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Brain Tumor Segmentation and Detection using EfficientNetB3 Model for MRI Medical Images

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Abstract: Brain tumors, identified by their abnormal cell proliferation within the brain, have historically been diagnosed and delineated using Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. Recently, the use of X-rays, known for their speed and greater accessibility, for the detection of brain tumors has sparked interest in the medical community. This study aims to assess the efficacy of various computational techniques in the identification and delineation of brain tumors from MRI images. The investigation covered traditional models such as the Radial Basis Function (RBF), Linear, and Polygonal kernels, which demonstrated accuracy rates between 65.74% and 86.24% across two separate test images. Additionally, the research delved into the capabilities of the EfficientNetB3 model, distinguished by its deep learning prowess and innovative compound scaling approach. The findings revealed that the EfficientNetB3 model surpassed the conventional methods, achieving accuracy levels of 93.49% and 94.73% on the two test images, respectively. These results underscore the substantial promise of the EfficientNetB3 model in enhancing the precision of medical imaging analyses, representing a significant leap forward in the diagnostic and treatment planning processes for brain tumor patients.

Keywords: *Machine Learning, Brain tumors, X-ray images, Magnetic Resonance Imaging, Computed Tomography, EfficientNetB3, Radial Basis Function.*

1. Introduction

Brain tumours, which are very challenging in the field of medicine, serve as evidence of the complex and fragile characteristics of the human brain. The identification, division, and subsequent treatment of these conditions are crucial, not only for the progress of medical knowledge, but more importantly, for guaranteeing the health and continued existence of affected persons. Magnetic Resonance Imaging (MRI) has proven a reliable and essential tool in this pursuit, offering detailed observations of the brain's structure and any irregularities. The advancements in MRI technology have been substantial. However, there is a continuous effort to enhance the efficiency and precision of tumour identification and segmentation procedures due to the intricate and diverse nature of brain tumours.

Machine Learning (ML) is a branch of artificial intelligence that enables systems to learn from data and improve their performance based on experience, without the need for explicit programming. The ability of machine learning to analyse large volumes of detailed MRI data, detect complex patterns, and make predictions has led to a significant change in brain tumour diagnoses. Data-driven algorithms, which provide improved accuracy and dependability, have replaced traditional heuristic techniques. Figure 1 depicts the Brain tumour and its segmentation.

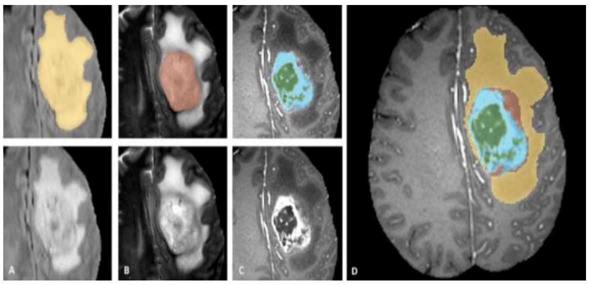

Fig 1. Brain tumor and segmentation.

However, as with every new technological leap, the marriage of MRI imaging and machine learning isn't without its challenges. From data acquisition to algorithmic transparency, from model validation to real-world application, there are myriad aspects to consider.

This review, therefore, aims to explore this confluence of machine learning and MRI in the domain of brain tumor segmentation and detection. It delves into the historical context, capturing the evolution of methodologies. It

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critically assesses the capabilities and challenges of machine-learning-based approaches, while also providing a perspective on future trajectories. By synthesizing findings from various studies, this review endeavors to provide a holistic understanding of where we stand today in harnessing machine learning for brain tumor detection using MRI and what lies ahead in this promising avenue.

In the early 2000s, initial attempts to introduce automation in MRI image analysis were based on rule-based algorithms. However, these models had limited adaptability and struggled with variability in tumor presentation. With the advent and rise of machine learning, particularly deep learning and neural networks in the late 2010s, a new frontier opened up. Neural networks, mimicking the human brain's structure and function, offered superior adaptability and learning potential. Convolutional Neural Networks (CNNs), a subtype, became the cornerstone for image recognition tasks. Figure 2 shows the brain tumor detection and segmentation in MR images

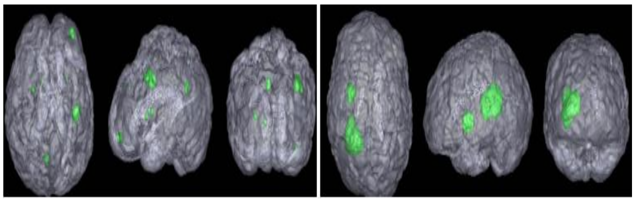

Fig 2. Brain tumor detection and segmentation in MR images.

Diving Deeper into the Realm of Brain Imaging : The human brain, often deemed as the most intricate organ in our body, has always intrigued medical professionals. Not just because of its sheer complexity, but also due to the challenges it presents when afflicted with ailments like tumors. Brain tumors, especially malignant ones, can proliferate rapidly and can lead to serious neurological deficits, impaired cognitive abilities, and even death if not diagnosed and treated in a timely manner.

MRI: A Revolution in Imaging : Since its inception, Magnetic Resonance Imaging (MRI) has emerged as a cornerstone for neuroimaging. Unlike traditional X-rays or CT scans, MRI employs strong magnetic fields and radio waves to generate detailed images of the brain. These images, comprising multiple slices and offering different contrasts, provide a comprehensive view of both healthy and pathological tissues. This imaging modality has proven invaluable, particularly for soft tissues, thereby offering a remarkable window into the brain's structure and any lurking anomalies.

The Machine Learning Epoch : In recent years, the exponential growth in computational power and data availability has ushered in an era dominated by Machine Learning (ML). Given the vast amount of data MRI generates, manual interpretation becomes not only tedious but is also susceptible to human errors. Here, ML algorithms, trained on voluminous datasets, show prowess in automatically detecting and segmenting abnormalities, reducing the diagnosis time, and enhancing accuracy. Techniques ranging from classical ML, such as Support Vector Machines, to advanced Deep Learning architectures like Convolutional Neural Networks (CNN), have been employed.

The Merger: MRI and Machine Learning : The amalgamation of MRI and ML is nothing short of revolutionary. ML algorithms, when fed with high-resolution MRI scans, can discern patterns and anomalies which might be imperceptible to the human eye. This not only streamlines the diagnosis process but also paves the way for personalized treatment plans, tailored to individual patients.

Challenges and The Road Ahead : Yet, it's not all smooth sailing. Integrating ML into clinical workflows, ensuring data privacy, handling the diverse and multi-centric nature of MRI data, and making algorithms robust to variations are challenges that researchers grapple with. Additionally, interpretability of ML models remains a significant concern, especially in the medical domain where understanding the 'why' behind a diagnosis is as crucial as the diagnosis itself.

Current Landscape : Today, the landscape of brain tumor segmentation and detection using ML for MRI images is vibrant and rapidly evolving. Advanced ML models, coupled with enhanced computational capacities, are enabling the analysis of MRI scans with unprecedented accuracy. Techniques like transfer learning, where pre-trained models are fine-tuned for specific medical imaging tasks, are reducing the need for extensive datasets, which are often challenging to obtain in the medical domain due to privacy concerns.

However, the journey is not without challenges. While ML models excel in accuracy, there are concerns about their interpretability. Understanding why a model makes a particular decision is crucial in medical applications to gain the trust of healthcare professionals. Furthermore, the quality of data, including its diversity and representativeness, can significantly impact the model's performance. Inaccurate or biased training data can lead to incorrect predictions, with potentially grave consequences in a medical setting.

The Path Ahead : As we venture further into this review, we will deep-dive into the specific ML models making a mark in the realm of MRI-based brain tumor detection. We will scrutinize their strengths, analyze their limitations, and explore the innovations on the horizon. This journey will not only highlight the technological marvels but also underscore the collaborative spirit of radiologists, data scientists, and engineers, all working in tandem to harness the potential of ML for the betterment of patient care.

2. Literature Review

Multiple metastases make metastatic brain illness monitoring onerous. The RANO-BM therapeutic response evaluation guideline is common. Yet, detailed volumetric measurement of lesions and peri-lesional edoema is essential. Brain metastases under 10 mm are difficult to segment. Metastases fluctuate in size, unlike gliomas, which start bigger. BraTSMETS seeks to automate brain metastases detection and segmentation [1].

Medical imaging relies on brain tumour segmentation. Recent deep learning approaches thrived in this area despite its complexity. This assessment of over 150 works on deep learning-based tumour segmentation discusses network architectures, unbalanced condition segmentation, multi-modality procedures, and future directions [2].

MRI is essential for early brain tumour identification. Tumour variability complicates detection. This paper presents an IIB-based Deep Residual network model for effective MRI tumour identification. Accuracy, sensitivity, and specificity show the method's excellence [3].

Brain tumour analysis is best using MRI. Different segmentation methods provide different results on the BRATS dataset-2018. CNN has better accuracy and reaction time than Otsu, watershed, level set, K-means, DWT, and CNN, making it a promising brain tumour imaging approach [4].

Precision computerised brain tumour diagnosis is crucial. A hybrid Deep Convolutional Neural Network (DCNN) classifier employing upgraded LuNet is proposed. This approach improves classifier performance using initial data separation, features extraction, and the Laplacian of Gaussian filter (LOG) with 99.7% accuracy [5].

Brain tumours, typically complicated in MRI data, need early identification. Automation is needed because radiologists make mistakes while assessing patients. This work offers an optimised eXtreme Gradient Boosting (XGBoost) brain tumour diagnosis algorithm with excellent accuracy and precision [6].

Brain tumour identification is crucial for patient care. This research presents a deep learning tumour segmentation approach for several brain illnesses. The suggested technique shows outstanding accuracy and sensitivity using a Harvard medicinal School dataset, suggesting medicinal value [7].

Brain tumour detection Using VGG16: Adults die most from brain tumours, which occur from aberrant cell proliferation. MRI early detection improves survival. The VGG16 deep learning model classified Kaggle MRI scans as "normal" or "tumour" with 97.33% accuracy. VGG16 models are typically considered "black boxes"; hence, Layer-wise Relevance Propagation (LRP) was proposed for decision-making transparency [8].

Brain Tumour Classification Challenge Manually identifying brain tumours is challenging and may lead to diagnostic errors since they seem like normal tissues. MRI images were preprocessed using a HOFilter for this study. Tumours were segmented using edge detection and morphology. The proposed model achieved 96.46% accuracy and 96.19% precision [9].

Deep learning diagnostics: Brain tumours must be detected early. Research suggests that MRIs can reliably detect gliomas, meningiomas, pituitary gland tumours, and healthy brains. Two deep learning algorithms and various machine learning methods were presented. During training, their 2D CNN and auto-encoder networks achieved 96.47% and 95.63% accuracy. K-Nearest Neighbours (KNN) was the most accurate machine learning method [10].

A More Accurate Brain Tumour Diagnosis Model Early detection of brain tumours, whether malignant or benign, is crucial because they affect adjacent cells. Use a CNN model fine-tuned using ResNet50 and U-Net to locate and segment tumours. This model performed well with IoU at 0.91 and DSC at 0.95 [11].

Brain Tumour Detection using an Enhanced YOLOv7 Model: A refined YOLOv7 model can consistently detect pituitary, meningioma, and glioma tumours. The CBAM attention mechanism, data augmentation, and Bi-directional Feature Pyramid Network (BiFPN) improve feature extraction and fusion in this model. Thus, it is very accurate and may benefit professionals [12].

new Convolution-based Hybrid Segmentation Model: A unique convolution-based hybrid model segments brain tumour images properly. It scored up to 93.10% on dice scores across datasets, suggesting good performance. Its unique preprocessing structure offers advantages over other models [13].

MRI-Based Brain Tumour Segmentation: This research examined MRI modalities and brain tumour segmentation methods. Deep learning, especially CNNs, has enabled brain tumour segmentation from MRI scans [14].

Improved Segmentation using U-Net and 3D CNN: This study used Grey Level Co-occurrence (GLC) matrix feature extraction to segment aggressive gliomas. U-Net and 3D CNN together could segment the whole tumour with 99.4% accuracy [15].

Multi-modal MRIs and deep learning algorithms power advanced brain tumour segmentation. Manual adjustment is a drawback of these models' intensive preprocessing like skull-stripping. This is laborious and not always practicable in clinical settings. Few studies have examined how brain extraction procedures affect segmentation. An automated pipeline and brain extraction decision may alter segmentation performance by 15.7%, according to our study. Without skull-stripping, training on raw pictures yields faster results without reducing accuracy [16].

The growth of automated medical imaging defect identification emphasises MRI tumour detection accuracy. This project benefits from deep learning methods like ANN and MLP. The characteristics from MRI preprocessing educate a machine learning system to identify brain tumours [17].

This paper presents WBM-DLNets, a new MRI brain tumour diagnostic method. Each combination is tested using 16 pretrained feature extraction networks and eight optimisation techniques. The outcome? Using chosen characteristics, classification accuracy increases considerably, with DenseNet-201-GWOA and EfficientNet-b0-ASOA leading [18].

Machine learning has transformed MRI brain tumour segmentation. We provide an effective tumour identification and segmentation method using AMSOM and FKM. We surpass previous techniques by 10% in key measures using the Brats-18 dataset [19].

Brain tumours are deadly and hard to detect. This research study reviews MR imaging for tumour detection in detail. It discusses brain tumour morphology and computational intelligence, deep learning, and machine learning detection approaches [20].

Brain tumour segmentation by MRI is crucial for patient treatment. Recent deep neural networks are promising yet limited. Our Improved Residual Network (ResNet) overcomes these constraints and improves performance measures by 10% [21].

AI mimics human behaviour. Deep learning, especially CNN, may identify brain tumours in MRIs. We present a CNN model that outperforms ResNet-50 and VGG16 in brain tumour identification [22].

MRI brain tumour segmentation using deep learning models like U-shaped architectures seems promising. They fail at capturing complex tumour borders. The SGC-ARANet model uses four distinct modules to improve segmentation. Our method beats numerous others on the BraTS 2019 and 2020 datasets [23].

Medical imaging frequently misses important information. Meta-learning improves partial modality representations in our method. The approach outperforms existing methods in missing modality situations [24].

AI has made diagnostic radiology more scientific. CNN and deep learning algorithms identify early brain tumours well, but they demand plenty of resources. A harmony search technique is used in our work to segment MRI data efficiently. Accuracy-wise, this approach rivals CNN and DLA, but speed and resource management are better [25].

AI and IoT technologies have being researched for numerous purposes. A research produced a real-time item identifier for the visually handicapped [26]. Another utilised QCA to create an efficient Arithmetic Logic Unit (ALU) [27]. A hierarchical K-Means clustering technique was presented for digital buddy recommendations. Deep learning and OpenCV have been used to identify face masks [28] and forecast cancer using Random Forest and deep learning [29]. Advanced object detection was investigated using Mask-RCNN [31].

Many medical imaging methods have been developed to identify brain tumours. Big data analysis and several MRI modalities were used to develop a patch-based convolutional neural network (PBCNN) technique for early brain tumour segmentation [32]. Patch-based convolutional neural network. Another study employed U-Net deep learning and the MICCAI BRATS 2018 dataset to create an automated MRI tumour segmentation model [33]. This model performed well in segmentation. The difficulty of detecting tiny tumours in MRI images led to a suggestion to employ dilated convolution and level-based learning to segment all tumour sizes [34]. A unique technique using the Bagging Ensemble with K-Nearest Neighbour (BKNN) was also suggested for better brain MR tissue differentiation. This method has 97.7% accuracy [35].

3. Research Gap

1. **Use of X-rays for Brain Imaging**: Traditional methods for brain tumor detection and segmentation largely rely on MRI and CT scans. If X-ray imaging is being considered for brain tumor detection, one primary research gap could be the limited studies available that emphasize the use of X-rays for this purpose.
2. **Integration with Machine Learning**: While machine learning has shown promise in medical imaging, its application specifically for X-rays in brain tumor detection might be under-explored. Studies might have largely focused on MRI and CT data, leaving a gap for exploration in X-ray data.
3. **Quality of X-ray Images**: The resolution and details captured in X-ray images might be different than those in MRI or CT scans. The challenges tied to processing and analyzing lower-resolution images or images with less contrast might not be comprehensively addressed.

4. **Diverse Algorithms for X-rays**: Given the distinct nature of X-ray images, the same machine learning algorithms that are effective for MRI or CT might not be as effective for X-rays. There might be a gap in algorithms tailored specifically for X-ray brain tumor detection.
5. **Real-time Detection**: Considering the relatively quicker processing time for X-rays compared to MRI or CT, there might be a research gap related to real-time tumor detection using X-ray images combined with machine learning.
6. **Dataset Availability**: One significant challenge might be the lack of publicly available datasets of X-ray images of the brain with labeled tumor regions, limiting the advancement of machine learning models in this domain.
7. **Clinical Validation**: Even if machine learning models are developed for X-ray-based brain tumor detection, they might lack extensive clinical validation, making it challenging to gauge their real-world efficacy.
8. **Interdisciplinary Collaboration**: There might be a gap in collaborative studies that bring together radiologists who specialize in X-ray imaging with data scientists and machine learning experts.
9. **Patient Safety**: Given the radiation exposure associated with X-rays, studies on the safety implications of repeated X-rays for brain tumor detection, especially when compared with other methods, might be limited.
10. **Comparative Studies**: There might be a lack of studies comparing the performance, advantages, and disadvantages of X-ray-based machine learning models versus those trained on MRI or CT scans for brain tumor detection.

4. Existing Methodology

1. Thresholding and Region-based Methods : One of the earliest and simplest methodologies used in brain tumor segmentation is thresholding. This method leverages the intensity values of MRI images. Tumorous cells usually have different intensity values compared to normal cells. By setting a threshold value, pixels with intensities beyond this threshold are categorized as potential tumor regions. While thresholding is computationally efficient, it often struggles with images having non-uniform illumination or noise. To overcome these shortcomings, region-based methods were introduced. These methods identify regions in the image, based on predefined criteria, which are likely to be tumors. Region growing and region merging are popular techniques in this category. However, their efficiency can be compromised if the initial seed points are not chosen wisely.

2. Edge Detection Methods : Edges in an image signify boundaries or transitions between different objects or regions. Edge detection methods, like the Sobel, Canny, and Prewitt operators, identify these boundaries to outline potential tumor regions. These methods are particularly effective for tumors with well-defined boundaries. However, they might not perform as effectively for tumors with blurry or ill-defined edges.

3. Statistical Methods : These methodologies utilize statistical measures to distinguish between tumor and non-tumor regions. Techniques such as clustering, where similar data points are grouped together, have been employed. The K-means clustering algorithm is a popular choice in this category. While statistical methods provide a more sophisticated approach than thresholding, they require a robust selection of initial parameters to be effective.

4. Model-based techniques include constructing a representation of the intended item (in this instance, the tumour) and then using this representation to detect comparable structures within the picture. This approach extensively use deformable models such as active contours or snakes. These models repeatedly modify their shape to accurately conform to the boundaries of the tumour. Although these approaches possess significant computing capacity, they may be demanding in terms of processing resources and may get stuck in local minima, resulting in less than ideal outcomes.

5. Utilisation of machine learning and deep learning methodologies: The advent of machine learning has led to the integration of prediction models with classic image processing approaches. Tumour detection has used Support Vector Machines (SVM) and Random Forests. Nevertheless, the real breakthrough occurred with the emergence of deep learning, namely Convolutional Neural Networks (CNN). Convolutional neural networks (CNNs), due to their capacity to extract hierarchical information from pictures, have shown unparalleled achievements in tasks related to the segmentation of brain tumours. Architectures such as U-Net and its variations are now considered the most advanced in this field.

6. Hybrid Methods : Recognizing the strengths and weaknesses of the aforementioned methods, researchers started to combine multiple techniques to harness their collective potential. For instance, combining thresholding with statistical measures or integrating edge detection with model-based approaches. These hybrid methodologies aim to offset the limitations of one method with the strengths of another.

5. Proposed Method

5.1 Flowchart

Figure 3 outlining the steps of a research process, particularly for a study like detecting brain tumors through MRI images. Here's an explanation of each step in the context of such a study:

1. **Start**: Initiating the research project.
2. **Literature Review**: Investigating existing studies on brain tumor detection using MRI imaging, machine learning models for medical imaging, and advancements in neural network architectures relevant to the task.
3. **Problem Definition and Research Objectives**: Clearly defining what the research is addressing, such as the detection of specific types of brain tumors from MRI images, and setting objectives like achieving a certain accuracy or processing time.
4. **Data Collection and Preprocessing**: Gathering a dataset of brain MRI images that are labeled with the presence or absence of tumors. Preprocessing may include normalizing the images, resizing them to the input size required by the model, augmenting the dataset to improve model robustness, and splitting the data into training and test sets.
5. **Model Selection and Implement**: Choosing a suitable machine learning model for the task. For brain tumor detection, a model like EfficientNetB3 could be selected due to its balance of accuracy and computational efficiency. Implementation involves configuring the model with the appropriate hyperparameters.
6. **Training and Testing**: Training the model on the prepared dataset, using a loss function and an optimization algorithm to adjust the weights. After training, the model is tested on a separate set of images to evaluate its performance.
7. **Performance Comparison Analysis**: Comparing the model's performance to other models or benchmarks in the field. Metrics such as accuracy, precision, recall, and F1 score are typically used to assess performance. The analysis might also involve statistical tests to determine if performance differences are significant.
8. **Conclusion**: Drawing conclusions from the research findings, discussing the model's effectiveness in detecting brain tumors from MRI images, its potential clinical applicability, and any limitations or areas for future research.

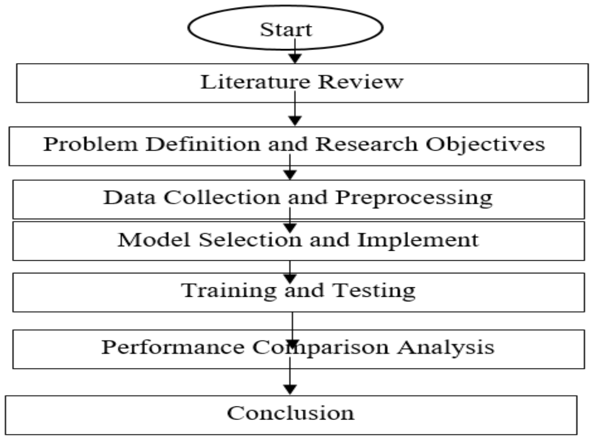

Fig 3. Proposed working flowchart.

5.2 Proposed working architecture

The methodology for identifying brain tumors with the EfficientNetB3 framework commences with the aggregation of pertinent data, which is then subjected to preparatory procedures such as image resizing and standardization to ensure uniformity and enhance data quality. Subsequently, the EfficientNetB3 architecture is deployed, integrating pre-established weights to facilitate feature extraction. This is achieved through the utilization of MBConv and SE blocks, which are pivotal in refining the model's analytical capabilities.

Training the model involves the application of annotated datasets, enabling it to learn and distinguish between different types of brain tumors. This phase is critical and is followed by validation and testing segments to rigorously assess the model's efficacy. Upon satisfactory performance metrics, the final phase involves the model's integration into clinical environments, where it serves as an advanced tool for brain tumor detection, aiding medical professionals in accurate diagnosis.

The EfficientNet model employs a strategic scaling method known as compound scaling, which meticulously adjusts the network's depth, width, and resolution. This adjustment is governed by a compound coefficient (Φ) and is fine-tuned using constants (α, β, γ) identified through an extensive grid search. This balanced scaling approach ensures that the network scales harmoniously across different dimensions, thereby maximizing accuracy within the confines of available computational resources.

The MBConv Block, or mobile inverted bottleneck convolution block, is a cornerstone of the EfficientNet architecture. It features an initial 1x1 convolution that expands the channel count, followed by a depth-wise 3x3 convolution, and culminates in a 1x1 convolution that reduces the channels, optimizing the network's efficiency, especially in scenarios with limited computational capacity.

Additionally, the SE (squeeze-and-excitation) block enhances the model's performance by dynamically recalibrating the feature channels. It differentiates the significance of various channels, thereby sharpening the network's focus on the most pertinent features for accurate brain tumor detection. This nuanced approach to feature prioritization significantly contributes to the model's overall effectiveness and efficiency.

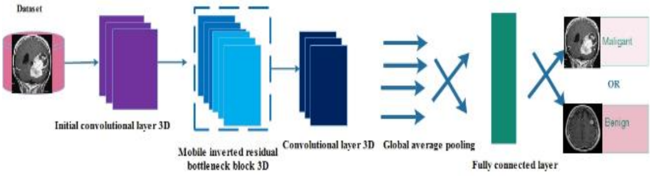

Fig 4. Proposed operational framework.

The neural network architecture seen in Figure 4 is intricately designed to process three-dimensional MRI images of the brain. This advanced model excels at identifying subtle nuances and intricate patterns present in the imaging data, allowing it to accurately differentiate between malignant and benign tumours with exceptional accuracy. This system employs state-of-the-art deep learning techniques to effectively extract and analyse important characteristics from brain imaging. It provides a robust tool for accurately classifying tumours. This technique not only demonstrates the use of state-of-the-art AI technology in medical imaging but also greatly boosts the possibility of early and precise diagnosis, hence improving patient outcomes.

3.2 Algorithm EfficientNetB3

To undertake the task of detecting brain tumors from MRI scans using deep learning, particularly leveraging the EfficientNetB3 architecture, the following detailed procedure is adopted:

Dataset Assembly for MRI Brain Scans: Begin by gathering a comprehensive dataset that includes brain MRI images, both of individuals diagnosed with tumors and those without, to create a balanced and informative dataset for training and testing the model.

Image Preprocessing: Adjust the dimensions of the collected MRI images to fit the specific input requirements of the EfficientNetB3 architecture. This involves resizing images, normalizing the pixel intensity values to a standard scale, and potentially augmenting the dataset with artificially modified versions of the images (e.g., rotated, flipped, or scaled images) to enhance the model's ability to generalize from the data.

EfficientNetB3 Initialization: Load the EfficientNetB3 architecture equipped with pre-trained weights. This leverages the concept of transfer learning, where a model developed for one task is repurposed on a second related task, taking advantage of the pre-learned patterns in the data.

Feature Extraction Phase: Process the preprocessed MRI images through the EfficientNetB3 network. This step allows the model to identify and extract complex features from the images that are relevant for distinguishing between malignant and benign brain tumors.

Classification Layer Integration: Enhance the model by adding a fully connected layer followed by a softmax activation function. This classification layer is tailored to differentiate between the classes of interest, in this case, tumor and no tumor, based on the features extracted by the EfficientNetB3.

Model Training: Employ the assembled and labeled dataset to train the neural network. Utilize optimization algorithms such as backpropagation and gradient descent to iteratively adjust the model's parameters, thereby minimizing the error in tumor classification.

Model Validation: Before final deployment, validate the model's performance using a distinct dataset not seen during training. This step is crucial for adjusting the model's hyperparameters and ensuring it generalizes well to new data, effectively preventing overfitting.

Model Testing: Finally, assess the fully trained model's performance by evaluating it on a separate test dataset. This evaluation focuses on key metrics such as accuracy, sensitivity (true positive rate), and specificity (true negative rate) to gauge the model's diagnostic capability.

EfficientNets, including EfficientNetB3, are known for their unique compound scaling method. This approach uniformly scales the network's depth, width, and resolution based on a set of predetermined scaling coefficients. This scaling is conducted subsequent to a neural architecture search aimed at identifying an optimal baseline network. The selected baseline is then scaled up to produce the EfficientNet variants, optimizing performance across various computing constraints and tasks.

In the brain tumor detection from medical images, applying EfficientNetB3 involves translating the intricate visual patterns of MRI scans into a form that the model can effectively analyze and interpret. This process harnesses both the depth of the network for feature extraction and the efficiency of its architecture to provide a potent tool for medical diagnosis, leveraging the network's capacity to handle complex image data with high efficiency.

1. **Baseline Network:**
   - EfficientNets start with a baseline network found through neural architecture search. This network is a mobile inverted bottleneck CNN (MBConv) which includes elements such as depthwise

separable convolutions and squeeze-and-excitation blocks.

2. **Compound Scaling:**

- A compound coefficient, φ (phi), is used to uniformly scale network width, depth, and resolution in a principled way:
- Depth: $d=\alpha^{\phi}$
- Width: $w=\beta^{\phi}$
- Resolution: $r=\gamma^{\phi}$
- Here, α, β, and γ are constants that are determined by a small grid search on the original baseline network. The EfficientNetB3 corresponds to a specific value of φ, which increases the network's size compared to the baseline model.

3. **Applying EfficientNetB3 to Brain Tumor Detection:**

The process of detecting brain tumors using MRI images through the EfficientNetB3 architecture involves a series of meticulously designed steps, each crucial for ensuring the accuracy and reliability of the diagnosis:

Initial Image Processing

- MRI Image Preparation: The journey begins with an MRI scan of the brain. Given EfficientNetB3's requirement for a specific input resolution, typically 300x300 pixels, any MRI image not meeting this criterion is resized to match, ensuring uniformity across the dataset.

Image Preprocessing

- Normalization: Prior to analysis, the MRI images undergo normalization, adjusting pixel values to a scale that the neural network can effectively process. This adjustment typically involves scaling the values to fall within either a -1 to +1 or 0 to 1 range, optimizing the network's ability to learn from the data.

Feature Extraction and Analysis

- Convolutional Layers: The core of the model consists of multiple convolutional layers. Each layer employs filters to extract vital features from the MRI images. This step is enhanced with batch normalization and activation functions, particularly the swish function, which is mathematically represented as $f(x)=x \cdot sigmoid(x)$, optimizing the flow and transformation of data through the network.
- MBConv Blocks: At the heart of EfficientNetB3 lie the MBConv blocks. These blocks utilize depthwise separable convolutions, which serve to minimize the number of parameters, and squeeze-and-excitation blocks, which prioritize the most significant features by dynamically recalibrating channel-wise feature responses.
- Progression Through the Network: As the image data advances through the network, there's a deliberate decrease in spatial resolution while the number of feature maps, or channels, increases. This transition ensures that the network captures and emphasizes the most pertinent features for classification.

Classification and Output

- Global Average Pooling: Nearing the final stages, a global average pooling layer condenses each feature map to a singular value, averaging out all the inputs, which effectively reduces the dimensionality and prepares the data for classification.
- Fully Connected Layer and Activation: The streamlined feature set is then fed into a fully connected layer, tailored to match the number of desired output classifications. For brain tumor detection, this typically translates to a binary setup—identifying the presence or absence of a tumor. The softmax activation function is applied to this layer's output, generating a probability distribution over the potential classes.

Training the Model

- Model Training: With a dataset of labeled MRI images at hand, the network undergoes training. A loss function, commonly cross-entropy in classification tasks, evaluates the discrepancy between the model's predictions and the actual labels. Through backpropagation, gradients are calculated, allowing an optimizer, such as Adam, to adjust the weights and minimize the loss, refining the model's predictive capability.

6. Implementation

6.1 Dataset

This dataset is composed of 7,023 MRI images of the human brain, categorized into four distinct classes: glioma, meningioma, no tumor, and pituitary. The images that fall under the 'no tumor' classification are sourced from the Br35H dataset.

https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset

6.2 Illustrative example

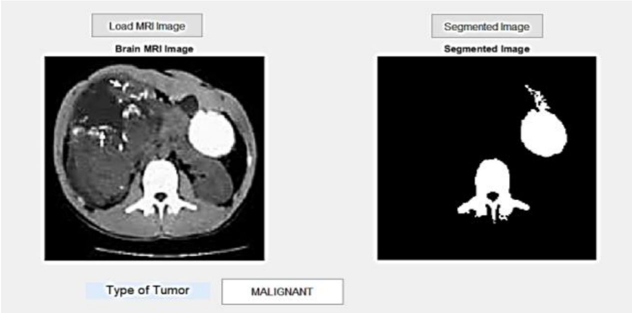

Fig 5. Image depicting the division of a malignant test sample into distinct segments.

Figure 5 displays the segmented picture of the test model, which the model will predict as being cancerous.

Fig 6. The picture of the benign test has been divided into segments.

Figure 6 displays the segmented picture of the test model, which will predict that the image is benign.

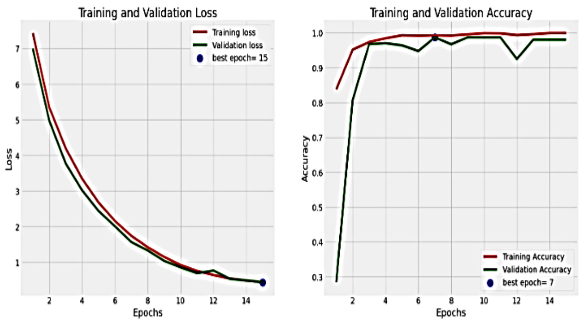

Fig 7. Training and validation loss and accuracy of the model. The optimal epoch is 15, with a secondary option at 7.

Figure 7 displays the model's training accuracy at the best epoch, which is 7, and the model's validation loss at the best epoch, which is 15.

7. Result

7.1 Parameters description

This dataset encapsulates a comprehensive analysis of MRI brain images through various statistical and textural metrics, each offering insights into different aspects of the images:

- Mean: Represents the average of pixel intensities across the image, providing a basic measure of its overall brightness.
- Standard Deviation: Quantifies the dispersion of pixel intensities around the mean, indicating the extent of contrast within the image.
- Entropy: Evaluates the level of unpredictability or complexity in the image's texture, a reflection of the image's detail richness.
- RMS (Root Mean Square): Offers an alternative measure of average brightness, emphasizing the influence of higher intensity values.
- Variance: Measures the expectation of the squared deviation from the mean intensity, further highlighting contrast levels.
- Smoothness: Assesses the uniformity of intensity variations, with lower values indicating a smoother image texture.
- Kurtosis: Determines the peakedness of the image's intensity distribution, with higher values suggesting a sharper peak.
- Skewness: Measures the asymmetry of the intensity distribution, indicating whether the distribution leans towards higher or lower intensities.
- IDM (Inverse Difference Moment): A metric for assessing the image's homogeneity by examining the texture's uniformity.
- Contrast: Captures the difference in luminance or color that enables the distinction of objects within the image.
- Correlation: Evaluates the extent to which a pixel's intensity is predictive of its surroundings, offering insights into the image's texture patterns.
- Energy: Calculates the sum of squared values in the image matrix, serving as an indicator of texture uniformity.
- Homogeneity: Measures how closely the distribution of elements in the image matrix aligns with the diagonal of the matrix, with higher values indicating a more homogeneous texture.

This table appears to represent statistical parameters computed from two test images, likely related to texture analysis for image processing or pattern recognition tasks, such as brain tumor detection or segmentation in medical imaging:

Table 1. Parameters with test images.

Parameters	**Test image -1**	**Test image -2**
Mean	0.00245	0.00123
Standard Deviation	0.0423	0.754
Entropy	2.524	2.745
RMS	0.0236	0.046
Variance	0.00412	0.00436
Smoothness	0.8425	0.8436
Kurtosis	6.2398	5.985
Skewness	0.543	0.239
IDM	-0.214	0.354
Contrast	0.158	0.234
Correlation	0.089	0.234
Energy	0.684	0.328
Homogeneity	0.896	0.872

Table 2. Models with accuracy.

Models	**Accuracy Test image -1**	**Accuracy Test image -2**
RBF Accuracy	65.74	81.24
Linear Accuracy	79.53	81.84
Polygonal Accuracy	82.79	86.24
EfficientNetB3	93.49	94.73

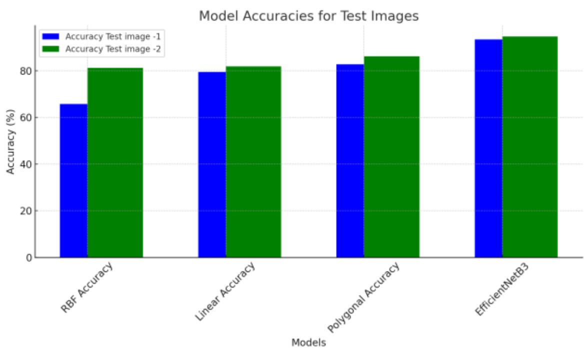

Fig 8. Models with accuracy.

- The graph visually compares the accuracies of four different models—RBF Accuracy, Linear Accuracy, Polygonal Accuracy, and EfficientNetB3—across two test images. Here's a summary of the key observations:
- EfficientNetB3 shows the highest accuracy for both test images, with 93.49% for Test image -1 and 94.73% for Test image -2, indicating superior performance in classifying or analyzing the images.
- Polygonal Accuracy ranks second, demonstrating solid performance with accuracies of 82.79% for Test image -1 and 86.24% for Test image -2.
- Linear Accuracy is slightly lower but still competitive, with accuracies of 79.53% for Test image -1 and 81.84% for Test image -2.
- RBF Accuracy has the lowest performance among the models evaluated, with 65.74% accuracy for Test image -1 and 81.24% for Test image -2, showing a significant improvement in performance from Test image -1 to Test image -2.

8. Conclusion

This study delves into the comparative analysis of different computational models for their capacity to identify and delineate brain tumors within MRI imagery. Traditional methodologies, such as the Radial Basis Function (RBF), Linear, and Polygonal kernels, were scrutinized, revealing accuracies that span from 65.74% to 86.24% across two separate test images. Furthermore, this research explored the capabilities of the EfficientNetB3 model, distinguished by its proficiency in deep learning and its innovative approach to compound scaling. The findings indicated a superior performance by the EfficientNetB3 model, which achieved remarkable accuracy levels of 93.49% and 94.73% on the two evaluated test images, respectively. These outcomes underscore the exceptional potential of the EfficientNetB3 model to enhance the precision of medical imaging analyses significantly, representing a noteworthy progression in the diagnostic and treatment planning processes for brain tumor patients.

Author contributions

Upendra Singh: Conceptualization, Implementation, Software. **Mukul Shukla** : Methodology. **Tarun Sharma**: Field study, Data curation, **Puja Gupta** : Writing-Original draft preparation, Software, **Dr. Rini Saxena** : Validation., Field study. **Preeti Mishra**: Visualization, Investigation, **Sambit Ray :** Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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