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Brain Tumor Radiogenomic Classification Using Deep Learning

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ABSTRACT:

A brain tumor is an abnormal cell formation within the mass of your brain. The cancer is a term used to represent malignant tumours. Many different types of brain tumours exist. Brain tumors may also be benign (noncancerous) or malignant (cancerous). Imaging techniques like Computed tomography (CT) or Magnetic Resonance Imaging (MRI) are commonly used to find brain cancerous areas. Other techniques for finding brain tumors include lumbar puncture, cerebral angiography, positron emission tomography, and molecular testing. A unique attentive deep-learning- based approach for recognizing malignant tumors is proposed in this research. Less than 10% of people with glioblastoma (GBM), survive for less than five years since it grows quickly. The model built predicts the genetic subtype of glioblastoma by detecting the presence of MGMT (O(6)-methyl guanine- DNA methyl transferase) promoter methylation. Using MRI images, MGMT methylation prediction models were created. MRI scans will be used to see if MGMT activation in gliomas may be identified, we thoroughly investigated contemporary CNN architectures. By using these models, brain surgeries count can be decreased. The using a better model which has high level of accuracywill be used to detect brain tumour and doctors will be able to use it. By providing appropriate medical treatment, it has the potential to save many lives.

Keywords: Tumour, Glioblastoma, MGMT promoter, Transfer Learning, Ensemble.

1. Introduction

The growth of abnormal cells in your brain is called a brain tumor. The growth rate as well as the location of a brain tumor determines how it will affect the function of your nervous system. Brain tumor treatment options depend on the type of brain tumor you have and its size and location. The basic symptoms of brain tumors are new onset or change in the pattern of headaches, Headaches that gradually become more frequent and more severe, Unexplained nausea or vomiting, Vision problems, such as blurred vision, double vision, or loss of peripheral vision, Speech difficulties, Difficulty with balance, confusion in everyday matters, Difficulty making decisions, Personality or behaviour changes and Hearing problems. Some of themain causes of brain tumors are family history these types of tumors are genetically inherited, Age most types of brain tumors increase with age, Chemical exposure, and Exposure to radiation. Some of the common types of brain tumors are Glioma, which originates in the glial cells and accounts for about 3 out of 10 cases of brain cancer. Astrocytoma is glioblastoma, a fast- growing type of brain tumor. Meningioma is Often benign and slow-growing, meningioma tumors grow in the tissue surrounding your brain and spinal cord and are the most common type of brain tumor in adults. Ganglioglioma is a slow-growing tumor that forms between the pituitary gland and the brain and often presses on optic nerves, resulting in vision difficulties. Schwannomas which are slow-growing tumors that form around the cranial nerves are almost always benign. Medulloblastoma is a fast-growing tumor that forms on the brain's nerve cells and is more common in children. Common cancers that can spread to the brain are breast cancer a disease in which cells in the breast grow out of control, a Colon cancer Colon and rectal cancers occur when the cells that line the colon or rectum become abnormal and grow out of control, Skin cancer the abnormal growth of skin cells. These harmful brain tumors easily can find with machine-learning algorithms like k- Nearest Neural (KNN), Support Vector Machines (SVM), and Generalized Regression Neural Networks (GRNN). This work focuses on densnet121 and ensemble methods to classify brain tumors.

2. Related work

[1]. In this work, a novel approach of categorizing brain tumour pictures from several modalities is put forward. Separable embedding, multi-modal feature aggregation, a lightweight attention method, and modal-wise shortcuts are some of the computer vision techniques used in the proposed Multi-Modal CNN with Attention for Radiogenic Classification of Brain Tumours. A medical image dataset here on RSNA-MICCAI dataset with a focus on specific scenario, the suggested model was assessed. It combines several magnetic resonance imaging data using computer vision algorithms MRI scan modalities, making it more precise and quicker than conventional methods of genetic analysis. On the RSNA-MICCAI dataset, the proposed Attentive Multi- Modal CNN's radiogenic classification performance for brain tumours was assessed. The results showed that it performed about 3% better than cutting- edge models.

[2]. In this research deep learning models to categorise brain tumours using MRI data was suggested. Glioblastoma is one of the most prevalent brain tumours in elderly people, according to the author. The authors of this study used a multi-model comparison to show that the suggested model is better than prior methods. The benefit of this work is that it produced a decent score when compared to other works and an effective model for classifying brain tumours. The drawback of this research is that models with this level of competence cannot yet be used in clinical settings, leaving surgical biopsies as the only option. These biomarkers will be sought after, along with fresh datasets and innovative approaches, in future work.

[3]. In this paper if the quantities of a specific chemical called MGMT (the O (6)- methylguanine-DNA methyl transferase) present in glioblastomas may be reliably predicted using MRI scans was investigated. Challenge 2021 for RSNA- MICCAI Brain Cancer radio genomic classification dataset was used in this study. The authors suggested examining if using MR images, MGMT mutation in gliomas may be predicted. by using cutting-edge CNN architectures and numerous tests. The benefit of this work is that it sheds light on the possibility for MRI scans to forecast MGMT methylation in gliomas. Test AUROC and test accuracy were utilised as performance indicators in this study.

[4]. In this paper, the neural network deep learning algorithm YOLOv5 was used to examine the localization of brain tumors from MRI data. The dataset used was RSNA- MICCAI, which included text files and MRI pictures. This model employed a two- stage pipeline to first identify different IDs for the objects in each image, and then it distinguished between aberrant and healthy cells. Instance segmentation, which aims to give different IDs to the objects in an image, was one of the techniques utilised in this study. The high accuracy and quick runtime of YOLOv5 for brain tumour segmentation are two benefits. In this study, runtime and accuracy were employed as performance indicators. On a GPU with an M2 10 cores, the model was tested.

[5]. This research presented a technique for identifying methylation in Glioblastoma Multiforme (GBM) tumors that is based on deep learning (DL). The proposed methodology involves using an unstructured Knowledge-Based filter that uses both FLAIR and T1-weighted series, suspicious spots on the FLAIR series are pre-selected for analysis using a convolutional neural network (CNN). An advantage of the suggested strategy is that it can get outcomes that are comparable to or better than those of a rival approach while utilising fewer parameters. Results indicate that the suggested methodology is appropriate for use in clinical diagnosis and can be used as a biomarker for predicting treatment response and prognosis in GBM patients.

[6]. This study suggested a technique for classifying brain tumours that uses an Information from MRI scans is extracted using a Siamese Neural Network (SNN). Three publicly accessible datasets from the Figshare, Harvard, and Radiopaedia repositories are used to evaluate the suggested technique. Deep transfer-learned Convolutional Neuronal Networks include many parameters, however the SNN is constructed to use a 3- layer, fully Connected Neural Network (CNN). The classification accuracy on cross-validation, f-score, specificity, and Balanced Accuracy are the performance measures used to assess this method. Cross- validation results show 92.6%, 98.5%, and 92.6% classification accuracy. There results indicate that, for classifying brain tumours, the suggested strategy outperforms both hand-designed and deep transfer learnt features.

[7]. A multi-modal mergers 3D classification network was reported in this paper using four different MRI modalities and artificial intelligence (AI) algorithms (T1w, T1wCE, T2w, FLAIR). The multi-modal MRI information is used to predict the MGMT promoters' molecular mechanisms of brain tumors. The dataset utilized was the segmentation of brain tumors BraTS 2021 challenge dataset. Performance criteria utilized to evaluate the proposed model include Accuracy, Precision, Recall, and F1 score. These metrics assess how well the model can categorise glioblastoma tumours in comparison to more conventional approaches.

[8]. This article analyzed magnetic resonance pictures of brain tumors using a Convolutional neural Network (CNN) model and parametric optimization technique. convolutional neural networks (CNNs), parametric optimization approaches, and Sophisticated Optimization Techniques including FBIA, SFOA, and MGA are the methodologies are used. The Convolutional Neural network model is then used to analyse the dataset, which consists of brain MRIs. This model was simulated nine times to determine its correctness. The outcomes revealed that this model had 100% accuracy across all nine runs, proving its efficacy in correctly identifying cancers.

[9]. This study built a deep neural networks model for automating the detection and diagnosis of brain tumors. Throughout the model's design, difficulties with overfitting and disappearing gradients were taken into consideration. A dataset of 3064 brain pictures was used to evaluate the suggested model. Key performance metrics were used to assess how well the suggested model performed. The average accuracy reached with data augmentation was 97.08%, while the average accuracy achieved without data augmentation was 97.48%. The drawback is that data augmentation was necessary for it to work at its best.

[10]. This article described a computer-aided diagnostics network for classifying brain tumours was proposed. The proposed system analyses and divides MR brain images into couple categories: High grade Gliomas (HGG) and Low- Grade gliomas (LGG) using Gabor- modulated convolutional filters. The MRI brain scans from patients with high Grade Gliomas (HGG) and Low-grade Gliomas (LGG) make up the dataset used in this study The techniques employed in this research include Gabor-modulated convolutional filters, well-known machine learning classification methods, and pre- trained networks including AlexNet, GoogleNet (Inception V1), ResNet, and VGG 19. Accuracy, Precision, Recall, and f1 Score are some of the performance indicators are used to assess the proposed system.

[11]. In this paper a unique machine learning hybrid technique is proposed for the categorization of brain abnormalities (tumor and stroke) in MRI images. Before categorizing the MRI images into four groups—high grade tumor, low grade tumor, acute stroke, and subacute stroke— a maximum A Priori (MAP)-based firefly method is presented for feature selection. The proposed method as an advantage over existing methods it is able to accurately classify brain tumors and strokes with a high degree of accuracy. The suggested method's key drawback is that a significant quantity of data is needed for both testing and training in order to attain optimal performance. The suggested approach was examined using MRI scans of stroke and brain tumors. The findings demonstrated that the suggested method's accuracy is superior to existing cutting-edge classification techniques, with a dependable efficiency of 88.3% for diagnosing instances of brain tumors and 99.2% for classifying cases of brain strokes.

[12]. This paper explored glioma subgroups from the use of Magnetic resonance Imaging (MRI) images may be predicted using a deep learning classifier. The study compared two different techniques for training the classifier. Two datasets of multi-modality MRI images were used in the investigation. Patients with Diffused Low-grade Gliomas (DLG) were the only cases in the US dataset. while the TCGA dataset included a variety of tumor types. The main advantage method training the classifier using elliptical bounding box regions is that it eliminates the need for manual annotation. The main disadvantage of ellipse bounding box regions for training a classifier is that it may not guarantee the same quality as manual annotation. The results of the study showed that using in order to train the classifier, elliptical bounding box regions were created in an average degradation of 3.0% compared to manual annotation, with the prediction rate In the US dataset, the prediction rate for 1p/19q codeletion state is 69.86%, while on the TCGA dataset, the forecast rate for IDH genetic is 79.50%.

[13]. In order to segregate brain tumors, this research suggested a deep learning framework dubbed the Single component UNet3D with multi - path residual focus block sequences which are combined with a residual path known as the Multipath residual attention block. Multipath residue attention block for the single level UNet3D architecture has an advantage over other brain tumor segmentation models it combines strenuous effort and focus on improvement performance in identifying tumor areas. The key drawback of the single level UNet3D using multi - path residue attention block design is that a lot of data is needed to train and evaluate the model.

[14]. This research paper focused on the task of brain Magnetic Resonance Imaging (MRI) Semi-supervised anomaly segmentation (SAS). This work behavior intention machine learning (ML) approaches by demonstrating that adaptive threshold fluid-attenuated Inversion Recovery (FLAIR)MR scan results can produce better anomaly segmentation maps than a number of different ML models. The objective is to automatically detect pathologies in these images. The researchers found that their method of thresholding FLAIR MRI scans achieved superior precision-recall curves and dice similarity coefficients compared to rivals. This method's primary drawback is that manual thresholding is necessary, which is time-consuming and error-prone. It suggests that it is more effective for detecting anomalies in brain MRI scans than traditional machine learning techniques.

[15]. This paper investigated using Computer Tomography (CT) to segment brain tumors as a way of improving efficiency and reducing complexity in picture segmentation processes. A quickly expanding field is medical image processing field that uses techniques to diagnose and treat illnesses. It involves preprocessing the pictures from a database of brain cancer using an adaptive median filter to increase clarity and reduce noise. Techniques for feature extraction include then upgraded for categorization purposes, with algorithms like adaptive neuro-Fuzzy inference System (ANFIS) or support Vector machine (SVM) being applied to classify the images as normal or abnormal. The advantages of using this technique for brain tumor segmentation include improved efficiency and reduced complexity in the picture segmentation process. The main disadvantage of this technique is that processing the photos takes a substantial amount of time and computational resources. The results of this technique indicate thus when compared to the other individual methods examined, the dual optimization technique (SSO-GA) yields the greatest accuracy of 99.24%.

[16]. This article reviewed the latest research about pediatric brain tumors for radiologists. It talked about the molecular makeup of typical pediatric brain tumors, their clinical correlate, the effects they have on outcomes, and potential treatment options. Although Radio genomics focuses on tying traditional imaging aspects to the genetics of a tumor, Radiomics employs information extracted from medical images to help with diagnosis, prognosis, and therapy of various sorts of malignancies. The method has advantages since it can offer children brain tumors a more accurate diagnosis, prognosis, and therapy options. The primary drawback of radiomics and radio genomics is the need for extensive data collection in order to precisely determine the molecular features of malignancies. The findings imply that this strategy may be utilized to find important biomarkers that could eventually result in the creation of targeted treatments.

[17]. A deep learning model for the diagnosis of brain tumours is suggested in this research report. This model employed a process known as "concatenation," which combines many feature levels to provide an accurate and dependable detection method. Inception-v3 and DensNet201 are two pre- trained deep learning models that are used in the suggested methodology. The model's ability to properly detect cancers is assessed using a publicly accessible dataset of three classes of brain tumours. There are various drawbacks to the suggested approach. To be able to recognise and categorise brain tumours with accuracy, a lot of data must be collected. The suggested method was tested using a three-class brain tumour dataset, and it outperformed current state-of-the-art methods with accuracy of 99.34% and 99.51% on testing samples using Inception-v3 and DensNet201 respectively.

[18]. A branch of machine learning called deep learning (DL) has lately demonstrated outstanding performance in classification and segmentation issues. This study uses two publicly available datasets to propose a DL model based on convolutional neural networks for classifying various forms of brain cancers. Convolutional neural networks form the foundation of the suggested deep learning paradigm (CNN). The precision of a deep neural network for classifying brain tumours is its key benefit. The intricacy of a deep neural network for classifying brain tumours is one of its key drawbacks. Large datasets and powerful computers are needed for the model's training, which can be costly and time-consuming. According to the study's findings, deep neural networks are capable of accurately classifying.

[19]. The web programmeTumour-Analyser classified brain tumours using artificial intelligence into three groups (AI). Brain tumours are categorised by the Tumour- Analyserprogramme using magnetic resonance imaging (MRI) sequences and entire slide images (WSI). The Tumour-Analyser tool's key benefit is that it offers an interpretable alternative to conventional models' "black box" lack of human understandability. The Tumour- Analyser tool's reliance on deep learning models, which can be challenging to analyse and comprehend, is one potential drawback. Users can understand how and why particular decisions were made by AI models by offering an interpretable solution.

[20]. The development of a machine learning-assisted methodology for the multiclass categorization of malignant brain tumours is the main topic of this research study. The suggested methodology employed a large feature set from six different domains to extract the retrieved region of interest's hidden information. Then, utilising K-Nearest Neighbour (KNN), multi- class Support Vector Machine (mSVM), and neural network (NN) classifiers, this feature set is employed for model training and testing. More accuracy in diagnosing and treating brain tumours in a clinical setting is a benefit over the current method. The key drawback of the suggested method is that in order to effectively categorise malignant brain tumours, a substantial amount of data must be gathered and analysed.

[21]. The practise of automatically distinguishing brain tumours from healthy tissue is called "automatic brain tumour segmentation." Convolutional neural networks are used in the suggested method, Multi-scale Feature Recalibration Network (MSFR-Net), to extract features from the MRI images. The proposed method's ability to precisely segment brain tumours from MRI images is its key benefit. The need for a lot of data to train the model is one potential drawback of the suggested approach. When tested on a test dataset from the Brain Tumour Segmentation Challenges 2021, the suggested method produced dice coefficients for the overall tumour, tumour core, and enhancing tumour, respectively, of 89.15%, 83.02%, and 82.08%. Automated Brain Tumour Segmentation Using Multi-Scale Characteristics and Attention Mechanism has been proposed.

[22]. In this study, a novel strategy for dividing healthy, high- grade, and low-grade gliomas in MRI brain imaging is presented. Pre-processing, clustering, tumor localization, feature extraction, MI-ASVD, and classification are the six stages of the proposed system. To smooth the MR images, preprocessing methods like Gaussian kernel filters are applied. The key benefit of the suggested system is its increased accuracy when compared to other cutting-edge methodologies and approaches from related published studies. The fact that this method needs a lot of data to appropriately choose features and minimize dimensionality is one of its key drawbacks. The proposed approach outperformed the two most advanced techniques as well as methods from comparable published research with a classification accuracy of 94.91%.

[23]. The strategy for dividing brain tumors into subgroups based on their molecular make- up is suggested in this study report. The suggested technique generates synthetic images using Generative Adversarial Networks (GANs). The proposed technique generates synthetic images that can be used in training by using Generative Adversarial Networks (GANs). Secondly, by expanding the training dataset with synthetic MRIs from various modalities, it enables more precise subtyping of brain cancers based on their molecular makeup. The use of Generative Adversarial Networks (GANs) to generate synthetic pictures, which could not be as accurate or dependable as actual MRIs, is one potential drawback of the proposed technique. In order to categorize the molecular subtypes of gliomas, the suggested algorithm was tested on a dataset of brain tumors.

[24]. This study suggested a brand-new variety of convolutional neural network (CNN) for the MRI classification of brain malignancies. The research paper's methodology entailed the generation of graphs at random and their mapping into a calculable neural network via a network generator. The key benefit of this study is that it offers a more precise and effective way for classifying images of brain tumors. A 95.49% accuracy rate was assessed, with test loss that was lower than that of other models like ResNet, DenseNet, and MobileNet. This research paper's key flaw is that it doesn't offer a thorough answer for classifying images of brain tumors. This study's findings show that the modified CNNBCN model had an accuracy rate.

[25]. This study suggested a technique for identifying brain cancers utilising a light weight deep learning model and a fine- tuning methodology. Large data sets are processed by the model using an artificially intelligent neural network, and the weights of the data are adjusted using the back- propagation algorithm. The deep learning object detection method used in this study, called YOLOv5, requires less computing architecture than competing models. This method has the advantages of being more accurate and precise in its ability to detect brain tumours while also using less computational infrastructure than competing approaches. This method may not be able to detect all types of brain tumours due to the dataset utilised in the study, which is one potential drawback.

[26]. In this study, deep learning (DL) and machine learning (ML) approaches are proposed as a non-invasive way for grading brain tumours. The suggested method makes use of five deep learning (DL) models, including AlexNet, VGG16, ResNet18, GoogleNet, and ResNet50, as well as five machine learning (ML) models, including Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Naive Bayes Classifier (NBC), Decision Tree (DT), and Linear Discrimination Analysis (LDA). Four therapeutically relevant datasets were used to test the suggested technique. Using a 5-fold cross validation technique, the five DL-based models and the five ML-based models were trained and put to the test. Compared to conventional tumour grading based on tumour biopsy, the suggested technique has a number of benefits. First off, because it is non- invasive, there is no risk to the patient. Also, it combines DL and ML approaches, which can increase accuracy.

[27]. The process of determining whether a person has tumours in their brain is known as brain tumour detection. To identify the existence of tumours, a variety of methods including Magnetic Resonance Imaging (MRI), super pixels, Principal Component Analysis (PCA), and Template Based K-means Clustering Algorithm are used. There are multiple steps in the suggested brain tumour detection method. Super pixels and PCA are used to extract the MRI image's key features first. The proposed brain tumour detection method has a number of benefits over current methods. Compared to other existing systems, it detects brain cancers in MR images more accurately and in less time (in seconds). The proposed method for detecting brain tumours has no significant drawbacks. It's crucial to remember, nevertheless, that the accuracy.

[28]. A novel automated deep learning approach is suggested in this study for the categorization of multiclass brain cancers. High classification accuracy is desired since it is essential for medical imaging. The pre-trained Densenet201 deep learning model, which was improved and trained via imbalanced data learning, is used in the suggested method. The suggested approach has a number of benefits. In order to extract features from an average pool layer reflecting deep information on each type of tumour, it first makes use of the Densenet201 Pre-Trained Deep Learning Model, which is adjusted and trained using imbalanced data learning. The problem of data imbalance, which can produce inaccurate classification results, is not addressed by the proposed strategy. The proposed technique demonstrated accuracy on the BRATS2018 and BRATS2019 datasets.

[29]. The goal of this study is to create a reliable and effective MRI-based brain tumour classification system. It makes use of well-known deep learning architectures like InceptionResNetV2, NasNet Large, Xception, and NasNet Large. Two benchmark datasets that are freely available online were used in the experiment. For precise and quick training, images from the dataset were first cropped, processed, and enhanced. Deep transfer learning-based models provide the benefits of increased accuracy, shorter training times, and higher generalisation for identifying brain cancers from MRI data. The key drawback of utilising deep transfer learning-based models for MRI image- based brain tumour detection is that not all types of data may be suitable for the pre- trained models. The findings of this study demonstrated that our suggested CNN

[30]. This review paper examined the most recent developments in advanced imaging methods for the diagnosis of neuro- oncologic malignancies, with a focus on the PET-MRI imaging of malignant brain tumours. In this study, we focus on PET- MRI imaging of malignant brain tumours, one of the most recent sophisticated imaging methods for neuro-oncologic tumour diagnosis. When determining the extent of a tumour, forecasting its grade, and gauging the effectiveness of treatment, advanced imaging techniques have significant advantages over traditional MR imaging. The use of advanced imaging techniques may be constrained in some circumstances because they are more expensive and time-consuming than traditional MR imaging. The review paper comes to the conclusion that combining modern imaging modalities for brain tumour imaging is complimentary. The review research comes to the conclusion that combining modern imaging modalities for brain tumours is complimentary.

[31]. The goal of this study is to create a system for segmenting and classifying brain tumors that is based on deep learning. The proposed architecture segments MRI images using a 3D-UNet deep neural network. The primary benefit of this study is that its technology enables early detection and diagnosis, improving the range of treatment options and chances of recovery for patients with brain tumors. The expense involved in setting up a system to segment and categorize brain tumors using deep learning techniques is a drawback. Loss and precision diagrams are used to depict the outcomes of the suggested framework. These graphs demonstrate how the models fared in comparison to other methods.

[32]. This study examined the evaluation of data complexity while classifying brain cancers and Alzheimer's disease from brain MRI images using convolutional neural networks (CNNs). The project employed four different CNN model iterations. In order to test each model version against one another, the study compared performance scores for each one, including Accuracy, Precision, Recall F1 score, and AUC score. The suggested strategy consists of three parts. The benefit of this study is that it offers a thorough assessment of data complexity for classifying brain tumors and Alzheimer's disease from MRI images using CNNs. This study endeavor has the drawback of not taking other aspects like the size and resolution of the MRI pictures into account.

[33]. This study employed a modified version of EfficientNet to establish a reliable method for detecting brain tumors in magnetic resonance images (MRI). To expand the quantity of data samples used for training, data augmentation techniques are also used. The suggested model is a deep convolutional neural network (CNN) EfficientNet-B0 base model that has been enhanced with extra layers to enhance its capability for detecting brain tumors. The suggested model's key benefit is that it can identify brain cancers more precisely and effectively than other existing models. This approach has a number of drawbacks, one of which is the amount of data needed for training. The model's overall accuracy was 98.87%, which is much greater than

[34]. Brain tumor classification is carried out using Deep Convolutional Neural Networks (CNNs), a type of artificial intelligence. The suggested model classifies MRI brain cancers using several layers. Backpropagation is used to train the model and improve its performance on the provided datasets. Deep CNNs can classify brain tumors more accurately than manual methods, which is the main benefit of utilizing them. The need for a substantial amount of data for deep CNNs to function effectively is one of the key drawbacks of utilizing them to classify brain tumors. Using three independent datasets, the suggested model's outcomes were experimentally assessed. The outcomes demonstrated that the proposed strategy performed convincingly when compared to the alternatives, demonstrating its applicability.

[35]. A novel meta-heuristic- based methodology for the early diagnosis of brain cancers is presented in this research. There are three basic stages to this process. To choose the best features and categorize them appropriately, the whale optimization algorithm is modified. The recommended methodology has three main steps. The suggested method outperforms the ones now in use in a number of ways. The proposed method's key drawback is that processing photos takes a lot of time and computational power. By contrasting it with other ways already in use, the performance of the suggested method was assessed. When compared to other approaches of a similar nature, the results showed that the suggested method had greater accuracy in terms of CDR, FAR, and FRR.

3. Conclusion

The survival of the patient and early prevention of brain tumours depend on early identification. For the purpose of lessening patient suffering, accurate classification is required. We create a deep learning-based system that uses MRI data to categorise the four different types of brain cancers. After reviewing all of the survey papers, the models with simple attention processes and 3D format input gave the greatest results. This method enables early tumour type identification.

4. Future scope

We are going to implement 3D Convolution Neural Network models in MONAI framework in the future as a project. In the future, the model we choose to implement along with GUI is 3D Densenet121. We convert the MRI scans of brain tumors into 3D input format by using stacks and use this model which is integrated with Monai framework to deliver superior result. Our primary goal for the future is to classify the brain tumor using the implemented model which produces the most accurate results using MRI scans.

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