International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

Deep Convolutional Neural Network Model to Enhance Brain Tumor Segmentation on Magnetic Resonance Brain Images

Dr.S.Krishna Kumar
Computer Science and Engineering
Sasi Institute of Technology and Engineeering
Tadepalligudem, INDIA

T.Hemanth
Computer Science and Engineering
Sasi Institute of Technology and Engineeering
Tadepalligudem, INDIA

S.Hemanth
Computer Science and Engineering
Sasi Institute of Technology and Engineeering
Tadepalligudem, INDIA

---***---

Abstract - The detection of brain tumors using MRI images is an important undertaking within medical imaging with hopes of early intervention and accurate classification. This work investigates meningioma tumors identifying from MRI scans employing a convolutional neural network (CNN). Techniques for data augmentation improve the dataset to enhance model generalization. The model under consideration classifies MRI images of the head, segments the areas with the tumor applying contouring and thresholding techniques, and marks them. The study states results, discusses, and suggests ways to improve the analysis of medical images in the future. The work aims at the development of automated systems for medical diagnostics with minimum human intervention to increase efficiency and precision in diagnoses.

Key Words: Deep Learning, Classification, Medical Imaging, Image Processing, Data Augmentation, MRI, Brain tumor detection, Convolutional Neural Network.

1. INTRODUCTION

Brain tumors have gained notoriety for their detection and treatment being a tedious process because of its complexity, and requiring early detection and precise categorization. MRI imaging is demonstrably important to medicine for the noninvasive identification of the tumors. This work utilizes deep learning, especially CNNs with the purpose of automating the brain tumor diagnostics to increase its accuracy and reduce the time for the diagnosis. Brain tumors have become an area of concern because of the complexity and variability that accompanies them. MRI imaging is extremely important for non-invasive detection of tumors. The traditional methods of diagnosing involve a manual approach, using human judgment which is always going to be unreliable due to width of variance in errors. The most recent achievement in deep learning that neural networks, especially convolutional neural networks (CNN) are interdisciplinary in nature, having a large impact on methods of medical image classification. The main focus of this paper is automation of brain tumor detection using CNN's architecture that is trained with MRI images for distinguishing between males with meningioma and non-males with meningioma aiming for more efficiency, accuracy, and timely diagnosis.

Brain tumours are abnormal growths of cells in the brain that can threaten life if not detected early. MRI for brain tumor staging MRI is a common method for brain tumor diagnosis as it provides detailed imaging for medical analysis. Conventional diagnosis techniques depend on manual evaluation, which may be tedious and susceptible to mistakes. The advent of Deep Learning from the year 2013 onwards, especially Convolution Neural Networks (CNNs), has led to a remarkable increase in the accuracy of automated Tumor Detection and the time it takes to make an accurate detection.

2. LITERATURE OVERVIEW

Several studies have explored deep learning techniques for brain tumor detection using MRI images. Traditional methods relied on manual feature extraction and classical machine learning approaches, which had limitations in handling complex patterns in medical images. Recent advancements in Convolutional Neural Networks (CNNs) have significantly improved accuracy by automatically learning hierarchical features. Researchers have integrated techniques such as data augmentation, transfer learning, and hybrid models to enhance classification performance. However, challenges such as data imbalance, computational complexity, and the need for interpretable AI models still exist. This study builds upon existing research by optimizing CNN architectures and implementing

efficient data preprocessing methods to improve classification

accuracy and robustness.Several studies have explored deep learning models for tumor classification. Early approaches relied on handcrafted feature extraction combined with machine learning classifiers. However, CNNs have demonstrated superior performance by automatically learning hierarchical features. Recent research has incorporated data augmentation, transfer learning, and attention mechanisms to enhance classification accuracy. Despite advancements, challenges such as data scarcity, variability in tumor appearance, and computational constraints persist, requiring further improvements in model robustness and interpretability. This study builds upon previous research by optimizing CNN architectures and enhancing feature extraction capabilities.

S.No	Author Details	Dissertation and Remarks
1	Agnesh Chandra Yadav, Gargi Kadam (2024)	• Single kernal k means SVM • Detection rate is 89.7.6% • Low sensitivity and specificity rate
2	Ayesha Younis, Qiang Li, Fida Hussain (2024)	• Back propagation neural network approach • The authors obtained 95.98% of SET, 96.89% of SPT, 97.17% of MSA, 96.38% of PR and 97.94% of FS • Detects only internal boundary of tumor pixel
3	Asad Ullah, Jawaid Iqbal, Sami Bourouis (2023)	• deep Convolutional neural network architecture • The authors obtained 97.10% of SET, 97.82% of SPT, 96.86% of MSA, 97.04% of PR and 97.18% of FS • Low learning rate
4	Surendran Rajendran, K.Shankar (2023)	• ANFIS classifier • SET rate is 95.6% and SPT rate is 96.2% • Tested only on high resolution brain MRI image
5	Kittipol Wisaeng (2023)	• Transfer learning approach • Detection rate is 97.6% • Low sensitivity and specificity rate
6	Hasnain Ali Shah, Anand Paul (2022)	• Deep learning approach • The authors obtained 94.3% of SET, 92.3% of SPT, 93.9% of MSA • Misclassification error

7	Naveed Ilyas, Aamir Raja (2022)	• Hybrid Convolutional neural network • SET rate is 94.8% and SPT rate is 94.2% • High consumption time for tumor pixel detection
8	Prilianti et al. (2019)	• Neural network optimizer • SET rate is 95.7% and SPT rate is 96.5% • Not supported / Tested on low resolution meningioma brain images

3.Methodologies and Approaches

Proposed System

This study proposes a CNN-based classification model to detect brain tumors in MRI images. The model is trained on augmented datasets, ensuring improved feature learning and generalization. The system consists of data preprocessing, model training, and tumor highlighting using image processing techniques. The classification results are validated using accuracy metrics, and predictions are further analyzed using threshold-based segmentation to enhance interpretability. The approach integrates image enhancement, deep learning classification, and visualization techniques to assist medical professionals in diagnostic processes.

System Architecture

The architecture involves a number of steps: Acquisition of data from MRI scans, image preprocessing such as resizing and normalization, Classification for tumor detection using CNN, and Post-processing to indicate tumor areas. The CNN includes convolutional layers for feature extraction, max-pooling layers for reducing dimensionality, and fully connected layers for classification. The system has an end-to-end learning method where input MRI images are automatically processed and classified with minimal manual intervention.

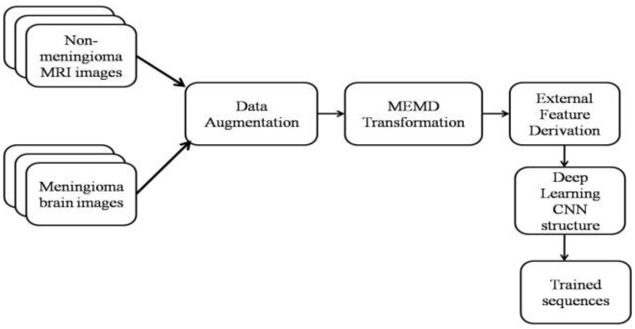


Fig.1 System Architecture

Data Preprocessing

The classification rate is improved by increasing the number of training samples.571 meningioma brain images and 750 non-meningioma brain images. 571 meningioma brain images are split into training dataset (271 images) and testing dataset (300 images).750 non-meningioma brain images are split into training dataset (500 images) and testing dataset (250 images).
Total training images used for training the CNN classifier is about 771.Data augmentation is left pixel flip, right pixel flip, left pixel rotate and right pixel rotate.Hence, the total number of 771 images are data augmented into 3084 images. The MRI images undergo grayscale conversion, resizing to 128x128 pixels, and normalization. Data augmentation techniques such as horizontal flipping, vertical flipping, and rotation enhance the dataset to improve model generalization. Images are split into training and testing sets using an 80-20 ratio. Preprocessing also includes noise reduction and contrast enhancement techniques to improve image quality before model training.

Algorithm Used

Modified Empirical Mode Decomposition (MEMD) is an improved version of the standard Empirical Mode Decomposition (EMD) algorithm. It enhances the decomposition process by addressing mode mixing, improving computational efficiency, and ensuring better signal reconstruction. MEMD is commonly used in signal processing applications like biomedical signal analysis, fault diagnosis, and image processing. The pixels in the source brain image are stored in a matrix, which is called a Mode Matrix (MM).

- Determine the maximum pixel value in MM
  Pmax = Maximum (MM)
- Determine the minimum pixel value in MM
  Pmin = Minimum (MM)

- Find the Absolute Averages (AA) Pmax & Pmin between using the following equations
  AA1 = (1/2)*(Pmax + Pmin)
  AA2 = (1/2)* (Pmax - Pmin)
  AA3 = Max(Pmax + Pmin)
  AA4 = Min(Pmax + Pmin)
  AA5 = Max (Pmax - Pmin)
  AA6 = Min (Pmax - Pmin)

- Find the Residual sub bands (Ri) using the computed AA.
  R1=MM-AA1
  R2=MM-AA2
  R3=MM-AA3
  R4=MM-AA4
  R5=MM-AA5
  R6=MM-AA6

- The final decomposed residual sub-band image is constructed by considering the maximum pixel value of each pixel position in all six residual sub-band images
  Rcombined = Maximum (R1, R2, R3, R4, R5, R6)

CNN (Convolutional Neural Networks):

Extracts hierarchical features from images,enabling the classification of forged and authentic images. It helps distinguish between different types of forgeries such as copy-move, image-splicing.

- Conventional AlexNet:
  5 Convolutional Layers (CL)
  5 Down Sampling Layers
  3 Fully Connected Neural Network (FCNN) Layers
- Proposed AlexNet:
  3 CL
  2 Down Sampling Layers
  2 FCNN Layers
- Details of Proposed AlexNet Configuration:
  Convolutional Layers:
  First CL: 256 filters (5×5 kernel)
  Second CL: 512 filters (5×5 kernel)
  Third CL: 256 filters (7×7 kernel)

Findings and Trends:

Mean:

For instance, if you're working with MRI images of brain tumors, you might calculate the mean pixel intensity in the tumor region to help characterize the tumor and distinguish between benign or malignant types.

$$Mean(M) = \sum_{i=1}^{M} \sum_{j=1}^{N} EMD_{ij}$$

EMF (Empirical Mean Function) – This refers to the empirical mean of a dataset or set of values. It’s an estimate of the true mean, calculated from a sample. For example, in the case of brain tumor classification, the empirical mean could be the average intensity value of pixel intensities in a region of interest (ROI) from MRI images

$$EmpiricalMeanFeatures(EMF) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(\frac{(EMD_{ij} - M) \times (EMD_{ij} + M)}{M} \right)$$

EVF (Empirical Variance Function) – This refers to the empirical variance of a dataset. It is an estimate of the true variance, calculated from the sample. Variance tells you how spread out the data points are. In brain tumor classification, it might measure how much pixel intensities vary in the tumor region.

$$EmpiricalVarianceFeatures(EVF) = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(\frac{(EMD_{ij} - V) \times (EMD_{ij} + V)}{V} \right)$$

Empirical Mean Energy Function (EMEF) typically refers to a function that measures the average energy (or some kind of intensity/strength) of a signal, feature, or image, based on an empirical (observed) dataset. In the context of **brain tumor classification** using MRI images or similar datasets, this term could have a few specific interpretations, depending on the feature or signal you're examining.

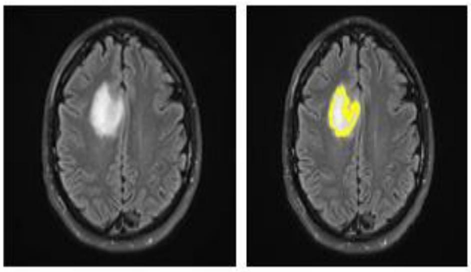
$$EmiricalMeanEnergyFeatures(EMEF) = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{=1}^{N}\left(\frac{(EMD_{ij}-M)^2 \times (EMD_{ij}+M)^2}{M}\right)$$

Empirical Variance Energy Function (EVEF): The **variance** is a measure of how much the values deviate from their mean. When applied to **energy** in the image, the variance indicates how much the pixel intensities or energy features vary across the dataset or region.

$$EmiricalVarianceEnergyFeatures(EVEF) = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{=1}^{N}\left(\frac{(EMD_{ij}-V)^2 \times (EMD_{ij}+V)^2}{V}\right)$$

SEGMENTATION

- Then, the morphological process is carried out to locate the pixels belonging to the tumor.
- This segmentation algorithm consists of dilation followed by erosion function.
- Dilated image = morphological opening(I ,'disk ' , 0.5)
- Eroded image = morphological closing (I ,'disk ' , 0.5)
- Tumor pixel = Dilated image - Eroded image



(a) (b)

Fig.2 (a) Meningioma brain image (b) Tumor region segmented image

Challenges And Gaps:

1. Data Imbalance and Scarcity:

Large-scale annotated brain MRI images with tumor segmentation datasets are not readily available. Even if datasets exist, there could be an imbalance in the ratio of tumor pixels to non-tumor pixels, which would cause the model to be biased.More publicly accessible, large high-quality datasets that have dense annotation to train the DCNN models are needed. In addition, no efficient methodologies are available for dealing with the class imbalance when training

2. Heterogeneity of Tumor Types:

Brain tumors exist in many different sizes, shapes, and types (gliomas, meningiomas, metastases, etc.), and tumor heterogeneity makes them challenging to segment. The boundary of the tumors can be not well defined, particularly for less obvious or small-sized tumors.DCNN models often struggle to generalize across different tumor types due to the diversity in appearance and texture. There's a need for more robust models that can generalize well across different tumor types and sizes.

3. Variability in Imaging Protocols:

MRI scans are acquired with different protocols (e.g., T1, T2, contrast-enhanced, etc.) on different machines and institutions, which can lead to inconsistencies in image resolution and quality. These inconsistencies can mislead deep learning models at training and inference time.Robust models against imaging variations and handling of multi-modal or multi-center MRI data without any difficulties are not available. Models need to be made adaptable to varying imaging protocols through further research.

4. Noise and Artifacts in MRI Data:

MRI images tend to have noise and artifacts like motion artifacts, partial volume effect, and magnetic field inhomogeneities, which would hamper tumor segmentation in an accurate manner. Preprocessing operations (such as denoising or artifact removal) may be beneficial, but deep learning models that can genuinely deal with noisy and artifact-contaminated images both at training and inference stages are still required.

5. Computational Complexity and Memory Constraints:

DCNNs are computationally intensive, utilizing a lot of hardware resources and time for training. In addition, big 3D MRI images or volumetric data may put a big load on GPU memory, particularly for 3D segmentation tasks.Deep learning architectures and methods for efficient memory optimization remain a research gap. The models must be less memory-intensive and computationally demanding in order to be viable for use in practice.

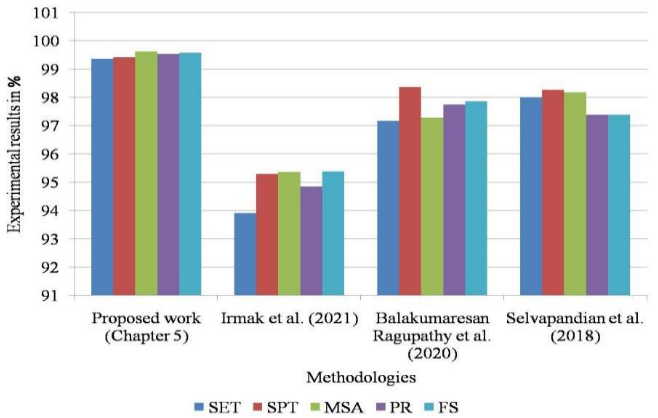


Fig.3 Graphical analysis of proposed algorithm on brain web dataset

Results:

The proposed MEMD-CNN system is expected to make a significant impact on the field of medical imaging, providing a reliable, efficient, and scalable solution for the early detection of meningioma tumors. The successful implementation and validation of this system could lead to its integration into clinical workflows, thereby enhancing the overall quality of healthcare delivery and patient outcomes. Additionally, the findings from this research are anticipated to contribute valuable insights to the academic community, paving the way for future advancements in automated medical imaging and artificial intelligence applications in healthcare.

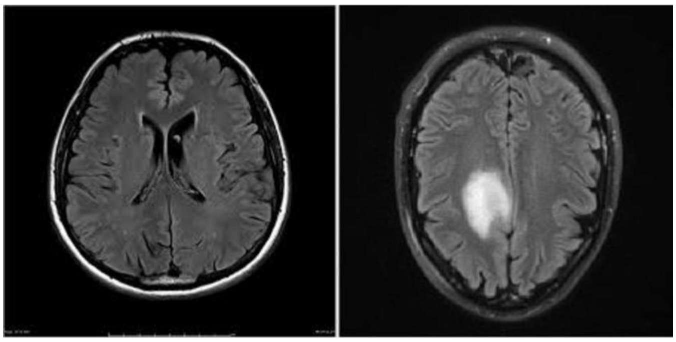


Fig.4 (a) Non-Tumor (b) Tumor

References:

- Çinar A, Yildirim M (2020) Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture. Med Hypotheses 139:109684.
- Deepak S, Ameer P (2019) Brain tumor classification using deep CNN features via transfer learning. Comput Biol Med 111:103345.
- Kabir Anaraki A, Ayati M, Kazemi F (2019) Magnetic Resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms. Biocybern Biomed Eng 39(1):6374.
- Mehrotra R, Ansari MA, Agrawal R, Anand RS (2020) A Transfer learning approach for AI based classification of brain tumors. Mach Learn Appl 2(9):1–12.
- Muhammad K, Khan S, Ser JD, Albuquerque VHC (2021) Deep learning for multigrade brain tumor classification in smart healthcare systems: a prospective survey. IEEE Trans Neural Netw Learn Syst 32(2):507–522.
- Rehman A, Naz S, Razzak MI, Akram F, Imran M (2020) A Deep Learning-based framework for automatic brain tumors classification using transfer learning. Circuits, Syst, Signal Process 39(2):757–775.
- Shirazi AZ, Fornaciari E, McDonnell MD, Yaghoobi M, Cevallos Y, Tello-Oquendo L, Inca D, Gomez GA (2020) The application of deep convolutional neural networks to brain cancer images: A survey. J Personal Med 10(4):1–27.
- Tiwari A, Srivastava S, Pant M (2020) Brain tumor segmentation and classification from magnetic resonance images: review of selected methods from 2014 to 2019. Pattern Recogn Lett 131:244–260.
- Irmak, E. Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework. Iran J Sci Technol Trans Electr Eng 45, 1015–1036 (2021).
- Jasmine Hephzipaha J, Thirumurugan P, Performance Analysis of Meningioma Brain Tumor Detection System Using Featur Learning Optimization and ANFIS Classification Method",IETE Journal of Research, Vol.1, No.3, 2020, pp.1-12.

- Guoli Song, Tian Shan, Min Baod, Yunhui Liud, Yiwen Zhao, Baoshi Chen, "Automatic brain tumour diagnostic method based on a back propagation neural network and an extended set-membership filter" , Computer Methods and Programs in Biomedicine, Volume 208, September 2021, 106188.