

Automatic Medical Image Diagnosis for Brain Tumor Detection by Using AI Techniques

Gopi. R¹, Sivasathya. M², Subhiksha.R³, Thenmozhi. B⁴, Viji. R⁵

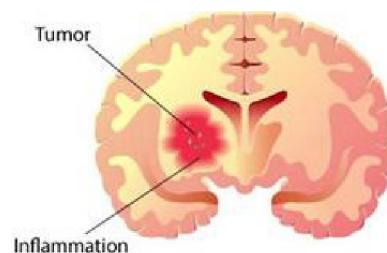
¹Associate Professor of CSE, Dhanalakshmi Srinivasan Engineering College, Perambalur

^{2,3,4}Student of CSE, Dhanalakshmi Srinivasan Engineering College, Perambalur

Abstract: Brain tumor are perilous and serious issues impacted by uncontrolled cell development in the cerebrum. Cerebrum growths are one of the most moving sicknesses to fix among the various diseases experienced in clinical review. Early characterization of mind growths from attractive reverberation imaging (MRI) assumes a significant part in the finding of such sicknesses. There are numerous demonstrative imaging techniques used to distinguish growths in the cerebrum. MRI is regularly utilized for such undertakings on account of its unequalled picture quality. The customary technique for distinguishing growths depends on doctors, which is tedious and inclined to mistakes, placing the patient's life in danger. Distinguishing the classes of cerebrum growths is troublesome because of the great physical and spatial variety of the mind cancer's encompassing locale. A robotized and exact finding approach is expected to really treat this serious infection. The importance of man-made consciousness (artificial intelligence) as profound learning (DL) has altered new techniques for mechanized clinical picture conclusion. Therefore, great arranging can safeguard an individual's life that has a mind growth. Utilizing the 2D Convolutional Brain Organization (CNN) strategy, this undertaking proposes PC Supported Finding (computer aided design) a profound learning-based wise mind cancer discovery structure for cerebrum growth type (glioma, meningioma, and pituitary) and stages (harmless or threatening). CNN is utilized to characterize growths into pituitary, glioma, and meningioma. Then, at that point, it characterizes the three grades of arranged infection type, i.e., Grade-two, Grade-three, and Grade-four. The presentation of the CNN models is assessed utilizing execution measurements, for example, exactness, responsiveness, accuracy, particularity, and F1-score. From the trial results, our proposed CNN model in view of the Xception engineering utilizing ADA Analyzer is superior to the next three proposed models. The Xception model accomplished exactness, awareness, accuracy particularity, and F1-score upside of 99.67%, 99.68%, 99.68%, 99.66%, and 99.68% on the X-ray enormous dataset. The proposed strategy is better than the current writing, showing that it tends to be utilized to arrange mind growths rapidly and precisely.

I. INTRODUCTION

The frontal cortex is a baffling organ that controls thought, memory, feeling, contact, composed developments, vision, breathing, temperature, hunger and every connection that deals with our body. Together, the mind and spinal string that stretches out from it make up the focal sensory system, or CNS. Weighing around 3 pounds in the normal grown-up, the cerebrum is around 60% fat.



The leftover 40% is a mix of water, protein, starches, and salts. The actual mind is not a muscle. It contains veins and nerves, including neurons and glial cells. A brain tumour is a growth of abnormal cells in the brain. The anatomy



of the brain is very complex, with different parts responsible for different nervous system functions. Brain tumours can develop in any part of the brain or skull, including its protective lining, the underside of the brain (skull base), the brainstem, the sinuses and the nasal cavity, and many other areas.

Brain Tumour

There are many types of brain tumours. Each type can differ in growth rate, typical location, size at the time of diagnosis, and who they affect. Brain tumours are the most common type of tumour in children, and the second or third most common type in young adults (breast cancer is highest in females). Some brain tumour types affect males more often than females, or vice versa. The following are a few of the more common brain tumours and the percentage of the tumour count among all brain and other central nervous system (CNS) tumours. Meningioma (38%) arises from the membranous covering of the brain (meninges). Most are benign and grow slowly inward from the meninges to push on the brain and surrounding structures. Glioma (25%) arises from glial cells that surround and support the neurons of the CNS. Tumours in this category are further classified according to the type of glial cell from which they originate (astrocytoma, glioblastoma multiforme, ependymoma, oligodendroglioma, mixed glioma). Although some types are relatively benign, gliomas comprise 80% of malignant brain or other CNS tumours. Pituitary tumour (17%) arises from the pituitary gland at the base of the brain.

The pituitary gland is important for normal hormone release. Most pituitary tumours are benign. However, large tumours can compress nearby nerves and tissues, causing vision defects and hormone abnormalities. Other brain tumour types include acoustic neuroma, craniopharyngioma, chordoma, chondrosarcoma, or brain metastases. Most brain metastases arise from cancers in the lung, breast, colon and rectum, skin (melanoma), and kidneys (renal cell carcinoma). In adults, brain metastases are more common than primary brain tumours. Brain tumours can arise from tissues within the brain (primary brain tumour) or from a cancer located elsewhere in the body (secondary or metastatic brain tumour). Benign brain tumours typically grow slowly and stay within the brain without invading surrounding tissues.

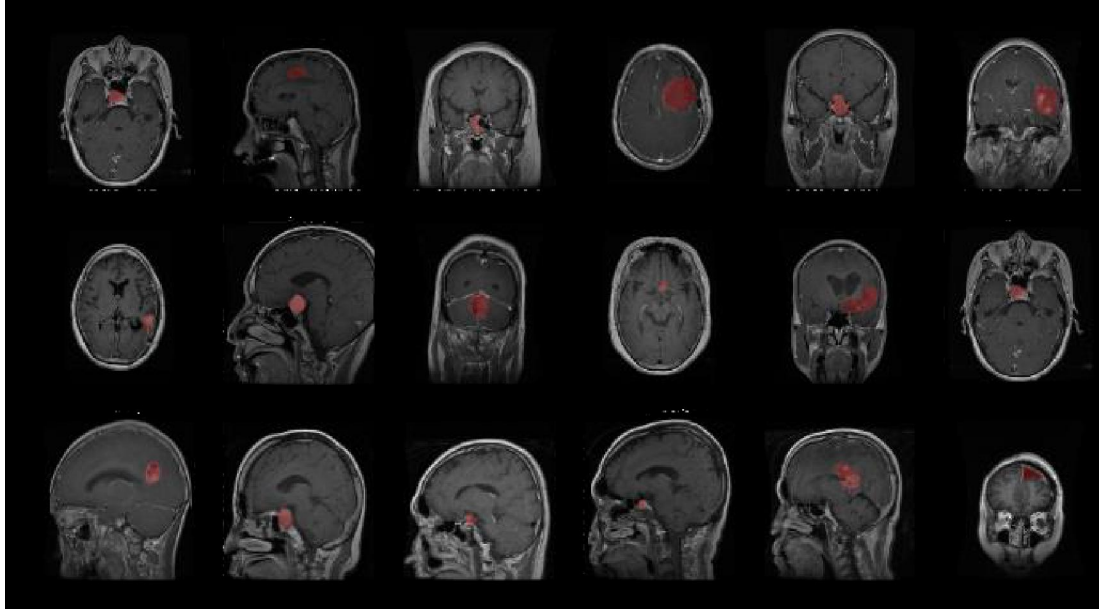
In contrast, malignant brain tumours can grow quickly and spread to other body parts through a process called metastasis. Grades of Tumour Normally, the severity of cancer is assessed using a staging system that's broken into 4 or 5 stages depending on the size and development of the tumour. Brain cancers, however, are assessed using a system of grades, with the 'grade' of a tumour denoting how aggressively it grows. Higher grade tumours tend to grow faster, have an aggressive course, and are more likely to be malignant. Grade I – The tumour is benign. The cells look nearly like normal brain cells. This grade is the least aggressive. Grade II – The tumour is malignant. The cells look more abnormal, but they are generally slow-growing cells Grade III – This is a malignant tumour with cells that look very abnormal and are actively growing (anaplastic).

Grade IV – The malignant tissue has cells that look most abnormal and tend to grow quickly. Diagnosis of Brain Tumour Sophisticated imaging techniques can pinpoint brain tumours. Diagnostic tools include computed tomography (CT or CAT scan) and magnetic resonance imaging (MRI). Other MRI sequences can help the surgeon plan the resection of the tumour based on the location of the normal nerve pathways of the brain. Intraoperative MRI also is used during surgery to guide tissue biopsies and tumour removal. Magnetic resonance spectroscopy (MRS) is used to examine the tumour's chemical profile and determine the nature of the lesions seen on the MRI. Positron emission tomography (PET scan) can help detect recurring brain tumours. Sometimes the only way to make a definitive diagnosis of a brain tumour is through a biopsy. The neurosurgeon performs the biopsy and the pathologist makes the final diagnosis, determining whether the tumour appears benign or malignant, and grading it accordingly. Objective Of The Model To solve this problem, it is necessary to develop an automatic CAD system for diagnosing life threatening diseases such as cancer, which is the main cause of death of

patients worldwide. The objective of the model is to propose a new automated deep learning system for examining MRI of the brain and providing early diagnosis with improved performance. Cancer Rehabilitation plan also provided for the predicted disease type and grade.

II DATASET DISCRPTION

BraTS 2020 utilizes multi-institutional pre-operative MRI scans and primarily focuses on the segmentation (Task 1) of intrinsically heterogeneous (in appearance, shape, and histology) brain tumors, namely gliomas. The dataset includes four different types of brain tumors: glioblastoma, pituitary and meningioma.



III PROPOSED MODEL

The main goal behind the development of our proposed model is to automatically distinguish people with brain tumors, while reducing the time required for classification and improving accuracy. The methodology robust DL framework CNN for detecting brain tumors using MRI datasets were implemented in the model. The proposed model is a four-step process, in which the steps are named:

- 1)Pre-processing,
- 2)Features Extraction,
- 3) Features Reduction, and
- 4) Classification.

Median filter, being one of the best algorithms, is used for the removal of noise such as salt and pepper, and unwanted components such as scalp and skull, in the pre-processing step. During this stage,the images are converted from grey scale to coloured images for further processing. It uses Grey Level Co-occurrence Matrix (GLCM) technique to extract different features from the images. In third stage, Color Moments (CMs) are used to reduce the number of features and get an optimal set of characteristics. Images with the optimal set of features are passed to CNN classifiers for the classification of BT Type and their grades.

IV RELATED WORKS

In this model CNN architecture was used for brain tumor classification of three tumor types: meningioma, glioma, pituitary tumor and their grades from T1-weighted contrast-enhanced magnetic resonance images. The proposed framework model includes four stages. First, the input MR image is pre-processed (noise filter, resize and binarization). Firstly, the prepared dataset collected by creating the annotations for input images to specify the exact location of tumors. Next train the model using created annotations for tumor localization and classification. During training, an input sample along with the bounding box annotation is passed to the improved CNN framework. A typical CNN can easily be divided into two main parts: extraction of features and classification/prediction.



The general architecture of the CNN models has five main layers (input, convolutional, pooling, fully connected, and classification). The convolutional and pooling layers are used to extract the features, whereas the fully connected layers and classification layers are used for prediction/classification. Finally, the pre-trained 2-class model was re-utilized using the transfer-learning method in order to re-adjust the weights of neurons to categorize the tumors into subclasses (glioma tumor, meningioma tumor, and pituitary tumor) and their grades.

Configuring and Training the Algorithms

Before starting the training process, the algorithms (DCNN) used in this model have to be configured to segment brain tumor. DCNN and SSD have separate configuration files which have been provided by TensorFlow Brain Tumor Detection API. The following configuration has been made to DCNN and SSD algorithms to be able to segment tumor present in an MRI Brain Image.

Dataset Splitting:

The dataset used in this split is split in such a way that 80% of the images are used for training the algorithms while the remaining 20% is used for testing.

Number of Classes:

Classes here is nothing but the number of segments that DCNN and SSD should learn and detect after training. In this case, the algorithms are responsible to detect 7 class.

Learning Rate:

Default learning rate of 0.0002 has been used to train the algorithms.

Label Map:

A label map tells the trainer and algorithms what each object is in an image, by mapping the class names to class id numbers.

Batch Size:

Batch size refers to the number of training samples which can be used by the algorithm in one iteration.

V METHODOLOGY & APPROACH

1. Brain Tumor Diagnosing System
2. Brain Tumor Training Phase
 - 2.1. Import Dataset
 - 2.2. preprocessing
 - 2.3. RPN Segmentation
 - 2.4. GLCM Feature Extraction
 - 2.5. CNN Classification
3. Brain Tumor Prediction
 - 3.1. Input Image
 - 3.2. Prediction
4. End User Interface
 - 4.1. Web Admin
 - 4.2. User/Patient/Doctor
5. Recommendation
6. Performance Analysis



VI CONCLUSION

The latest developments in medical imaging tools have facilitated health workers. Medical informatics research has the best options make good use of these exponentially growing volumes of data. Early detection options are essential for effective treatment of brain tumors. This model presented a CAD approach for detecting and categorizing BT's radiological images into three kinds (pituitary-tumor, glioma-tumor, and meningioma-tumor).

The model also classified glioma-tumor into various categories (Grade-two, Grade-three, and Grade-four) utilizing the DCNN approach (i.e., our proposed work). Firstly, pre-trained DensNet201 deep learning model was used, and the features were extracted from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Secondly, the features from different Inception modules were extracted from pre-trained Inceptionv3 model and concatenated and then, passed to the softmax for the classification of brain tumors. The proposed method produced 99.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor. The outcome of the presented architecture shows high training and validation accuracy with low training and validation loss. Moreover, the testing phase determines the overall portable EM imaging system's capability and potential of CNN architecture in detecting and localizing the brain tumor with high accuracy.

VII FUTURE ENHANCEMENT

In the future, the model will be updated by increasing the MRI images in the used dataset to improve the accuracy of the proposed model. Moreover, Applying the proposed approach to other types of medical images such as x-ray, computed tomography (CT), and ultrasound may constitute a principle of future studies.

REFERENCES

- [1] M. O. Khairandish, M. Sharma, V. Jain, J. M. Chatterjee, and N. Z. Jhanjhi, "A hybrid CNN-SVM threshold segmentation approach for tumor detection and classification of MRI brain images," IRBM, Jun. 2021, doi:10.1016/j.irbm.2021.06.003.
- [2] Z. A. Al-Saffar and T. Yildirim, "A hybrid approach based on multiple eigenvalues selection (MES) for the automated grading of a brain tumor using MRI," Comput. Methods Programs Biomed., vol. 201, Apr. 2021, Art. no. 105945, doi: 10.1016/j.cmpb.2021.105945.
- [3] K. Muhammad, S. Khan, J. D. Ser, and V. H. C. D. Albuquerque, "Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey," IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 2, pp. 507–522, Feb. 2021.
- [4] E. Irmak, "Multi-classification of brain tumormri images using deep convolutional neural network with fully optimized framework," Iranian J. Sci. Technol., Trans. Electr. Eng., vol. 4, pp. 1–22, Oct. 2021.
- [5] D. Zhang, G. Huang, Q. Zhang, J. Han, J. Han, and Y. Yu, "Cross-modality deep feature learning for brain tumor segmentation," Pattern Recognit., vol. 110, Mar. 2021, Art. no. 107562.
- [6] P. R. Kshirsagar, A. N. Rakhonde, and P. Chippalkatti, "MRI image-based brain tumor detection using machine learning," Test Eng. Manage., vol. 4, pp. 3672–3680, Jan. 2020.
- [7] A. Tiwari, S. Srivastava, and M. Pant, "Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019," Pattern Recognit. Lett., vol. 131, pp. 244–260, Mar. 2020.
- [8] P. R. Krishnaveni and G. N. Kishore, "Image based group classifier for brain tumor detection using machine learning technique," Traitement Signal, vol. 37, no. 5, pp. 865–871, Nov. 2020.
- [9] B. Lei, P. Yang, Y. Zhuo, F. Zhou, D. Ni, S. Chen, X. Xiao, and T. Wang, "Neuroimaging retrieval via adaptive ensemble manifold learning for brain disease diagnosis," IEEE J. Biomed. Health Informat., vol. 23, no. 4, pp. 1661–1673, Jul. 2019.
- [10] C. Ma, G. Luo, and K. Wang, "concatenated and connected random forests with multiscale patch driven active contour model for automated brain tumor segmentation of MRI image," IEEE Trans. Med. Image., vol. 37, no. 8, pp. 1943–1954, Aug. 2018.

- [11] N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, and T. R. Mengko, "Brain tumor classification using convolutional neural network," in World Congress on Medical Physics and Biomedical Engineering. Bhopal, India: Springer, 2019, pp. 183–189.