as malignant or as a particular form of malignant tumor, one can use criteria such as High grade (HG), Low grade (LG), or tissue analysis. Most of the techniques that are taken into consideration are for automated and semi-automatic tumor diagnostics. In addition, most of the methods include pre-processing, feature extraction, feature reduction, segmentation, and classification. DTI (diffusion tensor imaging) and pathology are utilized toconstruct an artificial basis fortumor tissues and edema on magnetic resonance imaging.

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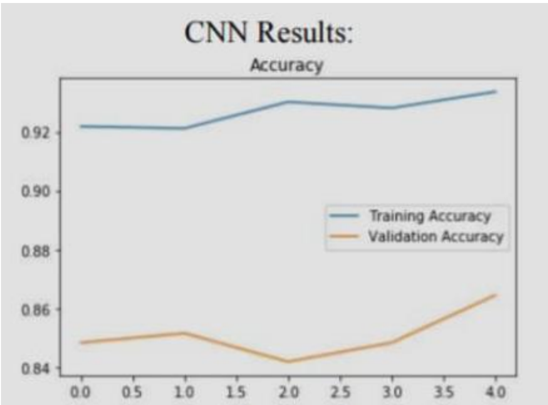

Fig.5.1.1.Accuracy chart

Recent research has demonstrated the efficacy of DL models in the interpretation of medical pictures, especially in the detection of brain tumors. In terms of accuracy, DL networks have exceeded classical ML techniques. Moreover, DL networks perform better with complex algorithms than traditional ML techniques when handling enormous volumes of data.

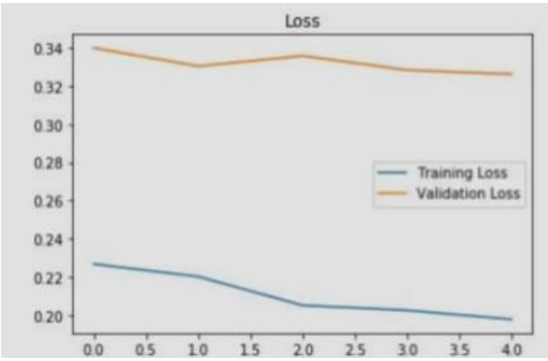

Fig.5.1.2.Loss chart

Advanced feature extraction and reduction techniques are necessary for traditional machine learning methods, however they are not required for deep learning approaches.

5.2 Discussion

Detection, distinction, and classification of brain tumors have all improved significantly in recent years, and our investigation aimed to highlight these developments. More advanced possibilities than the conventional methods of machine learning are available with the DL algorithm. The performance of traditional ML techniques has been found to be improved by the use of DL, a novel and important research tool. MR pictures and their characteristics can be thoroughly examined because of multiple levels of abstraction and representation. A sizable database is now necessary to create a competition for the greatest methods and devices for detecting brain tumors.

Reference	Review extraction	Methods for detection	Used data	Limitations
[7]	ROI histogram, co-occurrence matrices, and run-length matrices	LSFTPNN	Hellenic Air-Force Hospital	The method of external-cross validation has a lo- discriminatory accuracy.
[16]	Thresholding methods	Approximate reasoning- method	-	Computational-cost, complexities and optimization are very high.
[19]	Boot strap sampling	Shelf classifier	INTERPRET	Various diseases and pathological groupings are involved in a number of concerns.
[23]	GLCM	Neuro-fuzzy logy	Department of Radiology (Tata Memorial)	For entire photos, dynamic change cannot be enhanced.
[25]	DCT	PNN	-	Only a few pictures were used to train and to test the net-work.
[27]	Gabor texture-features	SVM	-	Due to the use of three approaches for feature extraction, the system complexity has increased.
				The process of extracting and selecting features is not discussed.
[28]	7 texture features	MK-SVM	CHU de Caen	The use of FDCT to dis-sect the in-put image adds to the complexities because the data set is nonstandard
[30]	GLCM	PNN-RBF	-	
[32]	CNN	CNN	BRATS2014	

Table 1:Brain Tumor Classification Techniques Using MRI.

6. CONCLUSION

These technologies offer improved speed, accuracy, and volume reduction over manual methods. Consequently, these methods have been thoroughly examined in relation to traditional ML applications and DL methodology. Standard databases are used to categorize and divide tumors. Cancers are being detected using traditional machine learning techniques; however, adding deep learning technology to these procedures should yield positive outcomes, as demonstrated below. Using DL methods, the current study has successfully detected tumorswith a maximum Dice score of 96.8%. Thus, it is necessary to combine the three processes (detection, classification, and segmentation) into a single completely automated system for brain tumor diagnosis in order to improve the DL evaluations in tumor detection and classification.At this point, it is not appropriate to evaluate DL algorithms while wearing glasses. Researchers employed both conventional machine learning (ML) and deep learning (DL) techniques to categorize cancers; both experiments, however, praccurate results.

• In general, ML deployments are

Favoured over DL deployments.

- Standard tumor detection and classification databases are to expand advanced tumor detection and classification investigations.

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