EAI Endorsed Transactions
on Pervasive Health and Technology

Research Article EAI.EU

An Effective analysis of brain tumor detection using deep learning

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Abstract

INTRODUCTION: Cancer remains a significant health concern, with early detection crucial for effective treatment. Brain tumors, in particular, require prompt diagnosis to improve patient outcomes. Computational models, specifically deep learning (DL), have emerged as powerful tools in medical image analysis, including the detection and classification of brain tumors. DL leverages multiple processing layers to represent data, enabling enhanced performance in various healthcare applications.
OBJECTIVES: This paper aims to discuss key topics in DL relevant to the analysis of brain tumors, including segmentation, prediction, classification, and assessment. The primary objective is to employ magnetic resonance imaging (MRI) pictures for the identification and categorization of brain malignancies. By reviewing prior research and findings comprehensively, this study provides valuable insights for academics and professionals in deep learning seeking to contribute to brain tumor identification and classification.
METHODS: The methodology involves a systematic review of existing literature on DL applications in brain tumor analysis, focusing on MRI imaging. Various DL techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models, are explored for their efficacy in tasks such as tumor segmentation, prediction of tumor characteristics, classification of tumor types, and assessment of treatment response.
RESULTS: The review reveals significant advancements in DL-based approaches for brain tumor analysis, with promising results in segmentation accuracy, tumor subtype classification, and prediction of patient outcomes. Researchers have developed sophisticated DL architectures tailored to address the complexities of brain tumor imaging data, leading to improved diagnostic capabilities and treatment planning.
CONCLUSION: Deep learning holds immense potential for revolutionizing the diagnosis and management of brain tumors through MRI-based analysis. This study underscores the importance of leveraging DL techniques for accurate and efficient brain tumor identification and classification. By synthesizing prior research and highlighting key findings, this paper provides valuable guidance for researchers and practitioners aiming to contribute to the field of medical image analysis and improve outcomes for patients with brain malignancies.

Keywords: Brain Tumor, MRI images, Deep Learning, Segmentation

Received on 28 December 2023, accepted on 27 March 2024, published on 03 April 2024

doi: 10.4108/eetpht.10.5627

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1. Introduction

The human brain serves as the central processing unit and a vital nervous system component, carrying out everyday tasks. The brain gathers messages or inputs from the body's sensory organs, manages the processing, and communicates final judgments and information to the muscles. One of the worst conditions affecting the human brain is known as BTs, in which an uncontrolled growth of aberrant brain cells occurs [1]. Primary and secondary metastatic BTs can be categorized into two basic groups. Brain cells from humans are the major source of primary brain tumors (BTs), which are often not malignant. However, the blood flow from other bodily areas causes secondary metastatic tumors to spread to the brain. Since brain tumors may be dangerous, it is crucial to accurately diagnose patients and administer any required treatments. Only thorough brain area scanning can prevent brain tumor illness at an early stage. One of the attractive approaches for finding brain tumors is (MRI)magnetic resonance imaging, and there are several MRI techniques. The many brain tissues that may be identified with each MRI method each have a unique composure time. The spread and ambiguous structure of brain tumors make it difficult for a single MRI modality to detect cancers with irregular forms over the whole brain. Different MRI procedures' conflicting information is crucial for identifying tumor areas [2]. Different MRI types are produced by the use of various pulse sequences, including weighted-T1 MRI, which separates tumors from healthy tissue, and weighted-T2 MRI creates patches of the clear picture where edema is present. Machine learning and deep learning are now employed as prominent methodologies for the early diagnosis of brain tumors. Deep learning achieved many health issues in humans to be diagnosed earlier, so this paper systematically reviews various brain tumor decisions and deep learning algorithms.

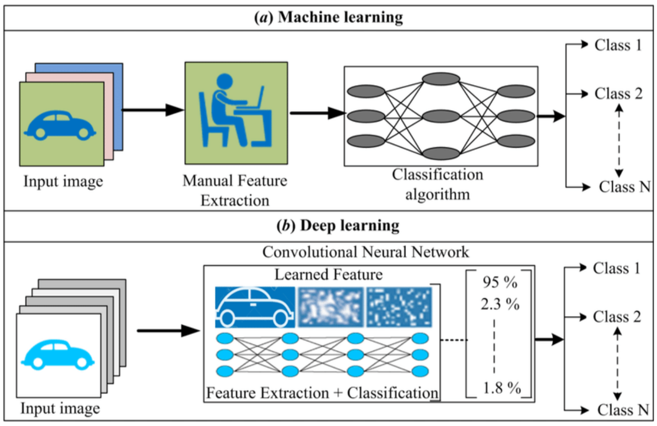

Fig 1. Difference between Machine Learning and Deep Learning.

Fig 1 shows that (ML)Machine Learning and (DL) Deep Learning are two subfields within the domain of artificial intelligence (AI) that are dedicated to the development of algorithms and models capable of facilitating computers in the process of learning from data and subsequently generating informed predictions or decisions. But they are different in how they work, are built, and are complicated. Here is a short description of the difference between ML and DL, along with an illustration to show the difference. Machine Learning is a broader term that incorporates a variety of algorithms and techniques that enable a computer to learn from data and enhance the performance of a specific task. ML algorithms can be classified broadly as supervised, unsupervised, or reinforcement learning. Deep Learning is a specialized domain within the study of machine learning that utilizes neural networks numerous neural layers commonly referred to as deep neural networks, to independently uncover hierarchical data representations. Deep learning architectures are intended to process unprocessed data, such as images, audio, and text, and can effectively manage high-dimensional and unstructured data [3].

Paper structure section 1: Represents the Introduction, Section 2: Related work, section 3: Represents the Basic overview of system architecture, section 4: Represents the Evaluation metrics, section 5: represents the conclusion, and Section 6: represents the references.

2. Related Work

Alrashedy et al. (2022) [4] In many deep learning models, The MRI brain pictures are produced and classified using ResNet152V2, MobileNetV2, and CNN. DCGAN and Vanilla GAN produce the pictures following which deep transfer models are trained and assessed for their performances on a test case set of real MRI brain images. According to the experiment findings, ResNet152V2 outperformed all other models with a 99.08% recall, 99.12% precision, 99.09% accuracy, 99.51% AUC, and a loss of 0.196 based on MRI brain pictures. Alanazi et al. (2022) [5], propose that a novel deep-learning model has been developed to facilitate the early detection of brain tumors by leveraging many subtypes, including glioma, pituitary tumors, and meningioma. Convolutional neural network models are specifically designed to assess the performance of MRI brain pictures. Tumour classification is then applied to the MRI brain pictures. When applied to an unreleased MRI brain dataset, the recommended method yields 96.89% high accuracy. Swati et al. (2019) [6], BT identification and classification were performed using block-wise, improved CNN models. When comparing the performance of hand-crafted features with the fine-tuned VGG-19 model utilizing the block-wise fine-tuning technique, it was observed that the latter achieved a classification accuracy of 94.84%. El Hamdaoui et al. (2021) [7], The researchers utilized a variety of pre-trained networks, including ResNetV2, Mobile-Net, InceptionV3, Xception, VGG16, DenseNet121, Inception, and VGG19, to perform the classification of HGG and LGG brain pictures. The magnetic resonance (MR) scans utilized in this study were acquired from the BraTS 2019 database, comprising a cohort of 285 individuals. This cohort was divided into two groups: 210 patients diagnosed with high-grade gliomas (HGG) and 75 patients diagnosed with low-grade gliomas (LGG). Following the conversion of the dataset's three-dimensional magnetic resonance imaging (MRI) volumes into two-dimensional slices, a collection of 26,532 pictures depicting low-grade glioma (LGG) and 94,284 images portraying high-grade glioma (HGG) was produced. To address the performance implications of the unequal distribution between the two classes in the classification task, the researchers decided to carefully choose a total of 26,532 photos from the HGG database. The test dataset exhibited an average accuracy of 92.5%, a f1-score of 85.2%, and a sensitivity of 98.33%. Bulla et al. (2020) [8], A collection of 3064 images, including 708 meningiomas, 1426 gliomas, and 930 pituitary tumors, from 233 patients—82 meningiomas, 89 gliomas, and 62 pituitary tumors—was utilized to classify the images using a previously trained InceptionV3 CNN model. Several validation techniques were employed throughout the training process, including holdout validation, and group 10-fold cross-validation. During group 10-fold cross-validation, the highest classification accuracy of 99.82% was attained for patient-level categorization. Loveleen et al. (2022) [9], during the pre-processing stage, Gaussian noise was included in the data with a mean of 0 and a standard deviation of 10 0.5 to improve the learning efficacy of the Convolutional Neural Network (CNN). The CNN architecture described in this study demonstrates a notable accuracy of 94.64% when applied to the MRI dataset. In addition, the suggested model offers an explanation that is not dependent on geographical factors, hence improving the qualitative comprehension of outcomes for the broader populace. Ruqianat et al. (2021) [10], The study examined the application of transfer learning techniques for the classification of brain tumors. The present study employed data from the BraTS 2019 dataset, consisting of a sample size of 335 participants diagnosed with brain tumors. Among these people, 259 were identified as having high-grade gliomas (HGG), while the remaining 76 were defined as having low-grade gliomas (LGG). The model demonstrated a classification Area Under the Curve (AUC) of 82.89% in a separate test dataset consisting of 66 patients. The constrained classification efficacy of the study poses a barrier to the advancement and implementation of transfer learning in the field of clinical practice. Nayak et al. (2022) [11], in the present work, the researchers employed Efficient-Net and min-max normalization techniques to classify brain tumors into four distinct groups, namely astrocytoma, neoplasm, interbrain, and benign. They also performed pre-processing to improve training using fuzzy thresholding, Gaussian and Laplacian filters, and dense-CNN models. Arpit Kumar Sharma et al. (2022) [37], The proposed architecture is derived from the ResNet-50 model and has a customized layer configuration consisting of five convolutional layers and three fully linked layers.

Table 1: Comparison of various deep learning algorithms and model metrics.

Ref.no	Tumor Classification Type	Algorithms	Performance Metrics	Accuracy
[1]	Multiclass (Meningioma, Glioma,, Pituitary)	Google Net	Precision=99.06,Recall=100 F1_score=99.66	99.67%
[2]	Multiclass (Meningioma , Glioma, Pituitary)	17-layered CNN, MobileNetV2 & M-SVM	NA	98.92%
[3]	Binary_class(Tumor, No Tumor)	CNN-LSTM	Precision =98.8,Recall =98.9, F1 Score of =99.0	99.1%
[4]	Binary_class(Tumor, No Tumor)	CNN ResNet152V2, and MobileNetV2	Precision =99.12 Recall=99.08 Aug=99.51	99.09%
[5]	Binary class(Tumor, No Tumor)	Custom CNN	NA	95.75%
[6]	Multi_class,(Meningioma ,Glioma , Pituitary)	VGG19	Sensitivity = 94.25%, Specificity = 94.69%, Precision = 89.52%, F1 Score of = 91.73%	94.82%
[7]	Multi_class,(Meningioma ,Glioma , Pituitary)	CNN	Precision =98.67% F1 Score =98.62% Sensitivity of= 98.33%	99.01%
[8]	Binary_class(Tumor, No Tumor)	InceptionV3, CNN mode	Precision = 97.57%, Recall = 99.47%, F1 _Score of = 98.40%, Auc of = 0.995.	99.82%
[9]	Multi_class,(Meningioma ,Glioma , Pituitary)	Dual-Input CNN	Accuracy =98.78%	98.78%

[10]	Binary_class(Tumor, No Tumor)	NA	Aug =82%	NA
[11]	Binary_class(Tumor, No Tumor)	Dense Efficient Net	Accuracy= 98.78%, Precision= 98.75%, Recall= 98.75%	98.78%
[12]	Binary_class(Tumor, No Tumor)	DL-MajVo (Alex Net, VGG16, ResNet18, Google Net, ResNet50)	Sensitivity = 96.76%, Specificity = 96.43%, Auc = 0.966	96.51%
[13]	Binary_class(Tumor, No Tumor)	Transfer learning with Alex Net	Recall = 100%, Precision = 100%, F1 Score = 100%	100%
[14]	Multi_class,(Meningioma ,Glioma , Pituitary)	Google Net	NA	98%
[15]	Multi_class,(Meningioma ,Glioma , Pituitary)	Residual networks	Precision = 99.0, Recall = 99.0, F1 Score of= 99.0%	99%
[16]	Multi_class,(Meningioma ,Glioma , Pituitary)	CNN model	Precision = 99.6%, Recall of = 98.6%, F1 _Score of = 99.0%	98.6%
[17]	Multi_class,(Meningioma ,Glioma , Pituitary)	CNN-GAN	Sensitivity = 94.91%, Specification = 97.69%, F1 _Score = 95.10%, Precision=95.29%	95.6%
[18]	Multi_class,(Meningioma ,Glioma ,Pituitary)	CNN model	Precision = 97.41%, Recall = 97.42%	97.42%
[19]	Multi_class,(Meningioma ,Glioma , Pituitary)	Transfer learning with Inception-v3	NA	93.31%
[20]	Multi_class,(Meningioma ,Glioma , Pituitary)	Transfer learning with ResNet50	Precision= 97.20%, Recall = 97.20%, F1 _Score = 97.20%	NA
[21]	Multi_class,(Meningioma ,Glioma , Pituitary)	CNN model	Precision= 95.79%, Recall of = 96.51%, F1_ Score of = 96.11%	96.56%
[22]	Multi_class,(Meningioma ,Glioma ,Pituitary)	CNN model	Precision of= 98.3%, Sensitivity of = 98.6%, F1 _Score of = 98.6%	98.70%
[23]	Multi_class,(Meningioma ,Glioma ,Pituitary)	CNN model	NA	96.90%
[24]	Multi_class,(Meningioma ,Glioma , Pituitary)	CNN model	NA	94.64%
[25]	Multi_class,(Meningioma ,Glioma , Pituitary)	CNN model	NA	98.95%

[26]	Multi_class,(Meningioma ,Glioma ,Pituitary)	CNN model	NA	99.8%
[27]	Multi_class,(Meningioma ,Glioma ,Pituitary)	CNN model	Precision of = 97.33%, Sensitivity of = 97.19%, F1 –score of = 97.26%	97.52%
[28]	LowGradeGlioma, HighGradeGlioma.	CNN model	Sensitivity = 98.0%, Specificity of = 96.3%, F1-score of = 97.0%, Auc of = 0.989	97.1%
[29]	LowGradeGlioma, HighGradeGlioma.	Alex Net	Auc = 82.89%	82.89%
[30]	LowGradeGlioma, HighGradeGlioma.	Resnet18	NA	95.87%
[31]	LowGradeGlioma, HighGradeGlioma.	CNN mode	Sensitivity = 84.35%, Specificity = 93.65	90.7%
[32]	LowGradeGlioma, HighGradeGlioma.	Transfer learning with ResNet50	Sensitivity = 93.5%, Specificity = 97.2%	96.3%
[33]	LowGradeGlioma, HighGradeGlioma.	3DCNN	Sensitivity = 90.16%, Specificity = 89.80%, Auc = 0.9398	90%
[34]	LowGradeGlioma, HighGradeGlioma.	VGG16, VGG19, ResNetV2, DenseNet121 Mobile Net, InceptionV3, Xception, Inception	Precision =98.67%, F1- Score of=98.67%, Sensitivity of =98.33%.	98.06%
[35]	LowGradeGlioma, HighGradeGlioma.	CNN mode	NA	99.46%
[36]	LowGradeGlioma, HighGradeGlioma.	EfficientNet-B0	Precision = 98.98%, Sensitivity = 98.86%, Specificity = 98.79%	98.87%
[37]	Binary class(Tumor, No Tumor)	Resnet50	Accuracy 92 Precision 100%	92%

From TABLE 1, existing authors are concentrated on the CNN and Transfer learning algorithms but still, we have scope to develop the CNN with auto encoder and decoders, CNN with U-net.

2.1 Datasets

A sizable training dataset is needed to build a reliable and effective deep learning-based classification system for classifying brain tumors.

Table 2. A list of datasets that are freely accessible.

S.NO	Name of the dataset	Size	Classes
1	Kaggle –navoneel [38]	253 Images (Tumors=155,Normal=98)	Binary Classification.
2	Figshare-Brain tumor dataset.[39]	Total images=3064 (Meningioma=708, Glioma=1426, Pituitary=930	Multi-class classification
3	BraTS-2019, BraTS-2018, BraTS-2017, BraTS-2015[40]	2019:HGG=259, LGG=76 2018: HGG=209, LGG=75 2017: HGG=210, LGG=75 2015: HGG=220, LGG=54	HGG, LGG
4	Clinical Trials.Gov[41]	HGG=52,LGG=61	HGG, LGG
5	Harvard Medical School Data[42]	540 Images(Normal=27,tumorous=513)	Binary Classification.
6	Brain Tumor MRI Dataset[43]	Training (5712 Images), Glioma-1321 Meningioma-1339,Notumor-1595 Pituitary-1457. Testing-(1311 Images), Glioma-300 Meningioma-306,Notumor-405 Pituitary-300.	Multi-class classification

The most extensively used dataset for classifying brain tumors among the available public datasets is that supplied by Cheng, which is a dataset from Figshare.

3. Basic overview of system architecture

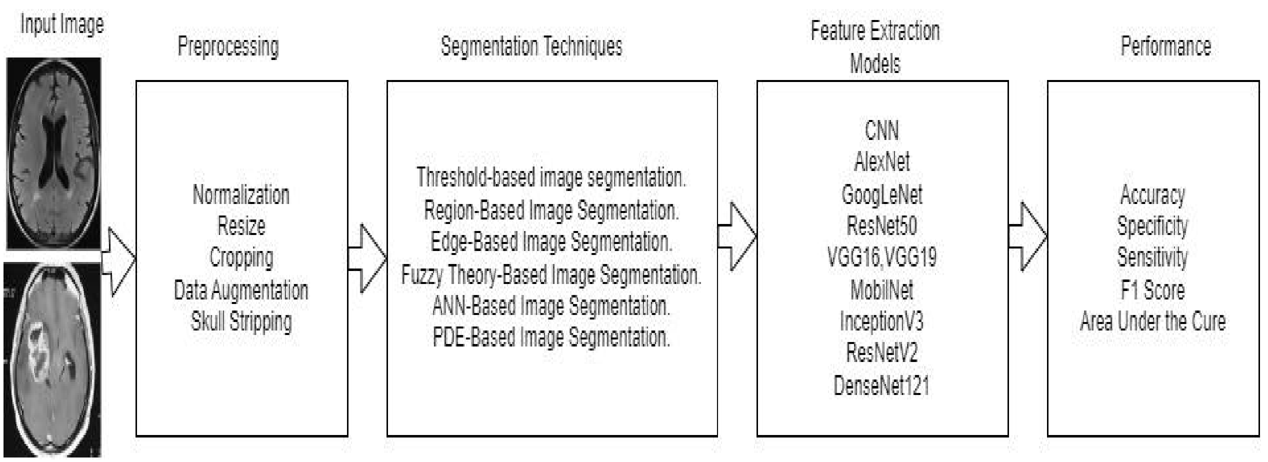

Fig 2. Basic System Architecture.

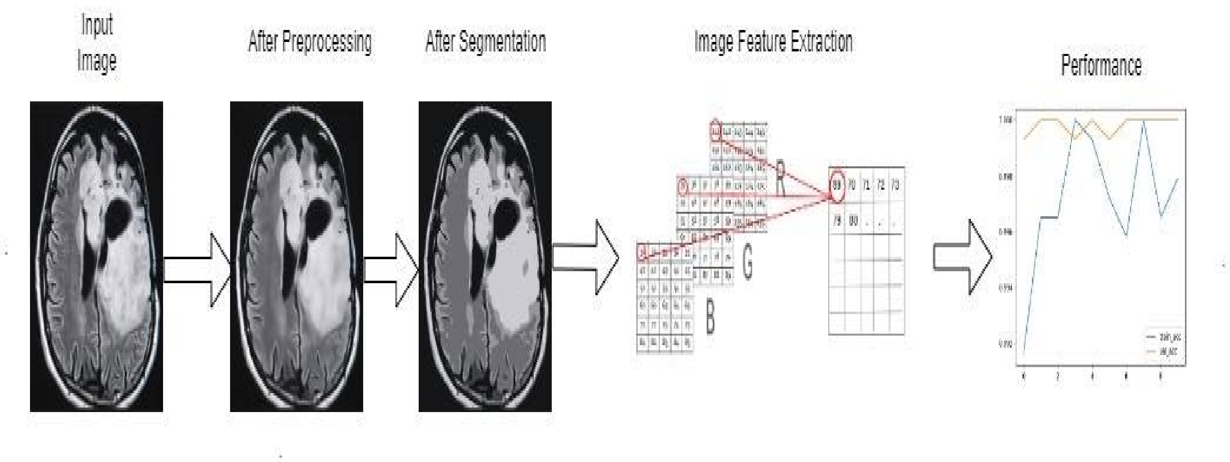

Fig 3. Basic flow of System Architecture.

The above figure, level 1. The input image is given as input to the model. level 2. Preprocessing: Various preprocessing approaches are employed to eliminate salt and pepper noise. and resize the Image. Level 3. Segmentation: Following the pre-processing stage, the picture undergoes segmentation to effectively isolate and identify the specific region of interest within the image.Level 4: Feature extraction refers to the process of reducing the dimensionality of raw data to create more manageable groupings for subsequent processing. Level 5: To demonstrate the effectiveness of a model.

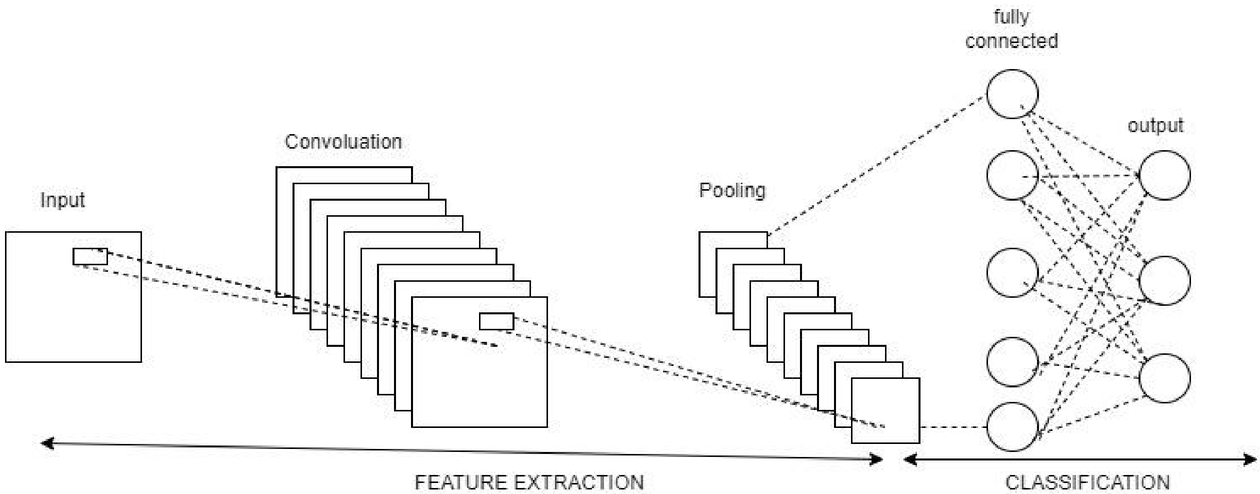

Fig 4. Basic CNN Architecture

Convolution layer: Within this particular stratum, the convolution operation, which is represented by a matrix, is executed by the Kernel/Filter component. The kernel adjusts the horizontal and vertical axes by the stride rate to scan the whole image. Although the kernel is lower in size, the picture possesses a greater surface area. Considering the aforementioned, if a picture is composed of three channels (red, green, and blue), the dimensions of the kernel would be rather tiny to contain all three components.

Pooling layer: The main aim of this layer is the decrease of dimensionality. The utilization of this approach aids in reducing the computational resources required for data processing. Maximum and average pooling are two distinct subcategories within the broader category of pooling. The process of max pooling involves selecting the maximum value inside a certain region of an image that has been covered by a kernel. The technique of average pooling was employed to compute the arithmetic mean of the variables included by the image kernel.

Fc layer: The connection between each input and each neuron is established using fully connected layers (FC), which also incorporate smoothed input. The conventional functional methods are thereafter performed on the flattened vector inside a few more fully connected layers. This is the point at which the classification process starts.

Fully connected layers are often located towards the last stages of Convolutional Neural Network (CNN) architecture if they are present. The utilization of this technique contributes to a reduction in computational resources required for data processing.

Activation function: The activation functions are the final completely connected layer that is usually distinct from the others. The appropriate way to activate each action must be chosen. The softmax function was utilized as an activation function in the problem of categorizing items into more than one group. It translates the real values from the last fully linked layer to target class possibilities, where each value is between 0 and 1 and all values are between 0 and 1.

Data augmentation: Data augmentation, which involves adding revised copies of present data using widely used phonological techniques like rotation and reflection, scaling, translation, and cropping, is another efficient method for expanding both the quantity and variety of the training data.

4. Evaluation metrics:

A research study's assessment of the CNN algorithm's classification performance is crucial. Here, we provide an overview of the assessment metrics that are regularly used in the literature on classifying brain tumors and get model accuracy, precision, sensitivity, F1 score, and area under the curve.

True positive (TP) in classification tasks refers to a picture that is accurately categorized into the positive class based on the ground truth. Equivalently, a genuine negative result occurs when the model properly places an image in the negative category. Contrarily, a false positive (FP) is a result when the model wrongly assigns a positive classification to an image while the actual classification is negative. A false negative (FN) result occurs when the model wrongly classifies a picture when it must be in a positive class.

Metrics:

Accuracy: The accuracy statistic expressed as a percentage of total accurate classifications divided by the total number of pictures assesses how well a model properly identifies the classes in a given dataset.

Accuracy=TP+TN/TP+TN+FN+FP

Sensitivity: A classification model's sensitivity indicates its capacity to recognize positive samples. It displays the proportion of actual positives in the data that are genuine positives.

Sensitivity= TP/TP+FN

Precision: The precision ratio is the proportion of real positives to all detected positives.

Precision= TP/TP+FP

Specificity: Specificity is the proportion of correctly identified negative samples to all other negative samples present in the data.

Specificity= TN/TN+FP

F1 score: One of the most often used measures, the F1 score, considers both recall and accuracy. It takes into account the volume of prediction mistakes a model generates as well as the nature of those errors to evaluate class imbalance concerns and the effectiveness of classification models. If PRECISION and SENSITIVITY are balanced, it is greater.

f1 _Score= 2* Precision* Sensitivity/ Precision +Sensitivity

4.1. Challenges and Future Works

This part talks about the future lines of research for finding and detecting brain tumors, as well as the big steps that need to be taken to improve the accuracy of Brain Tumour classification.ML and DL methods to detect and classify brain tumors have their good points, but they also have some limitations and problems that need to be solved.

- It has been hard to train DL methods for medical pictures because there haven't been enough good training data sets. DL needs a large training set because the performance of the Deep Learning Classifier rests on a large, high-quality training set.
- One of the key issues identified in this context is the lack of a baseline and the lack of flexibility.
- For effective identification and diagnosis of tumor images, a huge training collection should be taken into account.
- Resonance of Magnetism Imaging is the best method because it is used to trace the soft tissues in the training pictures.

5. Conclusion

The paper provides a comprehensive evaluation of the existing research conducted in the domain of brain cancer detection, specifically focusing on the use of Deep Learning techniques for the categorization of MRI images into tumor and non-tumor categories. Despite the existence of several algorithms that are both helpful and successful, it is important to note that each algorithm continues to face certain challenges related to standardization. This study presents a comprehensive and rigorous examination of the advantages and disadvantages associated with each proposed methodology. Table 1 in the comparative study demonstrates the substantial capabilities of deep learning approaches and algorithms in effectively managing vast quantities of data. The present use of the advantages of brain tumor research remains incomplete. The aforementioned comprehensive research suggests that there is a substantial requirement for a fully automated integrated framework that can effectively detect and categorize brain tumors across different classes with low complexity.

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