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Brain Tumor Classification using MRI-Based Detection.

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Abstract: Brain tumor classification and segmentation is highly useful to provide proper care for the patients. Identification of early disease detection can safeguard the life of the patients. The research paper has reviewed the literature with 66 previously published research papers on Image comparison for brain tumor disease using artificial intelligence based machine learning algorithms[1]. The research paper has explored the insights of image processing in detection of brain tumor images obtained from various diagnosis centers in UK and India. The fundamental working principles of deep learning concepts can generate efficient diagnosis of brain tumor disease[2]. The report also presented the experimental results conducted using MATLAB Simulink with the implementation of Convolutional Neural Networks. The results demonstrated that convolutional neural networks can perform the diagnosis with high accuracy within shortest period of time.

Key words: *Image classification and segmentation- Image processing – Brain tumor diagnosis - Grade I to IV.*

1. Introduction

Manual categorization of brain tumors involves the classification of tumor types based on visual examination and analysis of medical imaging data, such as magnetic resonance imaging (MRI) or computed tomography (CT) scans. This process is typically performed by expert radiologists or oncologists who have specialized knowledge and experience in interpreting these images. Here are the general steps involved in the manual categorization of brain tumors:

Data Acquisition: Obtain the medical imaging data, such as MRI or CT scans, from the patients. These images capture the structure and characteristics of the brain, including any tumors present.

Image Review: Review the acquired images thoroughly to identify the presence of any abnormal growths or tumors. Radiologists examine the size, shape, location, and other visual features of the tumors.

Tumor Localization: Determine the exact location of the tumor within the brain. This information helps in understanding the potential impact on nearby structures and planning further treatment.

Tumor Segmentation: If necessary, perform tumor segmentation to delineate the tumor region from the surrounding healthy brain tissues. Manual or semi-automatic techniques may be employed to trace the tumor boundary.

Tumor Characterization: Analyze the visual features of the tumor, such as its shape, texture, intensity, and enhancement patterns. These features provide valuable insights into the nature and behavior of the tumor.

Categorization and Grading: Classify the tumor based on established classification systems, such as the World Health Organization (WHO) classification for brain tumors. This categorization considers various factors, including cell type, genetic markers, histopathological characteristics, and clinical behaviour.

Report Generation: Document the findings and classification results in a detailed radiology report, including tumor location, size, characteristics, and the assigned tumor type or grade. This report serves as crucial information for treatment planning and subsequent clinical decisions.

. Brin-tumor is also known as Glioma. Brain-Tumor is classified into four grades from 1 to 4. Grade 1 brain-tumor is regarded as early stages of the disease. Grade 2 is big size and not so serious. Grade 3 brain tumor is associated with the cancer cells [3]. In stage 3 and3 the growth of the brain tumor cells is highly aggressive with rapid growth. Grade 3 Glioma is extremely aggressive and highly difficult to cure. But latest innovations and treatment methods need to be incorporate with great care[4]. Glioma Grade IV is highly aggressive and leads to death within a span of 12 to 18 months [5]. Grade I Glioma is an early stage of disease. Detecting the disease is highly beneficial for the patient to get easy survival. According to the World Health Organization, Grade II glioma has high cellular density, infrequent nuclear atypia, mitotic activity, and no necrosis or endothelial proliferation. This stage also enables the health care professionals to cure the disease with adequate treatment [6]. Stage III of Glioma is associated with the cancer cells mitotic activity with increased cellular density[7]. It is rich

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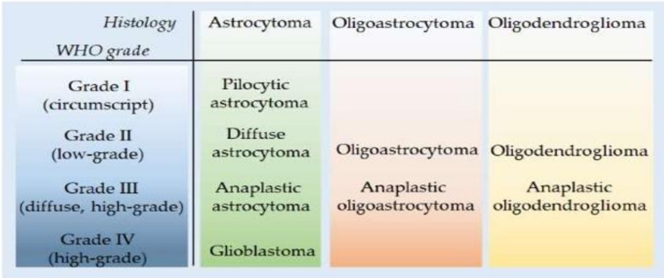
with distinct nuclear atypia and needs high attention to the patient to get survival. According to WHO Grate IV of Glioma is regarded as the tumor with high mitotic activity, necrosis present, endothelial proliferation presence[8]. This stage is highly dangerous for the patient and the mortality is inevitable in most of the cases [9]. 95 per cent of the patients could not survive and they may get detoriating state and encounter the death with in 12 to 18 months [3].



Histology / WHO grade	Astrocytoma	Oligoastrocytoma	Oligodendroglioma
Grade I (circumscript)	Pilocytic astrocytoma		
Grade II (low-grade)	Diffuse astrocytoma	Oligoastrocytoma	Oligodendroglioma
Grade III (diffuse, high-grade)	Anaplastic astrocytoma	Anaplastic oligoastrocytoma	Anaplastic oligodendroglioma
Grade IV (high-grade)	Glioblastoma		

Fig 1 WHO classification of Brain Tumor

Glioma may be easily detected with Magnetic Resonance Imaging. The size of the tumor and integral portion of the tumor with unique size of cell with mitotic activity granularity gap between the histologic parameters listed by WHO with various classifications may be demonstrated by an MRI scan [10]. Based on the biological understanding and priori assumptions the classification grades and histological diagnosis can be done. The distinct shape and gap between the histologic features the brain tumor classification should be done with great care and accuracy[4], [11].

Deep learning techniques are highly useful to distinguish the brain-tumor with specific grades. Deep learning techniques demands to collect the MRIs of different grade of brain tumor disease[12]–[15]. These pre-defined images are used for performing the training. Deep learning techniques are implemented based on training data set [15]. Then the technique can be implemented to identify the testing image with high accuracy using the testing images with the image comparison techniques. The image comparison is incorporated with different layers and pixels of the testing images which were already marked with distinct Glioma grade [16], [17]. The image comparison and processing technique incorporated by deep learning technique can provide 95.9 per cent of accuracy [7].

2. Methodology

The facts and figures have been taken from the previous research papers published in PubMed central, IEEE, ResearchGate from 2019 to 2023. The facts approved by WHO have been collected and compared with other research papers and published in this research work. The main concepts taken from the previous research papers are "Artificial Intelligence based deep learning concepts" used predominantly for classification and segmentation of the disease grade, WHO and clinical pathology concepts of disease classification of brain tumor and image processing using deep learning concepts [15], [18].

The research work has been developed from the samples collected from diagnostic centers from India and UK. For this research 1000 MRI samples who have been identified with the brain tumor disease ranging from I to IV grades. The Images have been used to understand the structure of the brain tumor disease. The images were keenly observed to understand the structural composition of different grades of brain tumor disease.

International Journal	Year	Concept
IEEE	2019-23	AI based Deep learning
IEEE	2019-23	Brain tumor classification
IEEE	2019-23	Image processing
PubMed	2020-23	Brain Tumor Classification
PubMed	2019-23	AI based Deep learning
PubMed	2019-23	Brain tumor classification
ResearchGate	2020-23	Image processing
ResearchGate	2020-23	Brain Tumor Classification

Total papers explored and taken into consideration for extracting the facts are 66 papers from all publishing Authorities.

Publishing Journal	Papers Explored
IEEE	20
PubMed	24
ResearchGate	22

The research methodology is incorporated purely based on qualitative research methodology collected from previous research papers published in the international journals.

Image processing

Image processing is the fundamental principle in distinguishing the brain tumor disease intensity and grade [19]. The brain tumor structure can be different for each grade of disease. A grade indicates the smaller size of brain tumor structure in the brain. B grade disease can be identified with the different structure with enlarged brain tumor. Disease with D grade is associated with malignity and severe enlargement of tumor. D grade is highly dangerous, and the spread of disease would be rapid [20]. The disease intensity can be clearly seen in the Magnetic Resonance Imaging with non-ionizing radiation. Basically, the brain tumor can be represented by Glioma-tumors in the brain's Glial Cells. In the early stages the brain tumor consists of cells which are developed by Central Nervous system. In the further stages the cell structure is rich with malignant cells [19], [21]. When Malignant cells are formulated, it would be resulting to mortality and difficult to cure. Grade – I Brain Tumors are benevolent and consist of highly similar surfaces to the Glial Cells. Grade – II cell structure is different and can be identified with its granularity. In the Grade – III the cell structure is identified with the strange tissue appearance. And Grade – IV cell structure can be identified with the extreme tissue irregularities and gliomas which can be visible with even necked eye [22].

To identify the brain tumor disease grades with better accuracy computer-based image processing would be suggestable. In this process the distinguished and identified image with distinct grade can be taken as the base image and it can be compared with the targeted unidentified image. If the targeted image is matched with its structure and cell size it can be marked with the grade of disease. In the computer image processing the image which needs to be identified will be compared with the available and collected images which are pre-defined with distinct grades [23]. Advanced image processing with high accuracy and fast processing can be done using Artificial Intelligence based Machine learning algorithms. This process is highly accurate and perform the image processing with great speed and demonstrate the results to the user[23], [24]. Image pre-processing is the most important image processing technique. The MR pictures must be converted into smaller JPEG or GIF files. Then the images should be marked with distinct grades with pre-defined grades obtained from the diagnostic centers. The predefined pre-processed images are need to be kept in a training folder. The training folder is highly essential to generate the impressions in the image processing algorithms. The testing image will be compared with the training images. The most identical image with distinct grade can be marked for the testing image. This image processing with ordinary image processing algorithm can provide accurate results but the duration for processing would be more [25].

3. Classification

To overcome this difficulty image processing with classification and segmentation has been regarded as new technique for image comparison and processing. This classification and segmentation can be done using Artificial Intelligence based machine learning algorithms [26]. At this juncture the image processing using machine learning concepts has attracted the researcher's attention. The result of the research was performing the image comparison with classification and segmentation. The major challenge in detecting the brain tumor in different locations of the brain. The brain tumor could not be identified in an exact location of the brain. It may be identified in different locations of the brain[27]. At this movement the image process should identify the brain tumor in specific location and it should be classified with distinct grade. Imaging of intra tumoral heterogeneity has been identified as the prime thing in image processing [6]. The segmentation and classification should be associated with the anatomy of brain tumors [28]. This could be done by exploring the facts from public datasets which presents different brain tumors located in different locations of brain [29]. The main aspect of segmentation of the brain tumor is the first step in the image processing then the identified brain tumor should be analyzed and classify the grade[30]. The advanced algorithms have come up in the machine learning concepts namely deep learning concepts. These deep learning concepts and its algorithms are highly beneficial in providing highly accurate results within less duration of time [31].

AI based machine learning algorithms are widely used for demonstrating the improved results by validating the pre-processed images according to the FDA regulations[32]. In this process reliable distinct grade reporting was identified and remarkable processing speed was attained with promising results [33]. “In the further due course AI driven Image analysis has been invented in central nervous system tumors with traditional machine learning, deep learning, and Hybrid models”[34]. In these models deep learning models could get more accuracy within shortest period. The reporting time was found to be less, expedite management was enabled with improved outcomes in the implementation of deep learning algorithms[33] [34].

Locating the brain tumor and detection of high grade glioma brain tumor is distinguished as classification. MRI provides the discrimination of soft tissue located in the brain with the biochemical information. MRI always provides the accurate tumor detection. Based on the images obtained from MRI the classification needs to be done by the machine learning or deep learning algorithms [35]. Localization of brain tumor images in the brain can be done by the image classification process. This process is highly essential to identify the brain tumors rich with malignant cell structures especially in Grade III and Grade IV. It is highly essential to identify the brain tumors with Grade I and Grade II to provide better treatment to cure the patient from mortality [36]. Classification process is predominant to identify the brain tumor in the brain. Most of the methods used in the deep learning and machine learning methods are used with the classifier methods to augment the real location of the brain tumor in the brain. Once the localization of brain tumor is completed the brain tumor image can be processed for segmentation of its grade [36].

Brain tumor segmentation

The basic segmentation process is to understand the brain tumor intensity whether it is benign or malignant. The lower grade indicates the benign and the higher grade indicates the malignant. The lower grade starting from Grade one and Grate two are considerably benign. The grades III and IV are treated as Malignant. Malignant tumors are highly dangerous, and mortality is associated. The benign grade tumors can be treated with medication and better treatment [37].

Brin tumor segmentation is predominant in the identification of disease with distinct grade. Brain tumor segmentation can be done effectively with the image processing using deep learning algorithms. Deep learning algorithms like convolutional neural network and Artificial Neural Networks are predominant to provide high accuracy [38]–[40].

Image segmentation and classification can be effectively conducted using machine learning techniques[41]. Deep learning techniques are highly effective in the machine learning concepts in performing classification of the brain tumor disease with distinct grade. It is highly difficult task for the radiologist to classify the brain tumor image with distinct grade[42]. Hence the deep learning algorithms are implemented to provide accurate results within short span of time. Predominantly the feature extraction technique is used in the deep learning algorithms in the classification process [43].

In the classification process conducted by deep learning model the image which needs to classify can be processed in 23 layers. Each layer consists of part of the pixels of the image [44]. Similarly the training images or training dataset also processed and stored in 23 layers [45]. When a testing image needs to be processed the testing image layers will be compared with the training data set layers with the pixel comparison. The process is highly essential to obtain highest level of accuracy of 98 per cent in distinguishing the grade of the disease intensity [43].

According to the classification provided by the World Health Organization the brain tumor in adults can be classified into 4 grades based on the intensity of the disease[46]. These can be distinguished by implementing deep learning techniques. The classification process conducted by the deep learning concepts have become a great advantage for the neuroradiologists [47].

Brain tumor classification using convolutional neural networks is an application of deep learning techniques to analyze medical images and distinguish between different types of brain tumors. Because of its capacity to automatically learn and extract relevant features from input data, convolutional neural networks (CNNs) are well-suited for image analysis applications.

Here is a general overview of the process for brain tumor classification using CNNs:

Dataset preparation: Collect a dataset of brain tumor images that are labeled with their respective tumor types. This dataset should include a diverse range of tumor images to ensure the model's generalization ability.

Data preprocessing: This step ensures that the photos are in the correct format for input to the CNN. Preprocessing methods that are commonly used include shrinking photos to a uniform size, standardising pixel values, and enriching the dataset with techniques such as rotation, scaling, and flipping.

Create a model of the CNN architecture for brain tumor classification. A CNN is typically made up of numerous convolutional layers, pooling layers to minimise spatial dimensions, and eventually fully linked layers for classification. Various CNN designs, like as VGG, ResNet, or Inception, can be utilised as a starting point, with their layers customised to the task's individual requirements.

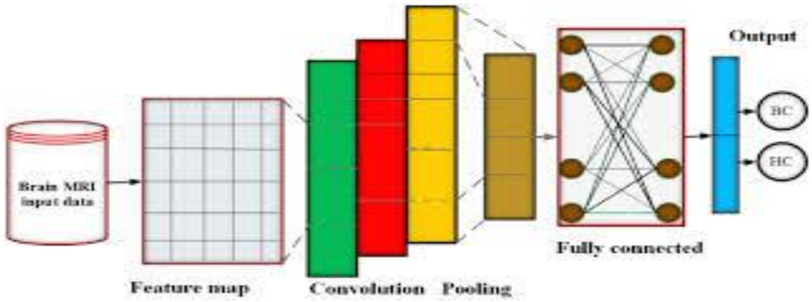
Split the pre-processed dataset into training and validation sets for model training. Feed the pictures through the network and change the model's parameters to minimise classification loss using the training set to train the CNN model. Backpropagation and gradient descent methods are utilised to optimise the network during training.

Evaluation of the model: Evaluate the trained model's performance using the validation set and fine-tune the hyperparameters as needed. Accuracy, precision, recall, and F1 score are all common assessment criteria.

Prediction and testing: Once trained and assessed, the model may be used to predict the tumor type of fresh, previously unknown brain tumor pictures. The model takes an input picture, runs it through the network, and then predicts based on the learnt features and classification layer.

Model deployment: The trained CNN model can be deployed in various ways depending on the application. It can be integrated into a software application, used for research purposes, or deployed in a healthcare setting for assisting medical professionals in diagnosing brain tumors.

The deep learning concepts are rich with convolutional neural networks algorithms. Through the convolutional neural networks the classification can be conducted in different layers namely convolution layer, BATCH_NORMALIZATION layer, Clipped Relu layer, Grouped Con_layer , SoftMax layer and classification layer. These layers will be repeated several time based on the pixels integration and matching sequence. The pixels are stored in the fully connected convolutional layers for image comparison process. The image comparison is conducted in a very complex process with the combination of different layers and its pixels of the images. Every image in training data set will be stored in the layers to compare them with the testing image [48].



The process of classification is conducted in the deep learning concept with different stages [49]. In deep learning, the process of classification typically involves several stages, including data preprocessing, model architecture design, model training, and model evaluation. Here's a breakdown of these stages:

Data Preprocessing:

Data Collection: Compile a dataset of labelled samples for each category or class you wish to categorise.

Data Cleaning include removing any noisy or unnecessary data points, dealing with missing values, and dealing with any data quality concerns.

Data Transformation: Convert the data into a format that the deep learning model can understand. This might include data resizing, normalisation, or standardisation.

Data Augmentation: To expand the variety of the dataset, generate extra training instances using transformations such as rotation, scaling, or flipping.

Design of a Model Architecture:

Selecting a Deep Learning Architecture: Choose a classification architecture that is appropriate for your purpose, such as convolutional layers (CNNs) for object recognition or recurrent neural networks (RNNs) for sequence data.

Determine the amount and kind of layers in your network, such as the input layer, hidden layers, and output layer. Consider aspects such as the problem's complexity and the amount of accessible data.

Activation Functions: To incorporate non-linearity into the network, identify suitable activation functions for each layer.

Loss Function: Choose a loss function that calculates the gap between the expected and true labels. For multi-class classification, common loss functions involve categorical cross-entropy and binary cross-entropy.

Model Education:

Dataset Segmentation: Divide the dataset into three parts: training, validation, and testing. The training set is used to update the model's parameters, the validation set is used to fine-tune the hyperparameters, and the testing set is used to do the final assessment.

Initialization: Set the parameters of the model at random or using pre-trained weights from another model.

Forward Propagation: To create predictions, the training data is sent through the network in the forward direction.

Backpropagation is the process of propagating the error backward through the network by calculating the gradient of the loss function with respect to the model's parameters.

Optimization: Use optimization procedures such as gradient descent or its variations to update the model's parameters, altering the weights to minimise the loss function.

Experiment with various hyperparameter variables, including as learning rate, batch size, and regularisation approaches, to enhance the model's performance.

Model Assessment:

Performance Metrics: Use relevant metrics to evaluate the model's performance on the validation or testing set, such as accuracy, precision, recall, F1 score, or area under the ROC curve (AUC-ROC).

Fine-tuning: If necessary, modify the model by altering hyperparameters, changing the architecture, or increasing the training duration based on the assessment findings.

Overfitting Detection: Examine the performance of the model on the training and validation sets for evidence of overfitting, which occurs when the model remembers the training data but fails to generalise effectively to new data.

Techniques for Regularization: To reduce overfitting, use regularisation techniques like as dropout, weight decay, or slightly earlier stopping.

These stages are typically iterated multiple times to refine the model until satisfactory performance is achieved. Once the model has been validated, it may be used to make predictions on previously unknown data.

The predominant stage of the image processing is conducted with pre-processing, samples selection, Morphological segmentation, Feature extraction process using Xception Model, parameter tuning using sooty tern optimization and finally classification process using attention based LSTM model. The performance evaluation can be done by recall, specificity, accuracy, precision, ROC and F-score[50]. This segmentation process could give 98 per cent of accuracy in distinguishing the testing image with grade I to Grade IV [51].

The data input can be extracted into the feature map. The extracted and stored data in feature map will be distributed into various layers available in the convolution neural network layers [52]. The data of each image will be stored in the convolutional neural networks. The pooling process of the data with distinct identification of pixels are stored in the fully connected layers[53]. The process done in fully connected layers can be performed with neurons. The convolutional neural networks classification and segmentation process is highly accurate in distinguishing the disease grade with 98 per cent of accuracy[50].

Experiment

The research paper is supported by an experiment conducted with the MATLAB Simulink software with the implementation of Convolutional Neural Networks. In this experiment nearly 980 pre distinguished images were taken from different diagnostic centers. These images were loaded in the training folder. Nearly 20 images which were also identified with the distinct grade were taken for testing. To test the software and check the performance of Convolutional Neural Networks. The experiment was conducted using 20 images keeping them in the testing folder. The experiment was now repeated for 20 photographs. Initially, ten photos were used in the diagnosing procedure. In the first batch for 10 images, it has taken 8 seconds for each image identification. The images were branded with its original and predefined grade. In the second round 20 images were tested. In the second round the diagnosis process has taken 8 seconds. In the third batch again, the process has run for another 20 images. The taken for each image was 10 seconds. Finally, 10 images kept in the testing folder and run the diagnosis process for 10 images. It has taken 9 seconds.

The diagnosis process has done for 980 training images which are marked with “Grade – I”, “Grade – II”, “Grade – III” and “Grade – IV”. When the diagnosis process was running each testing image was compared with 980 pre-defined and marked with distinct grade images. Each image was marked with diagnosis grade. The grades identified by the image processing application has been verified and found correct. The test has given 100 per cent results in identifying the exact grade. In four batches the time taken for each image comparison is 8 to 10 seconds. On an average the time taken for image comparison and identification of its grade. The application demonstrated the time and distinguished grade of each image loaded in the testing folder.

4. Result

ANN Algorithms classification			
Grades classification	No of Images in Training folder	No of images in testing folder	Time taken
I	980	10	8 sec
II	980	20	8 Sec
III	980	20	10 Sec
IV	980	10	9 Sec
Normal	980	10	8 Sec

5. Conclusion

The research paper has presented the fundamental working principles of the image processing. The research paper has presented the working principles of machine learning algorithms as well as deep learning algorithms. Finally the paper presented the application developed with MATLAB Simulink to distinguish the brain tumor disease segmentation with the grades for 20 images. The results were presented in the research paper to demonstrate the time taken for processing each image and to distinguish the disease intensity with the grade. The results showed 98 per cent of accuracy in identifying the grades for each image and the shortest time taken for image processing was 8 seconds with the 980 training images.

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