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Deep Learning Algorithm For Predicting The Brain Tumor: An Survey

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Abstract : The organ that controls the activities of all parts of the body is our brain. Brain tumor is one of the serious and utmost emergent aliments. Brain Tumors can affect people of any age and it also increase the death ratio. Recently computer aided diagnosis based system have promised to diagnose the Brain tumor through MRI.In this analysis we invesitage the efficiency of Deep learning algorithm Feature Extraction Segmentation for detecting Brain tumor. This will be helpful for the researchers for their future enhancement.

***IndexTerms* - Brain Tumor, Machine learning, Neural Network, Magnetic resonance imaging**

I. INTRODUCTION

Brain has a very complicated structure in which the tissues are connected with each other in a complex manner. It regulates the various actions like breathing, operation of our senses and muscles. If a development of a cell is decreased in capability, stop their growth and become abnormal such conditions are called tumor. Brain Tumor is nothing but a irregular propagation of cells in brain. Due to complex the complex nature it is very difficult to cure brain tumor.

Brain Tumor are classified into primary and metastatic brain tumor based on its origin. Primary brain tumor is originated from the brain where else Metastatic brain tumor originate from the body parts. Further Tumors are classified into Cancerous(or Malignant) and Non-Cancerous(benign). The tumors that grow fast and spread to other parts of the body which is life-Threating is called Cancerous (or malignant). The tumors that grow at slow rate and les s likely to spread is called Non-Cancerous(or benign).

There are three remarkable types of brain tumor: Glioma, Meningioma, Pituitary. The most common type of brain tumor in adults is Glioma. On basis of severity it is graded into I to IV as per World Heald Organization grading system. The layer that covers the brain and spinal cord is known as meninges, tumor which arises from such type of layer is called Meningioma tumor, they are non-cancerous which grows at a slow rate and less likely to spread. Tumors which develops on the pituitary gland is called Pituitary Tumors. These tumors are also non-cancerous .It is necessary to detect this dreadful disease in earlier stage.

Using Postrion Emission Tomography(PET), Computed Tomography(CT), Magnetic Resonance Imaging(MRI) these imaging modalities is used for obtained the image for the medical image diagnosis. For Prediction of these brain tumors classification based on Magnetic Resonance Imaging(MRI) has received considerable interest over decades .Even though there exist a wide variety of approaches to segment and classify the brain tumor it is a challenging task to find the accurate results because of its varying size, shape, appearance and area of location. So At recent days, studies show that implementing Deep learning algorithm for detection of Tumor and other kind of diagnosis gives the better and accurate results. Deep Learning has the significant payback in identifying the damaged part.

The structure of this article is as follows. Section II provides a comprehensive evaluation of the body of previous research. Conclusion and future work are provided in Section III.

II. LITERATURE REVIEW

Disha Sushanth Wankhede et al. (2022)[1] In their work used the concept of Dynamic architecture based deep learning approach for detecting the different types of brain tumor. By their work the tumor can be automatically segmented into compartments using mutually exclusive rules which further uses Modified Fuzzy C means clustering (MFCM). This approach is very beneficial in MR tumor segmentation in which it categorize the pixels using certain radiomics features. But by using radiomics based machine learning model it leads to problem in dimensions of data that is rectified by them in their research work by dealing it with GWO (Grey Wolf Optimizer)with rough set theory a dimension reduction algorithm can be proposed. By implementing these the images with High-grade can be obtained from GBM. This also proposed the dynamic architecture of Multilayer modelling in faster R-CNN(MLL-CNN) which is an approach that is mainly based on weight factor. The first step in this method was pre-processing. For removing the impurities in images intensity normalization by histogram normalization and de-noising utlilizing bilateral filter has been done for enhanching the image. Segmentation is carried out using MFCM clustering algorithm especially for radiomic feature segmentation. The mst informative features are selected by choosing Rough Set Theory-based Grey Wolf Optimization. Then the total survival prediction is done by using FR-CNN. Their method was evaluated based on metrices like Specificity, Sensitivity, PSNR, Mean square error, Segmentation error and Prediction Accuracy. Their model has more number of advantages like it takes less segmentation time of only 10 sec for the entire processing and prediction of Accuracy rate. It is more effective than any other methods with reduced error rate of 2.3% MSE. From their model this system produces a greater accuracy and prediction of about 95% with reduced noise ratio for entire set of images they have chosen.

Muhammad Rizwan et al…(2022)[2] In their research work used the model Gaussian Convolutional Neural Network(GCNN) for predicting different types of brain tumor types. For his experiment he took two dataset. One dataset is used to classify tumors into pituitary, glioma, and meningioma. The other dataset had three grades of Glioma i.e. Grade-two, Grade-three, Grade-four. The one dataset had 233 patients with 3064 T1-weighted complexity improved pictures and the another dataset contains 73 patients with 516 T1-weighted complexity improved pictures. The first pre-processing is done by using a Gaussian imaging filter, and then 16 layer based network is generated. This GCNN algorithm framework is then applied to MRIM. The normal execution time for this test would take only 8.4 to 9.4 millisecond for per picture. This method gives an accuracy results of 97.14% and 99.8%.

Amin Ul Haq et al. (2022)[3] In their research work proposed a model IOT based brain tumor classification and detection with an AI model. CNN and LSTM based intelligent integrated framework is used to detect brain tumor from brain tumor image in an IOT environment. CNN module is used to extract the features from an image while LSTM module analyse and classify the tumor. The extracted features are forwarded to a long Short term Memory model that performs final classification. They applied Augmented techniques for their model to increase the data size and boosting their model. They used hold-out Cross validation technique for validating their method. The proposed model CNN-LSTM obtained 98.78% accuracy, 88.48% specificity, 96.82% precision, 97.98% MCC, 98.40% F1 score and 98.10% AUC respectively on the original BTDS. Aditionally this model obtained 97.91% accuracy with specificity 87.92% and sensitivity of 92.23%.

A.S.M. Shafi et al.(2021)[4] In their research used machine learning algorithm (ensemble learning) method to classify brain tumors or neoplasms (i.e. glioma, meningioma, pituitary adenoma) using magnetic resonance imaging(MRI) of brain tumors. The model proposed by them involves five phases which includes data acquisition, pre-processing, feature extraction, and classification. To ensure the accuracy of the experimental result done by them they used cross-validation method for each data that they have collected. From their research they found Glioma is one the most common malignant and deadly brain tumor. They model also gives an excellent sensitivity of 98.788% and total accuracy of 98.573% for classifying glioma tumors. For classification of meningioma and pituitary tumors their model gives correct prediction rate of 96.664% and 97.645%. Their overall training and testing accuracy of their model was 97.957% and 97.744% which gives better results than the existing algorithms.

Muhammad Imran Sharif et al.(2021)[5] In their research work proposed a automated deep learning method for the classification of multiclass brain tumors. For this the Densenet201 Pre-trained Deep learning Model is fine tuned and then trained using a deep transfer of imbalanced data learning. The features for their trained layer were extracted from pool layer that represents the deep information of each type of tumor. But it is not sufficient for classification so they took two techniques, for the selection of features were proposed. The first technique is Entropy-Kurtosis-based High Feature Values(EkbHFV) and the second technique is modified genetic algorithm(MGA) based on metaheuristics. They are further refined by new threash-old function. Both the technique features were fused using non-redundant serial-based approach and then classified using SVM cubic classifier. For their experiment two dataset that includes BRATS2018 and BRATS2019 were taken. Then they classified brain tumors into four types such as T1W,T1CE, T2W, and Flair. This model proposed by them gives an accuracy of 95%.[5]

Neelum Noreen et al.(2020) [6] In their proposed a method of multi-level features extraction and concatenation for early diagnosis of brain tumor. They use two pre-trained deep learning models (Inception-v3 and DensNet201) for making their model more valid. Two different scenarios were assessed on their research. Firstly pre-trained DensNet201 deep learning method was applied for their research and various features were extracted from various DensNet blocks. The features extracted from these are passed to softmax classifier for classify the type of brain tumor that they have observed from the dataset. Secondly, the extraction of features from different Inception modules from Inception-v3 model and then also those features concatenated and passed to softmax classifier for classifying brain tumor. These scenarios are evaluated with the help of publicaly available three-class brain tumor dataset. The method propsed by them gives an accuracy of 99.51% and achieved a highest performance in brain tumor detection.

Yakub Bhanothu et al.(2020) [7] In their research work proposed faster deep learning Algorithm(R-CNN) for detecting the tumor and marking the area of occurrence with Region Proposal Network (RPN). Their proposed algorithm uses VGG-16 architecture as a base layer for both region proposal network and the classifier network. This proposed algorithm efficiently identifies the brain tumor region by choosing optimal bounding box that is being generated by RPN. A better mAP has been achieved for detecting brain tumor using test dataset. The detection and classification rate for the algorithm they proposed was an average precision of 89.45% for meningioma, 75.18% for glioma, and 68.18% for pituitary tumor. As the performance measure the algorithm proposed by them gives a mean average precision of 77.60% for all classes.

Chandan Ganesh Bangalore Yogananda et al.(2019) [8] In their research they use deep learning algorithm and developed a convolutional neural networks(3D Dense Unets) for MRI based glioma segmentation and subsequent molecular profiling for detection of brain tumor. Their approach facilitates clinical translation by requiring only T2W images. In their research work they have applied deep learning algorithm for glioma molecular marker such as Isocitrate dehydrogenase(IDH), Methylguanine-DNA Methyltransferace(MGMT) this reflects the accuracies ranging from 80% to 93%. Fluid Attenuated inversion recovery (FLAIR) MR images along with genomic information have been used to classify IDH mutation in brain tumor. They also developed residual deep learning network for predicting IDH status along with multicontrast MRI for specifying tumor segmentation, co-recognition, resampling, N4biascorrection and intensity normalization. By using 3D Dense-Unet it has a cross validation accuracies of 97.14 ± 0.04%, 93.4±0.80%, 94.73 ±0.66% for determining IDH mutation, 1p/19q co-deletion and methylation of MGMT promoter respectively. Additionally their model have a mean sensitivity and specificity of 0.97±0.03% and 0.98 ±0.003% and 0.95 ±0.01% 0.96 ±0.04% and 0.91±0.2% for determining IDH mutation, 1p/19q co-deletion and methylation of MGMT promoter respectively.

Ercan AVSAR et al. (2019) [9] In their research work used faster Region-based Convolutional Neural Network (faster R-CNN) has been utilized and implemented for detecting and classification of brain tumor. For their research work they used publicly available dataset of 233 patients with 3064 MRI brain images(708 meningioma, 1426 glioma, 930 pituitary). The building process of CNN has six steps: convolution, rectified Linear unit, Pooling, Flattering, Fully connected layers and Softmax functions. For testing the each image for the data sample taken by him for each test image three parameters were returned (i) class label of the detected tumor (ii) probability of tumor being in the class (iii) location of the sample. From the images they have taken about 87.42% of the images have been correctly classified by using their algorithm. From their research work they have concluded that faster R-CNN is suitable algorithm for this problem it also gives an accuracy of 91.66%.From this analysis he also stated that Glioma has the lowest detection rate of 88.11% and Pituitary has the highest detection rate with a sensitivity of 95.19%.

Hossam H. Sultan et al.(2019) [10] In their research work they used Deep learning model based on conventional neural network is proposed to classify the different types of brain tumor types. For the execution of their model they decided to choose two publicly available datasets. One data set consist of 233 patients and 3064 images on T1-weighted contrast enhanced images and the another data set consist of 73 people with 516 T1-weighted contrast enhanced images and started working towards their model. Their proposed model consist a system which starts to load and extract images and labels from the raw dataset that they have taken. Then they applied pre-processing and augmentation techniques just after splitting the dataset into training, validation and testing sets. After this setting the hyper-parameters, regularization techniques, and optimization algorithms are applied. The proposed network is constructed from 16 layers starting from input layer which holds the pre-processed images that passes through the convolution layers and their activation functions (3 convolution, 3ReLU, normalization and 3 Maxpooling layers).Additionally, two dropout layers are used to prevent overfitting. It is followed by a fully connected layer and a softmax layer to predict the output. Finally a class satisfaction layer that produces the predicted class. Then the network training and performance computations are presented. Their proposed architecture has achieved the highest accuracy of 96.13% and 98.7% concerning from two dataset that that have chosen.

Mehdi Amian et al (2019) [11] In their research work proposed a model based on automated three dimensional(3D) seep segmentation approach for detecting gliomas in 3D pre-operative MRI scans. The classification algorithm based on random forest is used for survival prediction. The main objective of their research was to segment the glioma area and to produce segmentation labels for different sub-regions. Their model consist of two parallel stream-lines with two different resolutions. In their model the entire image is taken as input instead of taking the particular patches. Their algorithm was trained on BraTs 2019 that includes 335 training cases. The data set used for their analysis includes the cases of 125 patients. By taking the lower resolution path that is Inspired by U-Net architecture that modifies taking the whole image as an input rather taking a part of image. Al though this method eliminates the false positives the fusion of two resolutions leads to increasing accuracies specificity and sensitivity. This model reaches to the Dirac scores of 0.84, 0.74, 0.71 for whole tumor, core and enhanching tumor on the validation data and 0.82, 0.72, 0.70 on the test data set. This method acquired MSE and classification accuracy of 104773 and 0.52 for validation dataset and 4086323 and 0.49 for the challenged dataset that they have taken.

Amin Kabir Anaraki et al.(2018) [12] In their work proposed a model base on convolutional neural network (CNN) and Genetic Algorithm (GA) for classifying the different types of tumor non-invasively with the help of Magnetic resonance imaging (MRI). The proposed is based on trail and error method or by adopting predefined common structures. In order decrease the variance of prediction error, bagging as an ensemble algorithm is utilized by this model along with GA. The method proposed by them has detected tumors with high precision. Glioblastoma multiform tumors which is malignant that was classified with excellent sensitivity of 97.4% and total accuracy of 96.1%. Other types of tumors are also classified with the high precision of 95%. The overall accuracy for classifying Glioma, Meningioma, and pituitary tumors were about 96.5%, 94.5%, and 97.4% respectively. In this process there is no time requirement to perform time-consuming process like skull stripping or segmentation and decision is made only by the raw data of MR images.

Khalid Usman et al.(2017) [13] In their research work proposed a brain tumor and classification method from multi-modality MRI using wavelets and machine learning. The data from Multi-modal brain tumor segmentation challenge(MICCAI BraTS 2013) were utilized for their research. Their work mainly focused on extracting wavelet-based texture features to predict tumor labels and exploring supervised classifiers for brain tumor classification. The approaches in their model which includes pre-processing of an image, Feature extraction, and classification. In feature extraction process they intensity, intensity difference and neighbourhood information features and wavelet texture features were calculated. In their research work for wavelet features they initially decomposed the multi-modality images into third level and visualized it. They restrict the decomposition wavelet at second level after visualization and analysed the feature images at first and second level and selected the images that contains high-frequency components for their work. Leave-one-out cross-validation is performed separately for the data set they considered. They further classified the tumor into three different regions: complete tumor, core tumor and enhancing tumor. This method carried by them gives an accuracy 88% Dice overlap in for complete tumor region, 75% for core tumor region and 95% for enhancing tumor region.

Dong Nie et al(2016) [14] In their research work proposed a model using deep learning frame-work to automatically extract features from multi-model pre-operative brain images (i.e. T1MR1,fMRI, and DTI) of high-grade glioma patients. Along with this they adopted 3D convolutional neural Networks and gave a new network architecture for using multi-channel data and learning supervised features. For predicting the survival time either short survival period or long survival period they trained support vector machine for predicting the overall survival time(OS). For predicting the OS time the used binary classifier(e.g; SVM) Experimental results shows that their supervised-learning features significantly improved the OS time predictive accuracy. They also gave a conclusion that their 3D deep learning method can provoke computational model for extracting features for neuro-oncological applications. For building a successful predictive model DTI contributed slightly more than fMRI but they both played a significant roles as compared to T1 MRI. Their work gives an accuracy as high as 89.9%.

Y. Zhang et al.(2012) [15] In their research they presented the novel model to classify a given brain tumor image as normal or abnormal. At first they employee wavelet transform to extract the features from the images that they have taken by applying principle component analysis (PCA) for reducing the dimensions of the image features. Then the reduce features were submitted to a kernel support vector machine (KVSM). K-fold stratified cross validation is applied by them for enhancing the generalization of KVSM. For their model they choose seven common brain diseases (Glioma, meningioma, Alzheimers's disease, Alzheimers's disease plus visual agnosia, Pick's disease, sarcoma and Huntington's disease) as abnormal brains. They collected 160MR brain images (20 normal, 140 abnormal) for their research work from Harvard Medical School website. The model proposed by them was DWT+PCA+KSVM to distinguish between normal and abnormal brain tumors. The performed their analysis with 4 different types of kernels GRB kernel, LIN, HPOL, IPOL kernel. DWT+PCA+KSVM along with GRB kernel achieves a highest classification accuracy 99.38%. The LIN, HPOL, IPOL kernel achieves 95%, 96.88%, and 98.12%.The average processing time for their model taken was just 0.0448s per image.

Table 1 A comparison of several approaches for reviewed literature

YEAR	AUTHOR	PAPER	METHODS	RESULT
2022	Disha Sushanth Wankhede et al[1]	Dynamic Architecture based deep learning approach for glioblastoma brain tumor survival prediction	Dynamic Architecture based Deep learning algorithm	95%
2022	Muhammad Rizwan et al [2]	Brain tumor and Glioma Grade classification Using Gaussian Convolutional Neural Network	Gausssian Convolutional Neural Network	99.8%
2022	Amin ul Haq et al[3]	IIMFCBM: Intelligent Integrated Model for feature Extraction and classification brain tumor	LSTM and CNN framework	98.78%
2021	A.S.M. Shafi et al [4]	Classification of brain tumor and auto-immune disease using ensemble learning	Ensemble Learning	97.645%
2021	Muhammad Imran Sharif et al [5]	A decision support system for multimodal brain tumor classification using deep learning	Automated Deep learning	95%
2020	Neelum Noreeen et al [6]	A deep learning model based on concatenation approach for the diagnosis of Brain tumor	Inception-v3 And ddddesnsNet201	99.51%
2020	Yakuuuuuuuuub Bhanothu et al [7]	Detection and classification of brain tumor in MRI Images using Deep Convolutional Network	R-CNN	77.60%
2019	Chandan Ganesh Bangalore Yogananda et al [8]	Fully automated brain tumor segmentation and survival prediction of Gliomas using Deep learning and MRI	Deep learning algorithm	97.14%
2019	Ercan AVSAR et al[9]	Detection And Classifiaction of Brain Tumours from MRI	Faster R-CNN	95.19%

		Images using Faster R-CNN		
2019	Hossam H.Sultan et al[10]	Multi-Classification of Brain Tumor Images Using Deep Neural Network	Deep learning algorithm	98.17%
2018	AMIn KAbir Anaraki et al [12]	Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms	CNN and GA	97.4%
2017	Khalid Usman et al [13]	Brain tumor classification from multi-modality MRI using wavelets and machine learning	Muli-modality MRI and machine learning	88%
2016	Dong Nie et al [14]	3D Deep learning for Multi-model Imaging-Guided Survival Time prediction of Brain Tumor Patients	Deep learning algorithm	89.9%
2012	Y.Zhang et al	An MR Brain Images Classifier Via Principal Component analysis and kernel support vector machine	DWT+PCA+KSWM+GRB kernel	99.38%

III. CONCLUSION

To Forecast the occurance of heart disease many Deep Learning algorithms have been complied. Find out how well each algorithm performs predictions, then implement the suggested system where it is needed. Use more precise attribute selection techniques to increase the precision for programs. In the event that a patient is diagnosied with a certain of brain tumor, there are several treatment options available. Such an appropriate dataset can yield considerable information via Deep learning.
The notation of many stratergies that have been researched for detecting Brain Tumor is presented in this paper Theough systematic review of the literature. Using Deep learning, Machine learning along with the MRI is used to great success to analyses the prediction model with the highest level of accuracy. The primary goal of this study is to diagnose Brain tumor detection utilizing a variety of techniques and procedures to obtain a prognosis.In future well suggest a technique for predicting brain tumor for high accurate early diagnosis of this disease.

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