ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
IJARMATE International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

An Overview of Deep Learning for Detecting Brain Tumors

Mohammed Khizer Shaikh[1], Sathish S[1], Srinivasa[1] ,Prof. Prashanth Kumar[1]
Shaikhmohammed057@gmail.com,ssathishsathish253@gmail.com,srinivasajune@gmail.com
prashanthjune18@gmail.com
[1]Department of Computer Science and Engineering,[1]Alvas Institute of Engineering and Technology.
Moodabidri, Dakshina Kannada, Karnataka, India.

***Abstract*— Since brain tumors provide significant challenges for both diagnosis and treatment, accurate and efficient detection approaches are necessary. Deep learning is a subdivision of [21]artificial intelligence that may be used to [35] improve brain tumor identification and classification using medical imaging data. This paper provides a comprehensive review of recent advances in employing deep learning methods to analyze brain tumors [3].**

Model architectures, assessment metrics, feature extraction, and data preparation utilized in the context of brain tumor diagnosis and classification are only a few of the subjects covered in the paper. Covnets are examples of deep learning models. [2](CNNs), (RNNs), and their derivatives have been extensively studied for automated tumor identification and classification tasks.

Furthermore, the application of[8] advanced techniques including transfer learning, ensemble approaches, and attention mechanisms has shown promising results in[6] improving the sensitivity and accuracy of brain tumor detection systems. There is also discussion of potential fixes for problems with interpretability, class imbalance, generalization to different populations, and data scarcity.

The study also highlights the most recent state-of-theart procedures, benchmarks, and datasets frequently used in brain tumor research in order to aid in the comparability and repeatability of results. Finally, future strategies and research opportunities are presented to move the field toward more accurate and successful brain tumor diagnosis and therapy. Real-time decision support systems, personalized medicine, and multimodal imaging fusion are a few of these.

I. Introduction

Secondary brain tumors, commonly referred to as metastatic brain tumors, arise when cancer cells from tumors in other parts of the body[3], such the skin, breast, or lungs, travel to the brain via the lymphatic or circulatory systems. These tumors typically arise at the interfaces between the brain's gray and white matter, and they are frequently numerous. Depending on the tumor's size, location, and rate of growth, there might be a wide range of symptoms. Headaches, seizures, altered cognition, altered personality, motor impairments, and sensory disturbances are typical symptoms. But unless they grow to a large size or squeeze nearby brain regions, some Brain tumors could not exhibit any symptom.Brain tumor diagnosis usually entails a mix of histological examination, neuroimaging, and clinical assessment. When assessing brain tumors, magnetic resonance imaging[34] (MRI) is the recommended modality because of its excellent soft tissue contrast and[22],multiplanar imaging capabilities. In situations where an MRI is not recommended or in emergency situations, computed tomography (CT) scans may alternatively be utilized.

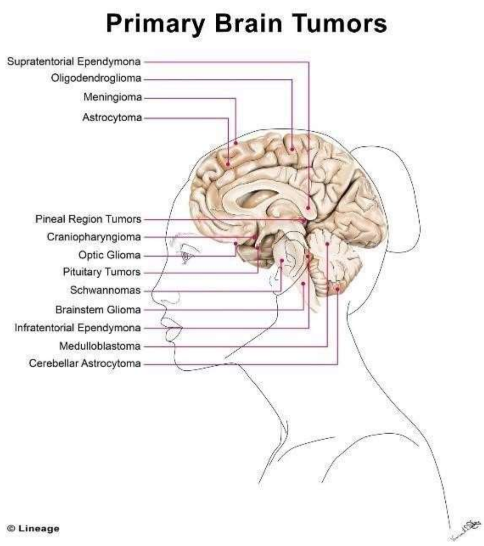

Fig 1.primary brain tumor

Histopathological examination of tissue samples taken by biopsy or surgical excision is necessary to verify the diagnosis and identify the grade and subtype of the tumor. Given that higher-grade cancers are more aggressive and may need more extensive therapies, this information is essential for helping guide treatment decisions.Brain tumor treatment options are contingent upon a number of parameters, such as the kind, location, size, and grade of the tumor in addition to the patient's preferences and general health. A combination of these strategies, as well as surgery, radiation therapy, chemotherapy, targeted therapy[29], and immunotherapy, may be used as treatment options.

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
IJARMATE
International Journal of Advanced Research in Management, Architecture, Technology and Engineering
(IJARMATE)
Vol. 10, Issue 5, May 2024

Reducing the tumor's size, relieving symptoms, maintaining neurological function, and increasing survival are the objectives of treatment.Around the world, brain tumors continue to be a major cause of morbidity and mortality despite advancements in diagnosis and treatment. In order to enhance patient outcomes, research efforts are still concentrated on learning the biology underlying brain tumors, finding new therapeutic targets, and creating more potent treatment plans. Furthermore, the incorporation of artificial intelligence and machine learning[13] algorithms[6], along with developments in imaging technologies like functional magnetic resonance[31] imaging[33] (MRI) and positron emission tomography (PET), show promise for enhancing the early diagnosis and individualized care of brain cancers in the future.

A.Importance of deep learning:

Because deep learning can extract complicated patterns and representations from large volumes of complex data, it is extremely important in many different sectors and has revolutionized science, technology, and industry Deep learning has made significant progress. medical imaging analysis in the field of healthcare, making it possible to detect and diagnose diseases like cancer, cardiovascular issues, and neurological disorders with more accuracy. Medical personnel may now interpret medical images with previously unheard-of precision thanks to deep neural networks, which will facilitate early detection and better patient outcomes[25].

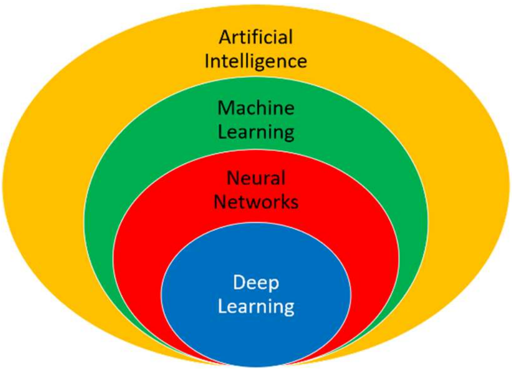

Fig 2.Deep learning Approach

Deep learning is essential for vision, navigation, and decision-making in robotics and autonomous vehicles. In order to ensure safe and effective operation, deep neural networks allow vehicles to read sensor data, recognize objects and barriers in the environment, and make decisions in real time.

Deep learning models have demonstrated exceptional effectiveness in natural language processing (NLP) and[19] machine translation, particularly in comprehending and producing human language. Applications that help people communicate and access information across a variety of linguistic obstacles include chatbots and virtual assistants as well as language translation services.

Deep learning models analyze massive amounts of financial data to identify suspicious activities, forecast market trends, and optimize investment strategies, thereby improving decision-making and mitigating risks. Ultimately, the significance of deep learning lies in its ability to unlock the potential of big data, enabling machines to learn complex patterns and make intelligent decisions across a wide range of applications. As data continues to grow in volume and complexity, the role of[12] deep learning in driving innovation and progress is poised to expand further, shaping the future of technology and society. Deep learning algorithms are used in finance and business for fraud detection, risk assessment, and predictive analytics..

B.Brain Tumor using deep learning:

In medical imaging analysis, brain tumor identification and classification[1] are crucial jobs because prompt and precise diagnosis is crucial for directing treatment decisions and enhancing patient outcomes. Artificial intelligence's deep learning branch has shown promise in automating these procedures and improving the effectiveness and precision of brain tumor detection.

Convolutional neural networks (CNNs) are[8] particularly good Deep learning techniques for recognizing pertinent features from medical imaging data, like computed tomography (CT) and magnetic resonance imaging (MRI) images.Deep learning models outperform conventional machine learning techniques in[2] the detection and localization of brain tumors, thanks to their ability to use vast datasets of annotated pictures. These models have great sensitivity and specificity[22].

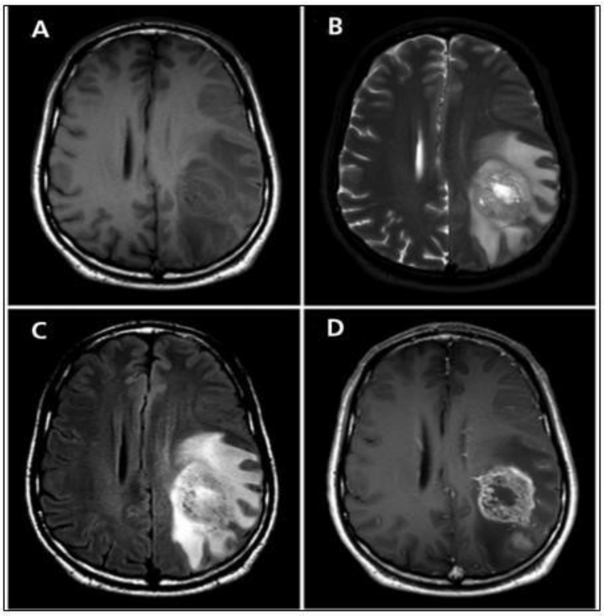

Figure 2: MRI segmented images of brain

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

The capacity of deep learning to automatically discover hierarchical representations of intricate patterns in imaging data is one of its main advantages in the investigation of brain tumors. CNN architectures can extract high-level semantic information from input images[17], such as tumor shape and border, as well as low-level data, such edges and textures. These designs are composed of numerous layers of convolutional and pooling operations. This makes it possible for deep learning algorithms[8] to identify minute variations between tumor and non-tumor regions, regardless of imaging procedure variability or noise. Furthermore, several tasks in brain tumor analysis, such as tumor segmentation, classification[30], and grading, can be tailored to deep learning approaches. For example, to aid in treatment planning and monitoring, researchers have created segmentation algorithms based on CNN that can identify tumor[23] boundaries and measure tumor volume. Deep learning models have also been[1] used to classify brain cancers into multiple classes[11] according to their genetic profiles or histological subtypes, which has given researchers important new information about the[29] biology and prognosis of these tumors.

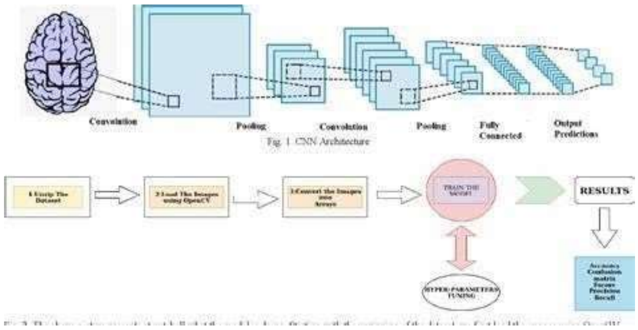

Fig 4.block diagram of CNN

Not with standing these developments, there are still difficulties in applying deep learning models in clinical settings. These difficulties include the requirement for reliable validation across a range of patient populations, the interpretability of model predictions, and workflow integration with current healthcare systems. However, continued research shows promise in realizing deep learning's full potential to transform brain tumor diagnosis and treatment, ultimately leading to better patient outcomes.

C. Advantage of deep learning in brain tumor The application of deep learning to brain tumor analysis provides a number of benefits over conventional techniques, leading to more precise, effective, and thorough diagnosis and treatment planning. Among the principal benefits are: Automated Detection and Segmentation:From MRI and CT scan data, brain tumors can be automatically identified and segmented using deep learning techniques, in particular convolutional neural networks (CNNs). By easing the workload for radiologists and other medical staff, this automation makes tumor diagnosis and delineation quicker and more accurate.

Improved Sensitivity and Specificity: When compared to conventional image analysis techniques, deep learning models trained on extensive datasets may identify complex patterns and traits linked to brain cancers, resulting in enhanced sensitivity and specificity in tumor diagnosis. By lowering the possibility of false positives and false negatives, this improved accuracy boosts patient care and diagnostic confidence.

Early Detection and identification: Deep learning algorithms help in early brain tumor identification by enabling automated and accurate tumor detection. This is important because it allows for timely therapeutic interventions and better patient outcomes. Additionally, premalignant lesions or smaller tumors that may go unnoticed by human observers can be found by early detection. Identification of Biomarkers and Quantitative Analysis: Tumor size, shape, and growth dynamics can be quantitatively analyzed using deep learning-based segmentation algorithms, which offers important insights about the biology and course of the tumor. Furthermore, imaging biomarkers linked to tumor grade, subtype, and response to treatment can be found using deep learning models, which helps with prognostication and customized treatment planning. integration of Multimodal Data: To supply a more thorough assessment of brain tumors, deep learning approaches allow the integration of multimodal imaging data, including MRI, CT, and PET scans. Deep algorithms have the potential to improve[10].diagnosis accuracy.and offer supplementary information about tumor features and tissue composition by merging data from various imaging modalities.

Adaptability and Generalization: Deep learning algorithms are highly adaptive and generalizable, enabling them to learn from a variety of datasets and adjust to differences in patient groups, imaging methods, and scanner types. Deep learning models can be deployed in many healthcare settings and geographical locations because to their flexibility, which enhances the scalability and accessibility of brain tumor analysis tools.

Better detection accuracy, early diagnosis, quantitative evaluation, and customized treatment planning are just a few benefits of using deep learning to brain tumor analysis. These benefits will ultimately enhance patient outcomes and care quality.

II.LETARATURE REVIEW

A handful of the algorithms are examined in detail in this part for the purpose of detecting brain tumors. Brain tumors can be successfully segmented using the supervised approach (random forests) (Geremia et al., 2010). Gaussian tumor segmentation is accomplished by applying the mixture model (GMM) (Van Leemput, Maes, Vandermeulen, & Suetens, 1999).

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

Better outcomes for brain tumor detection are obtained with morphological/contextual features (Rao, Ledig, Newcombe, Menon, & Rueckert, 2014). MRF is used to precisely segment the area of the lesion (Mitra, 2014). Deep learning techniques are effective[26] because they automatically extract highly discriminative characteristics in the form [22]of a hierarchy. Better outcomes on predefined and manually created characteristics are provided by these features. For the purpose of classifying the enhance, nonenhance, and core tumor region, the input images are fed into a fivelayer CNN model (Kleesiek et al., 2014). In order to segment HGG and LGG cases, several patches are taken out of the original photos and sent to Alves, Silva, Pinto, and Pereira (2015) on CNN. 2D CNN, Havei (2017) discusses deep neural networks (DNN); Pereira, Pinto, Alves, & Silva (2016) discusses CNN; Wu, Chen, Zhao, & Corso (2014) discusses pairwise affinity and super pixel; Bauer et al. (2012) discusses hierarchical classification; Kwon, Shinohara, Akbari, & Davatzikos (2014) discusses generative models; Huang et al. (2014) discusses local independent projection-based classification; Kamnitsas (2017) discusses multi-scale 3D CNN; Reza, Mays, & Iftekharuddin (2015) discusses multi-fractal Detrended fluctuation analysis (MFDFA); and random field (RF) Many methods, such as fully convolutional neural networks (FCNNs) (Zhao et al., 2018), cascaded CNN (Havaei, Dutil, Pal, Larochelle, & Jodoin, 2015), and Tustison (2015), are used to detect brain cancers.All performance measures still have space for improvement, despite the literature's extensive efforts. Consequently, The proposed model has demonstrated good performance on all performance criteria on five challenge datasets.. This is because the novel fused CNN model for precise brain tumor diagnosis presented in this work is to blame. Brain tumors are identified using a variety of techniques, including the use of generative models (Kwon, Shinohara, Akbari, & Davatzikos, 2014), cascaded CNN (Havaei, Dutil, Pal, Larochelle), random fields (RF) (Tustison, 2015), and fully convolutional neural networks (FCNNs) (Zhao et al., 2018).,[1] & Jodoin, 2015).All performance measures still have space for improvement, despite the literature's extensive efforts. Thus, The suggested model has performed exceptionally well[15].across all performance criteria on five challenge datasets. This is because the publication reports on a unique fused CNN model for precise brain tumor diagnosis.

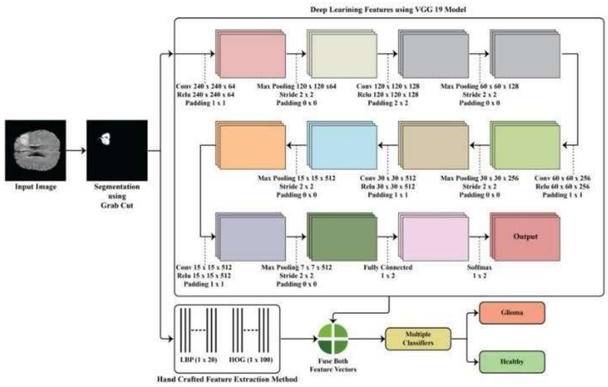

Fig. 1. Handcrafted and deep features fusion for brain tumor classification.

Fig 5. Deep feature fusion and customized for the categorization of brain tumors.

Many methods are used to identify brain tumors: random field (RF) (Tustison, 2015), fully convolutional neural networks (FCNNs) (Zhao et al., 2018), cascaded CNN (Havaei, Dutil, Pal, Larochelle, & Jodoin, 2015), and handcrafted and deep features fusion for generative models (Kwon, Shinohara, Akbari, & Davatzikos, 2014)[10]. All performance measures still have space for improvement, despite the literature's extensive efforts. Consequently, the proposed model has demonstrated good performance across all performance parameters on five challenge datasets. This is because the novel fused CNN model for precise brain tumor diagnosis presented in this paper is to blame. We provide an overview of relevant publications in this field that use deep learning techniques to diagnose brain diseases. There have been a lot of CNN-dependent recently developed automated brain tumor segmentation techniques. This section reviews a few CNN-based techniques before describing other ways for segmenting MRI images.

A 3D CNN design was presented by Urban for the multiple model MRI glioma segmentation task. Multimodality 3D patches, which are essentially voxel blocks.Detached from the unique brain To predict the tissue mark of the central voxel of the solid shape, MRI modalities are added to a CNN. Information includes one extra measurement for MRI modalities additionally to 3D spatial force data. In this regard, CNN handles 4D input data appropriately. High dimensional handling increases the network's preparation stack can more easily relate to the 3D concept of organic

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
IJARMATE
International Journal of Advanced Research in Management, Architecture, Technology and Engineering
(IJARMATE)
Vol. 10, Issue 5, May 2024

structures. There are organized engineering.A fourstage CNN was used at first, with the data cover containing 15 3D channels with 53 spatial measurements. An additional measurement represented the associated MRI approach, resulting in a channel state of 5 x 5 x 5 x 4. 53 spatial measurements are also available for two of the hidden layer channels, in addition to one measurement related to the number of channels in the preceding layer[11]. There were specifically twenty-five deep stage channels. The softmax course, which is the final cover, consists of six courses that is absorbed through any tissue type to provide an orderly comprehension of the yield as possibilities. The network that follows is nearly identical, with the exception of an additional hidden layer that has forty channels of size 53. Related components perhaps post-process the results. A method to access the standard EEG signal was proposed by Narayanan et al. [5]. First, an estimate of the peak voltage of the EEG signal is calculated. Ultimately, according to the wavelet transform, the signals were sent into an image using a created time-frequency transformation technique. The firefly algorithm-based approach was further handled to pick the primary features of the signal used in testing and training [25] the classifying method. In addition, the S-transform access was intended to disengage the major aspects of signals to the classifier scheme[1]. The SVM, RF, and KNN techniques were created with this approach.Thus, the performance confirmed that, with an average accuracy of 80.39%, our approach produced better results on the chosen EEG signal.

A novel classification technique based on a firefly algorithm created as a controlled learning algorithm was presented by Mashhour et al. [12]. As a result, the analysis relied on the firefly algorithm, which was developed by mimicking etiquette of a firefly to attract various partners based on intensity and distance.

The three stages of this algorithm's process were: 1) feature selection, which reduced the features and selected the most valuable features; 2) model development, which was important in identifying the moderators of the firefly class; and 3) model forecast, which used class contributors to distribute the testing or hidden sample among related classes. Eventually, some datasets were associated with the Ant-Miner method. The trial showed that the firefly approach was the most effective.

An approach called the (HBBEPSO) was introduced by Tawahid and Dsouza [13]. In order to obtain a better result[8] in the search area, this method employs a bat-based evolutionary algorithm to assess the feature space using echolocation and enhanced PSO rendition.)In comparison to the other approaches looked at, the overall effectiveness and methodology of the algorithm were found to be the best.

Therefore, the outcome has proven that is capable of locating the feature space for the ideal feature sequence. An method for identifying breast cancer[24] was suggested by Sangaiah and Kumar [14] using a relief attribute reduction with GA based on entropy. The hybrid sequence of this strategy was applied to handle the dataset that had more dimensions and concerns. The technique was calculated and compared with other noteworthy feature selection processes. The experimental outcome suggests that the work has a remarkable capacity to create a decreased subspace of critical features while generating significant classification accuracy for massive datasets. The information was obtained from the WISCONSIN datasets and classified based on various properties. For the PIMA Indian diabetes dataset from UCI, Harithaa [15] proposed the search-based feature selection techniques based on cuckoo and firefly, which have detached high accuracy and lower training upward.Cuckoo and firefly search algorithms' outcomes were compared using an empirical setup using the UCI dataset and the KNN classifier.) Precision, accuracy, and recall were examined to determine parameters.Historically, this method produced high precision 1. Deep Learning Algorithms

Some of the common types of machine learning algorithms are listed by finding the best line to fit, linear regression determines the relationship between independent and dependent variables [11]. A linear equation the regression line, which is the line of greatest fit.

$Y = AX + B$ (4.7)

Where Y is the dependent variable

A is the slope

X is the independent variable B is

an intercept.

Using the provided set of independent variables, logistic regression is used to predict discrete values (such as binary values like 0/1, yes/no, and true/false). The output values of logistic regression fall between 0 and 1, as it forecasts the likelihood.

A type of supervised learning technique called a decision tree is typically applied to classification issues. For both continuous and categorical dependent variables, decision trees are used. The population is divided into two or more homogeneous groups in this instance. In order to create as many unique groups as possible, this process is carried out based on more important characteristics or independent factors.

Machine Learning Types

Reinforcement of Supervised and Unsupervised Learning

Acquiring Decision Tree Knowledge kNN random forest

Regression using logic

K-means algorithm Markov decision process appropriate method.

Figure Variety of algorithms for machine learning. 74 Machine Vision Inspection Systems Classification is done using Support Vector Machines (SVM). In this case, every data point is represented as a point in an ndimensional space, where n is the number of features, and the value of each feature corresponds to a certain position. One method for classification that is based on the Bayes theorem is called Naïve Bayes. The Naïve Bayes classifier relies on the

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
IJARMATE
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

presumption that a specific characteristic exists within a class. The existence of any other feature has no bearing on this class.

For very large datasets, Naïve Bayes model is easily built.

Bayes theorem is used for calculating posterior probability using this formula, P(c|x) = [P(x|c) · P(c)] ÷ P(x) (4.8)

Where P (c|x) denotes the posterior probability of target class given predictors (attributes).

P (c) denotes the prior probability of class. P (x|c) denotes the likelihood which is the predictor probability of the given class.

P (x) denotes the prior probability of the predictor. The kNN technique is applied to problems involving regression and classification.

This algorithm stores every instance that is accessible and classifies new cases based on the majority vote of their k neighbors. The kNN algorithm is thought to be computationally costly. If the variables are not normalized, there is a possibility that [10]they will all be biased by upper range variables. This algorithm functions during the preprocessing phase.

The k-means algorithm is an unsupervised method used to address the clustering problem. The k-means technique uses a specific number of clusters is given collection of data. Within a cluster, data points are homogeneous in nature, although they differ from other clusters in that regard. Random forests are collections of decision trees. Tree votes for each class are employed for categorization new objects. Ultimately, the forest selects the classification with the highest number of votes.

Boosting is an ensemble of learning techniques that enhances robustness over a single estimator by combining the prediction of several base estimators [12]. GBM is utilized when working with a large amount[17] of data to get a prediction with a high prediction power. Well-known gradient boosting techniques include catboost, LightGBM, XGBoost, and others

2. The efficiency of classifying photos into three groups is evaluated using the same performance metrics as the preceding references: accuracy, specificity, sensitivity, precision, and F1 score. These performance metrics' calculation formula is expressed as below in Eqs. 3–7 respectively: ReLU(x) = (2) { x, if x > 0,
0, otherwise
Accuracy = (3)
TP + TN (TP + TN
+ FP + FN)
Specificity = (4)
TN
TN + FP
680 W. Ayadi .where True Positives are identified by TP, True Negatives by TN, False Positives by FP, and False Negatives by FN. The confusion matrix[14], which offers information on the accurate and inaccurate classification of photos across all categories, estimate these parameters.

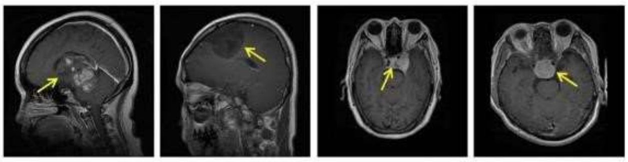

Fig 6. Content-Based Image Retrieval Using Spatial Layout Information in Brain Tumor T1-Weighted ContrastEnhanced MRI Images.

3.Performance metrics including accuracy (Acy), sensitivity (Sny) /recall, specificity (Spy), precision (Prn), AUC, and F1 score are used to evaluate ML/DL detection systems in order to determine the chance of properly identifying AD, MCI, and NC. Various performance metrics suggest distinct inferences for a detection model. A model may produce excellent results in terms of accuracy, but its specificity may be appalling. We provide a tabular summary of the papers with the specified performance metrics based on the reasoning. Accuracy is the fundamental evaluation metric for any classification system. It can be expressed simply as the ratio of the total number of forecasts made to the number of accurate predictions. It has the following mathematical definition:

Acy = τp + τN τp + FP + τN + FN, ----------------------❼(1)
where τN and τP stand for genuine negative and positive, respectively, and denote accurately classifying negative as negative and positive as positive. False positive (FP) and false negative (FP) are the outcomes of labeling negative as positive and vice versa. While accuracy deals with both positive and negative findings, specificity and sensitivity/recall are used to assess a certain model's ability to detect positive or negative results, respectively. Consequently, sensitivity and specificity are defined mathematically as Sny = τP + FN, -
-------------------------❼(2)
Spy =
τN
τN + FP. ---------------------------------❼(3) These can also be referred to as true negative and true positive rates, respectively.

According to the sensitivity formula, it is a gauge of how well patients have been diagnosed with their illnesses. Precision, on the other hand, quantifies the actuality of the diagnosis, or the percentage of patients diagnosed by a system who were truly impacted by the illness. It has the following mathematical definition: Prn = τP + FP.---------
----------------❼(4)

Conversely, the harmonic mean of the sensitivity and precision is called the F1 score of that model which is defined as F1 = 2 ×
Sny × Prn
Sny + Prn .-----------------------------❼ (5)

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com

International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

Furthermore, Features of the receiver's curve in operation (ROC) is a commonly used graphic that compares the true positive rate to the false positive rate to evaluate how diagnostic a binary categorization scheme is. The model's capacity to discriminate between the binary choices under various discrimination thresholds is indicated by the area under the ROC curve[6] (AUC). Moreover, the ratio of specificity to sensitivity is the definition of MCC. it can be expressed as

MCC =

Spy

Sny.---------------------❼ (6)

Another evaluation metric is known as Jaccard similarity index (JSI) which can be calculated mathematically as

JSI = τP

τP + FN + FP. ------------------❼(7)

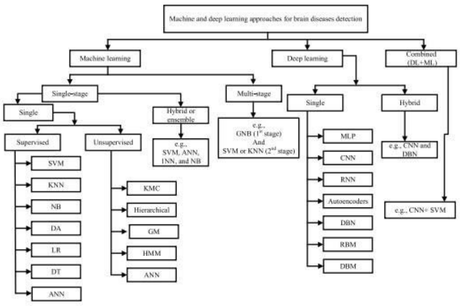

Fig 7.deep learning approach for dieases detection

VI. PROPOSED MODEL

1.Because the Brats data set is low in three dimensions, the input image is segmented. Thus, splitting an input into two subdivisions is required.

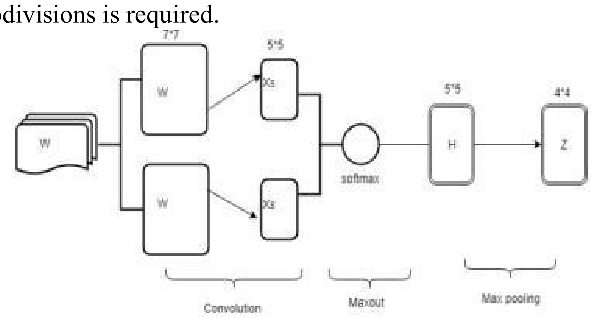

Fig 8. Madhupriya, G., et al. "Brain tumor segmentation with deep learning technique." *2019 3rd international conference on trends in electronics and informatics (ICOEI)*. IEEE, 2019.

There are two methods for creating an architecture because the input is segmented. Therefore, CNN and PNN are used in a two path design. Additionally, this 2-path convolutional neural network is employed in a cascaded design. Two path Architecture The figure and Description of Two path CNN will be given in detail below.

The input dataset image is 4*33*33 in size, as indicated in the above graphic. It will be processed in two ways:

The image is convolutioned and max pooled using a convolution filter of size 7*7, yielding an image of size 64*24*24. After that, it will go through a 3*3 convolution filter to create an image that is 64*21*21 in size, which will then be sent to the concatenation layer.

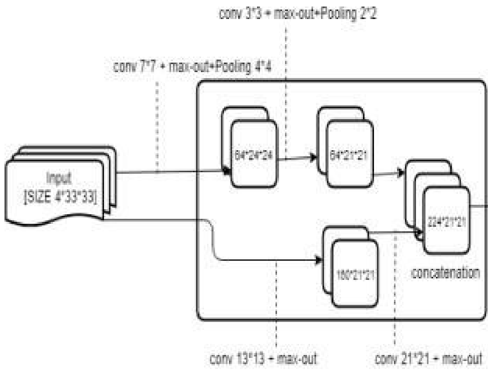

Fig 9. Madhupriya, G., et al. "Brain tumor segmentation with deep learning technique." *2019 3rd international conference on trends in electronics and informatics (ICOEI)*. IEEE, 2019.

The second method involves convolving a portion of the input[8] image with a 13*13 filter to create an image that is 160*21*21 in size.

The produced pictures of sizes 64*21*21 and 160*21*21 are transferred to the layer of concatenation, which requires both inputs to be of size 64*64 in order to generate a 224*21*21 size matrix. Next, a 21*21 convolution filter is performed here, go along with softmax operation, yielding an output with a size of 5*1*1.

An input image is processed into an output image using two path architecture in this way.

Cascaded architectures

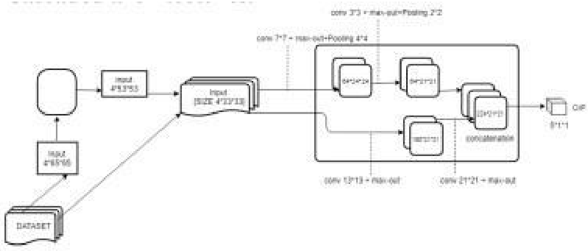

Fig 10. Madhupriya, G., et al. "Brain tumor segmentation with deep learning technique." *2019 3rd international conference on trends in electronics and informatics (ICOEI)*. IEEE, 2019.

Above diagrams provide an abstract overview of various cascaded architectures. These architectures are models on a deep neural network to do pixel level semantic segmentation. While kernels of various size cascade over a tumor region, our model reads feature of an image and detects the tumor region. Once the tumor identified successfully, all the other parts of brain image is set to black

ISSN (ONLINE): 2454-9762
ISSN (PRINT): 2454-9762
Available online at www.ijarmate.com
IJARMATE
International Journal of Advanced Research in Management, Architecture, Technology and Engineering (IJARMATE)
Vol. 10, Issue 5, May 2024

and makes tumor region to be white to show the tumor area or the tumor area is sliced and print on the output screen.

4. Training Dataset
Then, as usual, the model is trained using fit function along with accuracy, loss and F1_score attributes.

5. Testing Dataset and accuracy prediction. Once the training phase completed, an image is chosen from the dataset and preprocessed the data then used the model which is compiled and trained in the above phases and used predict function to do the prediction process. Finally, got the output segmented image as well as analyzed accuracy and loss of our models.

2. CNN is now extensively used in many different kinds of medical image processing applications, particularly in the segmentation[3] and classification of MRI brain tumors. This article proposes a novel CNN model for multi-class classification of brain tumors.

Fig. 2 depicts the broad architecture of the suggested sequential model, while Table 1 provides specifics. It is made up of multiple layers, each with a distinct purpose.A 256 x 256 image serves as the input model. Ten convolutional layers are used draw out important feature. A max-pooling layer is applied after every two convolutional layers bring down of the data[15]. Each convolutional layer uses 3 x 3 filters, while the pooling layers apply 2 x 2 filters. A non-linearity layer is added to improve CNN's ftting ability. Finally, a batch normalization is used after every two convolutional layers.

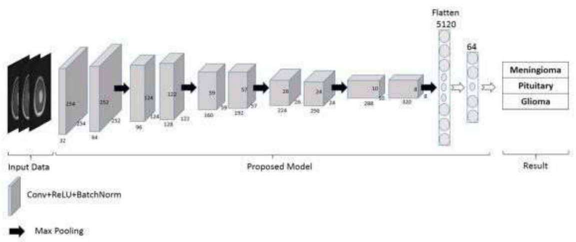

Fig 11. . Madhupriya, G., et al. "Brain tumor segmentation with deep learning technique." *2019 3rd international conference on trends in electronics and informatics (ICOEI)*. IEEE, 2019.

Deep learning techniques show promise in the efficient and precise identifying and categorizing of brain tumors. Scientiseach convolution layer to accomplish the highest level of optimization and speed up the network's convergence.

64 neurons are used in fully connected layers. The softmax classifier is used by the output layer. We will provide a brief overview of these levels in this section[5].

3.Deep learning has gained popularity recently high accuracy rate and wide range of applications in[6] computer vision [29–31], image processing [32,33], authentication system [34], and speech recognition [35,36]. CNNs are feedforward ANN)[4] promoted by

CNN proposed structure

Layer	Output shape			Kernel size
	Width	Height	Depth	
Conv/relu/BatchNorm	254	254	32	3
Conv/relu/BatchNorm	252	252	64	3
MaxPool	126	126	64	2
Conv/relu/BatchNorm	124	124	96	3
Conv/relu/BatchNorm	122	122	128	3
MaxPool	61	61	128	2
Conv/relu/BatchNorm	59	59	160	3
Conv/relu/BatchNorm	57	57	192	3
MaxPool	28	28	192	2
Conv/relu/BatchNorm	26	26	224	3
Conv/relu/BatchNorm	24	24	256	3
MaxPool	12	12	256	2
Conv/relu/BatchNorm	10	10	288	3
Conv/relu/BatchNorm	8	8	320	3
MaxPool	4	4	320	2
Flatten	1	1	5120	–
Dense	1	1	64	–
Sotmax	1	1	3	–

Fig 12. Ayadi, Wadhah, et al. "Deep CNN for brain tumor classification." *Neural processing letters* 53 (2021): 671-700.

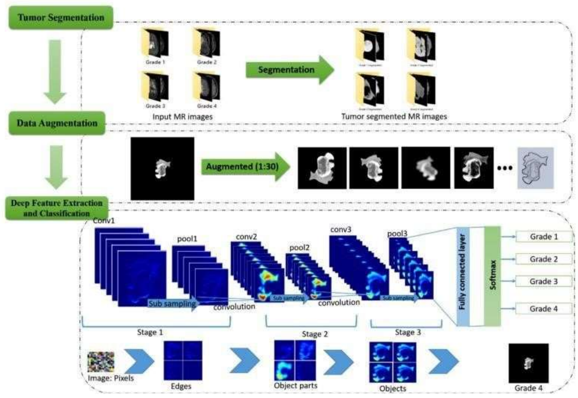

Fig 13.Sajjad, Muhammad, et al. "Multi-grade brain tumor classification using deep CNN with extensive data augmentation." Journal of *computational- science 30 (2019): 174182. natural processes designed to extract various patterns straight from picture data. Inspired by CNNs' recent successes on a range of difficult tasks, we applied CNN to the multi-grade brain tumor classification challenge. In this paper, we provide a unique deep learning framework that uses an optimized CNN model to segment and classify brain tumors into four distinct categories. There are three primary steps in the suggested system: 1) Tumor segmentation;

2) Data augmentation; and
3) Extraction and classification of deep features. Tumor areas in both datasets are segmented in the first stage. A CNN architecture that has been pre-trained and whose layers specifically allow segmentation is used to segment

tumor areas. The next stage is data augmentation, which involves adjusting various settings to add more data using transformational and noise invariance approaches.

VII. CONCLUSION

Deep learning techniques show promise in the efficient and precise detection and classification of brain tumors. Scientists are using MRI images and other medical imaging data to build algorithms that accurately detect and classify brain tumors. Convolutional neural networks (CNNs) and other advanced deep learning architectures are used in the construction of these models. These deep learning models have the potential to help radiologists identify brain cancers more rapidly and accurately, leading to an early diagnosis and treatment plan. Additionally, the automated nature of these models may reduce the workload for healthcare staff by handling routine examinations, freeing them up to focus on more challenging tasks. It's important to keep iResearch and development are now underway on topics like as interpretability of results, bias in datasets, and application to different populations. Before deep learning models may be employed in clinical settings, extensive validation and regulatory approval are also required to ensure their safety and efficacy. In conclusion, even though deep learning exhibits great promise for the identification and categorization of brain tumors, further research and development are needed to get past present challenges and maximize the benefits for patients and medical professionals and mind that deep learning models have limitations.

VIII. REFERENCES

1.Işın, Ali, Cem Direkoğlu, and Melike Şah. "Review of MRI-based brain tumor image segmentation using deep learning methods." Procedia Computer Science 102 (2016): 317-324.

2.Saba, Tanzila, et al. "Brain tumor detection using fusion of hand crafted and deep learning features." Cognitive Systems Research 59 (2020): 221230.

3.Khan, Md Saikat Islam, et al. "Accurate brain tumor detection using deep convolutional neural network." Computational and Structural Biotechnology Journal 20 (2022): 4733-4745.

4.Taha, Ashraf MH, D. S. B. B. Ariffin, and Samy S. AbuNaser. "A Systematic Literature Review of Deep and Machine Learning Algorithms in Brain Tumor and MetaAnalysis." Journal of Theoretical and Applied Information Technology 101.1 (2023): 21-36.

5.Gore, Deipali Vikram, and Vivek Deshpande. "Comparative study of various techniques using deep Learning for brain tumor detection." 2020 International conference for emerging technology (INCET). IEEE, 2020.

6.Rinesh, S., et al. "Investigations on brain tumor classification using hybrid machine learning algorithms." Journal of Healthcare Engineering 2022 (2022).

7.Haq, Ejaz Ul, et al. "A hybrid approach based on deep cnn and machine learning classifiers for the tumor segmentation and classification in brain MRI." Computational and Mathematical Methods in Medicine 2022 (2022).

8.Noreen, Neelum, et al. "A deep learning model based on concatenation approach for the diagnosis of brain tumor." IEEE access 8 (2020): 5513555144.

9.Amin, Javeria, et al. "A distinctive approach in brain tumor detection and classification using MRI." Pattern Recognition Letters 139 (2020): 118127.

10.Mahmud, Md Ishtyaq, Muntasir Mamun, and Ahmed Abdelgawad. "A deep analysis of brain tumor detection from mr images using deep learning networks." Algorithms 16.4 (2023): 176.

11.Kumar, T. Sathies, C. Arun, and Periyathambi Ezhumalai. "An approach for brain tumor detection using optimal feature selection and optimized deep belief network." Biomedical Signal Processing and Control 73 (2022): 103440.

12.Younis, Ayesha, et al. "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches." Applied Sciences 12.14 (2022): 7282.

12.Jia, Zheshu, and Deyun Chen. "Brain tumor identification and classification of MRI images using deep learning techniques." IEEE Access (2020).

13.Ali, Mahnoor, et al. "Brain tumour image segmentation using deep networks." Ieee Access 8 (2020): 153589-153598.

14.Nadeem, Muhammad Waqas, et al. "Brain tumor analysis empowered with deep learning: A review, taxonomy, and future challenges." Brain sciences 10.2 (2020): 118.

15.Abd El Kader, Isselmou, et al. "Differential deep convolutional neural network model for brain tumor classification." Brain Sciences 11.3 (2021): 352.

16.Swati, Zar Nawab Khan, et al. "Brain tumor classification for MR images using transfer learning and fine-tuning." Computerized Medical Imaging and Graphics 75 (2019): 34-46.

17.Kothari, Sonali, et al. "Cancerous brain tumor detection using hybrid deep learning framework." Indonesian Journal of Electrical Engineering and Computer Science (IJEECS) 26.3 (2022): 1651-1661.

18.Abdusalomov, Akmalbek Bobomirzaevich, Mukhriddin Mukhiddinov, and Taeg Keun Whangbo. "Brain tumor detection based on deep learning approaches and magnetic resonance imaging." Cancers 15.16 (2023): 4172.

19.Younis, Ayesha, et al. "Deep Learning Techniques For the Classification of Brain Tumor: A Comprehensive Survey." IEEE Access (2023).

20.Hamid, Khalid, et al. "Detection of Brain Tumor from

Brain MRI Images with the Help of Machine Learning & Deep Learning." International Journal of Computer Science and Network Security 22.5 (2022): 709-721.

21.Hashemzehi, Raheleh, et al. "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE." biocybernetics and biomedical engineering 40.3 (2020): 1225-1232.

22.Khan, Muhammad Attique, et al. "Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists." Diagnostics 10.8 (2020): 565.

23.Raza, Asaf, et al. "A hybrid deep learning-based approach for brain tumor classification." Electronics 11.7 (2022): 1146.

24.Brindha, P. Gokila, et al. "Brain tumor detection from MRI images using deep learning techniques." IOP conference series: materials science and engineering. Vol. 1055. No. 1. IOP Publishing, 2021.

25.Siar, Masoumeh, and Mohammad Teshnehlab. "Brain tumor detection using deep neural network and machine learning algorithm." 2019 9th international conference on computer and knowledge engineering (ICCKE). IEEE, 2019.

26.Choudhury, Chirodip Lodh, et al. "Brain tumor detection and classification using convolutional neural network and deep neural network." 2020 international conference on computer science, engineering and applications (ICCSEA). IEEE, 2020.

27.Magadza, Tirivangani, and Serestina Viriri. "Deep learning for brain tumor segmentation: a survey of state-ofthe-art." Journal of Imaging 7.2 (2021): 19.

28.Kalaiselvi, T., and S. T. Padmapriya. "Brain tumor diagnostic system—a deep learning application." Machine Vision Inspection Systems, Volume 2: Machine LearningBased Approaches (2021): 69-90.

29.Khan, Protima, et al. "Machine learning and deep learning approaches for brain disease diagnosis: principles and recent advances." Ieee Access 9 (2021): 37622-37655.

30.Madhupriya, G., et al. "Brain tumor segmentation with deep learning technique." 2019 3rd international conference on trends in electronics and informatics (ICOEI). IEEE, 2019.

31.Anaraki, Amin Kabir, Moosa Ayati, and Foad Kazemi. "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms." biocybernetics and biomedical engineering 39.1 (2019): 63-74.

32.Methil, Aryan Sagar. "Brain tumor detection using deep learning and image processing." 2021 international conference on artificial intelligence and smart systems (ICAIS). IEEE, 2021.

33.Sajjad, Muhammad, et al. "Multi-grade brain tumor classification using deep CNN with extensive data augmentation." Journal of computational science 30 (2019): 174-182.

34.Amin, Javaria, et al. "Brain tumor detection by using stacked autoencoders in deep learning." Journal of medical systems 44 (2020): 112.

35.Ayadi, Wadhah, et al. "Deep CNN for brain tumor classification." Neural processing letters 53 (2021): 671-700.

36. Saeedi, Soheila, et al. "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques." BMC Medical Informatics and Decision Making 23.1 (2023): 16.

37.Kang, Jaeyong, Zahid Ullah, and Jeonghwan Gwak. "MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers." Sensors 21.6 (2021): 2222.