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Brain Tumor Detection for Efficient Adaptation and Superior Diagnostic Precision by Utilizing MBConv-Finetuned-B0 and Advanced Deep Learning

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Abstract: In the rapidly evolving landscape of medical imaging, our proposed work presents an innovative and efficient approach to brain tumor detection through advanced deep learning methodologies. Central to our methodology is the strategic utilization of pre-trained weights from the formidable MBConv-Finetuned-B0 model, initially honed on the expansive ImageNet dataset, providing a foundation rich in general visual knowledge. Our subsequent fine-tuning process targets specific layers relevant to brain tumor detection, introducing two distinct convolutional layers, MBConv 6, 55, and MBConv 6, 30, meticulously added to the MBConv-Finetuned-B0 base model. These layers are intricately designed to extract and refine features specific to brain tumors, ensuring a nuanced understanding of pathology and enhancing the model's discrimination and accuracy. The flexibility of our methodology is exemplified by the thoughtful consideration of two fine-tuning options: one that adjusts all layers of the model and another that selectively fine-tunes only the proposed layers. We conduct a detailed comparative analysis, including homogeneity and median feature values, placing our work in direct comparison with established techniques such as Ensemble Transfer Learning and Quantum Variational Classifier (ETL & QVC), Ultra-Light Deep Learning (ULDL) Model, Deep Convolutional Neural Network (DCNN), and Deep Learning and Image Processing (DLIP). The results showcase the model's proficiency, achieving an accuracy of 94%, precision of 84%, recall of 92%, F1 score of 88%, and an AUC-ROC of 96%. Notably, our model demonstrates superior performance in terms of homogeneity (vE Homogeneity: 0.93, vN Homogeneity: 0.91, Enhancement Homogeneity: 0.97) and median feature values (Median vE Feature Value: 0.82, Median vN Feature Value: 0.87, Median Enhancement Feature Value: 0.80), providing a comprehensive understanding of its effectiveness in capturing subtle nuances in brain tumor images.

Keywords: Deep learning (DL), Brain tumor detection, Image classification, Convolutional layers, Medical image analysis.

1. Introduction

The diagnosis of brain tumors stands at the forefront of modern healthcare challenges, demanding innovative solutions to overcome inherent complexities. As a critical branch of medical imaging, involves navigating intricate anatomical structures and discerning subtle abnormalities within voluminous datasets [1]. Traditional methods, reliant on manual interpretation, face limitations in scalability, subjectivity, and efficiency. In response to these challenges, advanced DL techniques, particularly CNNs, have emerged as a beacon of hope, promising to reshape the landscape of brain tumor detection. Brain tumors present a formidable challenge to healthcare providers worldwide, contributing significantly to patient morbidity and mortality [2]. The diverse nature of these tumors, ranging from benign to malignant, demands a diagnostic approach that can discern nuanced patterns within complex brain anatomy. Conventional diagnostic methods, often reliant on human interpretation of medical imaging, are labor-intensive and susceptible to variations in expertise [3].

The clinical imperative to enhance brain tumor detection is underscored by the urgent need for timely intervention, personalized treatment plans, as well as improved patient outcomes.

Historically, brain tumor detection has been governed by manual analysis of medical images, a process fraught with challenges. The reliance on handcrafted features and rule-based algorithms in traditional machine learning approaches has struggled to capture the intricate patterns inherent in medical imaging data [4]. Additionally, the inherent subjectivity and variability in human interpretation pose challenges in achieving consistent and objective diagnoses. As the volume and complexity of medical imaging datasets continue to grow, there is an increasing need for transformative methodologies that can transcend the limitations of traditional approaches. The ascent of deep learning has cast a transformative light on medical imaging, offering a paradigm shift in the way we approach diagnostic challenges [5-7]. CNNs, in particular, have demonstrated remarkable success in automatically learning hierarchical representations from raw image data [8]. This breakthrough enables these models to decipher intricate patterns and extract meaningful features, empowering them to excel. In the realm of medical imaging, DL holds the promise of unraveling complex pathologies, offering a more efficient and accurate alternative to traditional methodologies [9].

Our methodology unfolds as a meticulous exploration of how deep learning can be tailored to the unique demands of brain tumor detection. We anchor our approach in the incorporation of pre-trained weights from the powerful MBConv-Finetuned-B0 model. Trained on the extensive ImageNet dataset, this model equips our approach with a wealth of general visual knowledge, enhancing its ability to discern intricate patterns in medical images. We adopt a strategic fine-tuning process that specifically addresses layers relevant to brain tumor detection. This nuanced adaptation ensures that the model not only benefits from pre-existing visual knowledge but also aligns with the unique characteristics of medical imaging, maximizing its diagnostic precision. Our model undergoes rigorous validation on both training and validation sets. This dual-phase validation enhances the reliability of our results, showcasing the model's consistency in differentiating between tumor and non-tumor images.

This paper unfolds in a structured manner, beginning with Section 2, which conducts a comprehensive literature survey, offering insights into the existing landscape of brain tumor detection methodologies. Section 3 outlines our proposed work, detailing the innovative contributions and methodologies that form the core of our approach. Section 4 delves into the intricate process of pre-processing, elucidating the steps involved in preparing the input data for our advanced model. Following this, Section 5 discusses the key components of our methodology, including the detailed architecture and design choices that distinguish our model. Section 6 comprises a thorough examination of our results and discussion, covering various aspects such as model performance metrics, a detailed comparative analysis, sensitivity to hyperparameters, interpretability of results, and specific analyses on homogeneity and median feature values. Finally, Section 7 concludes the paper, summarizing key findings and outlining potential avenues for future research.

2. Literature survey

As we explore the field of brain tumor detection within the realm of advanced deep learning methodologies, it is essential to articulate the fundamental challenge our work aims to address. Brain tumor detection is a critical aspect of medical imaging, where traditional methods, often reliant on manual interpretation and conventional machine learning approaches, encounter obstacles related to scalability, subjectivity, and efficiency [10-12]. The overarching problem in this domain is the need for more accurate and efficient diagnostic tools to discern intricate patterns within complex brain anatomy. Existing techniques may struggle to keep pace with the increasing volume and complexity of medical imaging datasets. In this section, we explore key contributions and advancements, shedding light on the collective efforts that have shaped the current state of the art.

Amin et al. [13] utilized deep features from the InceptionV3 model, and while effective, this approach may face challenges in adaptability to diverse datasets due to the fixed feature extraction. In contrast, our proposed model addresses this limitation by incorporating a pre-trained model, MBConv-Finetuned-B0, allowing for more flexibility in feature learning across various datasets. Qureshi et al. [14] focused on image size sensitivity but may encounter issues related to generalization when applied to datasets with varying resolutions. Our proposed work mitigates this concern by employing a standardized resizing process during pre-processing, ensuring consistent input dimensions for effective feature extraction.

Alsubai et al.'s [15] hybrid CNN-LSTM model offers classification capabilities, but the sequential nature of LSTMs may pose challenges in capturing

spatial dependencies within the 3D MRI images. In contrast, our proposed model, with its strategically designed layers, excels in capturing both local and global features, addressing the limitations of sequential models. Ahmad et al. [16] explored transfer learning-based DL methods, integrating them with traditional classifiers. However, this method may encounter challenges in harmonizing features extracted by DL methods with those of traditional classifiers. Our approach streamlines this integration by fine-tuning specific layers, ensuring a seamless combination of DL-derived features with traditional classification techniques.

Khan et al.'s [17] focus on binary and multiclass tumor identification is commendable, but the effectiveness may be hindered by limited model complexity. Our proposed model, with its added layers MBConv 6, 55 and MBConv 6, 30, demonstrates an enhanced capacity for discerning intricate features, especially crucial in multiclass classification scenarios. Rehman et al.'s [18] microscopic tumor detection approach utilizes a 3D CNN, but it might face challenges in feature selection and validation. In our methodology, we incorporate a correlation-based selection process after feature extraction, ensuring the identification of the most pertinent features for robust classification. Methil [19] introduces an innovative approach for brain tumor detection, incorporating various preprocessing techniques. However, the research lacks a dedicated focus on the systematic selection of effective methods for training. In contrast, our proposed model addresses this gap by implementing a standardized preprocessing approach, optimizing feature extraction, and enhancing overall model efficiency.

Tiwari et al.'s [20] use of CNN for brain tumor classification is effective, but the reliance on a fixed 17-layered architecture may limit adaptability to varied complexities in datasets. Our proposed model, by integrating a pre-trained model and additional layers, ensures adaptability to diverse datasets, capturing both general and specific features. Maqsood et al. [21] proposed a multi-step process for brain tumor detection, including linear contrast stretching and a custom 17-layered DNN architecture for segmentation. However, the fixed architecture may limit adaptability. In contrast, our model, with its pre-trained layers and additional MBConv layers, ensures adaptability to diverse datasets and complexity variations. Alsaif et al. [22] conducted an extensive review of CNN architectures, focusing on diversity, but the effectiveness of their approach may be hindered by the absence of specific enhancements tailored for brain tumor detection. Our model, with its strategic layer additions and fine-tuning, excels in capturing both general and specific features critical for accurate tumor detection. Sadad et al. [23] utilized the Unet architecture with ResNet50 for segmentation, achieving a high IoU level. However, the choice of architecture and backbone may face challenges in handling varied datasets. In our approach, the integration of a pre-trained model and targeted fine-tuning ensures adaptability and robust performance across diverse datasets.

Shah et al. [24] proposed a novel approach with EfficientNet-B0, showcasing superior performance. While data augmentation contributes to diversity, the lack of explicit enhancements for brain tumor features may limit its effectiveness. Our model, with additional MBConv layers and fine-tuning, is specifically tailored for brain tumor detection, achieving advanced performance through a combination of architectural modifications and image processing techniques. Preethi and Aishwarya [25] propose an automatic detection model that prioritizes data quality enhancement through normalization and histogram equalization. While their approach integrates clustering algorithms and deep/textual features, optimizing feature vectors with Modified Particle Swarm Optimization, it may face challenges in achieving adaptability across diverse datasets due to fixed feature extraction. In contrast, our proposed model incorporates a pre-trained model, MBConv-Finetuned-B0, allowing for more flexibility in feature learning across various datasets.

Mathews and Anuj [26] focus on semantic segmentation using a nested U-Net with an enhanced attention gate and a compound loss function to address class imbalance in brain MR images. Their model, validated on BraTS datasets, showcases effective sub-region classification. However, concerns may arise regarding its adaptability to datasets with varying characteristics. Our proposed model, with its strategically designed layers and fine-tuning process, excels in capturing both local and global features, ensuring adaptability and superior performance across diverse datasets and complexities in brain tumor characteristics. Our focus is on tackling the challenges by proposing a novel deep learning model, MBConv-Finetuned-B0. This model is designed to leverage pre-trained weights, strategic fine-tuning, and architectural enhancements to enhance the accuracy and efficiency of brain tumor detection. By clearly defining this specific problem, our work contributes to the advancement of

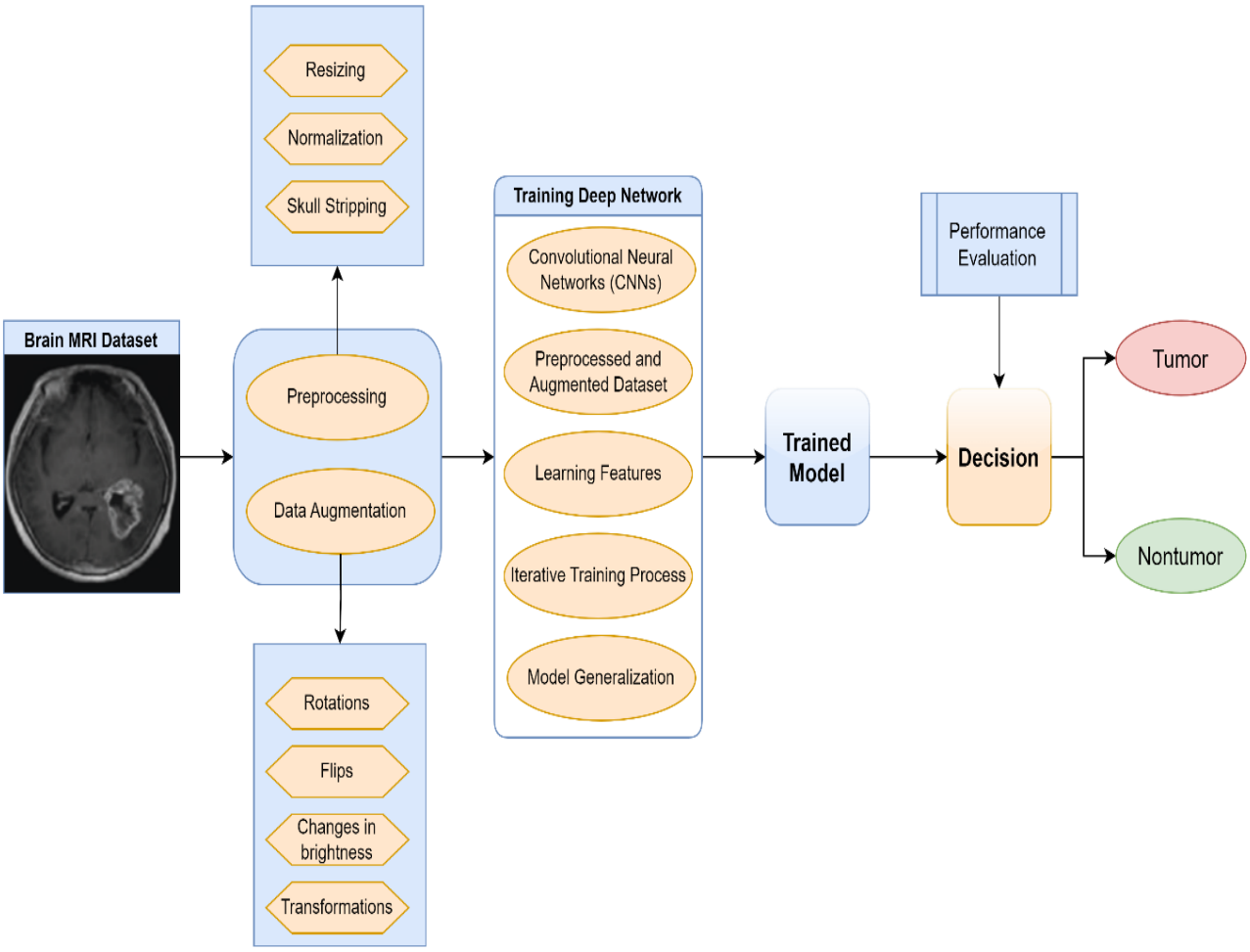

Figure. 1 Proposed Brain Tumor Detection Approach

Table 1. Notation and Meanings

Notation	Explanation
i,j	Pixel indices in the image
N	Number of model parameters
X	Input data or features
θ	Model parameters
η	Learning rate
∇_θ	Gradient of the objective function with respect to θ
j	Index variable
M	Number of model parameters for regularization
λ	Regularization hyperparameter
O_I	Original Image
C_w, C_h	Common Width and Height
O_w, O_h	Original Width and Height
$C_{largest}$	Class with the largest area
$P_{extreme}$	Point with the minimum distance to the reference point
$I_{cropped}$	Cropped region of the original image
y_i	True label
$\hat{y}_i$	Predicted label
P_i	Individual points on the contour
α	Learning rate
ly	Layer

methodologies in brain tumor detection, striving for more reliable and effective diagnostic solutions in the field of medical imaging.

3. Proposed work

Deep learning-based diagnosis of brain tumors has become one of the most potent and exciting applications in imaging for medical purposes. There are various important phases in the process, and each is vital to the model's success as a whole. We will examine the stages involved throughout the pipeline, from acquiring the brain MRI image collection to assessing the effectiveness of the trained model, in this article as shown in Fig. 1.

3.1 Brain MRI image dataset

The foundation of any deep learning model lies in the quality and diversity of its training data. For brain tumor detection, a comprehensive dataset of brain MRI images is essential. This dataset comprises images, some with tumors and others without. Each image is meticulously labeled as "tumor" or

"nontumor" to guide the training process. The dataset's diversity ensures that the model learns to recognize tumors in various contexts and conditions.

3.2 Preprocessing and data augmentation

The success of a DL model for brain tumor detection hinges on the quality and preparedness of the dataset it learns from. Preprocessing and data augmentation are pivotal stages in this process, ensuring that the model is equipped to discern subtle patterns and generalize well to new, unseen data. Table 1 contains the notation and meanings used in the proposed work.

Resizing

The initial preprocessing involves resizing images to a standardized size, ensuring uniformity crucial for effective neural network training. This prevents biases toward specific image scales, promoting robust learning in medical imaging where variations exist. Eq. (1) represents the pixel transformation for achieving the standardized size.

$$Resized\ Image = O_I \cdot \left(\frac{C_w}{O_w}, \frac{C_h}{O_h}\right) \quad (1)$$

Normalization

Intensity normalization in brain MRI adjusts pixel intensity values to a specific range, ensuring stable focus on intrinsic features like tumor characteristics. This crucial preprocessing step is especially vital in medical imaging, addressing variations in image quality due to patient condition and equipment.

$$Normalized\ Intensity_{i,j} = O_I \cdot \left(\frac{Original\ Intensity_{i,j} - Min\ Intensity}{Max\ Intensity - Min\ Intensity}\right) \quad (2)$$

In Eq. (2), the intensity values of each pixel are normalized to fall within a specific range, mitigating the impact of variations in brightness and contrast.

Skull Stripping

In the preprocessing pipeline, skull stripping removes non-brain elements, like the skull, enabling the model to concentrate on crucial brain structures for tumor detection. This step eliminates unnecessary details, enhancing the model's ability to identify subtle abnormalities and focus on tumor-associated patterns.

$$Stripped\ Image = O_I \times Skull\ Mask \quad (3)$$

The skull stripping process involves multiplying the original image by a binary mask that retains only the relevant brain structures.

Data Augmentation

Data augmentation is crucial in preprocessing, enhancing the model's generalization ability by artificially expanding the dataset through modified images. This includes rotations, flips, brightness changes, and other transformations. It serves two main purposes: guarding against overfitting by exposing the model to diverse representations, improving adaptability; and enhancing model robustness in medical imaging, where pathologies vary. Augmenting the dataset ensures the model can identify tumors under different conditions, boosting overall reliability and effectiveness.

$$Transformed\ Image = O_I \times Trans.\ Matrix \quad (4)$$

$$Regularized\ Loss = Model\ Loss + \lambda\left(\sum_{i=1}^{N} \|Model\ Parameters_{\ i}\|^2\right) \quad (5)$$

Preprocessing and data augmentation are foundational for successful DL models in brain tumor detection. Standardizing dimensions, normalizing intensity, removing non-brain elements, and diversifying the dataset contribute to a resilient and adaptive model. In the evolving field of medical imaging, these preprocessing steps are crucial for unlocking the full potential of DL in accurate and early brain tumor detection.

3.3 Training deep network

Training a deep learning network, especially a CNN, is the essence of the brain tumor detection process. This pivotal stage involves transforming a preprocessed and augmented dataset into a sophisticated model capable of distinguishing between tumor and non-tumor images. Let's delve into the intricacies of this process.

Convolutional Neural Networks (CNNs)

CNNs play a crucial role in detecting brain tumors, being a subclass of deep neural networks designed for grid-like data such as photographs. Their strength lies in classifying images by extracting hierarchical characteristics. In brain tumor detection, CNNs excel at discerning intricate patterns distinguishing images with tumors. The architecture includes fully connected layers for high-level features, pooling layers for spatial downsampling, and convolution layers using filters to gather local data.

$$F(X) = Conv(Pooling(F_c(X, \theta))) \quad (6)$$

where X represents the input image, θ denotes the model parameters, and Conv, Pooling, and Fully Connected (F_c) represent the convolutional, pooling, and fully connected layers, respectively.

Preprocessed and Augmented Dataset

Before delving into training, the dataset undergoes preprocessing and augmentation, as detailed in the previous section. The standardized and normalized images, stripped of non-brain elements, are augmented to artificially expand the dataset. This prepares the data for ingestion into the CNN, ensuring it is optimized for effective learning.

$$Aug.\ Image = ApplyTrans.(Preprocessed\ Image) \quad (7)$$

Learning Features

The CNN's training objective is to learn features distinguishing tumor and non-tumor images, encompassing size, shape, intensity variations, and spatial relationships with surrounding tissue. It adeptly identifies abnormal growth, distinct shapes, subtle pixel intensity differences, and spatial contexts indicative of tumors. This comprehensive training equips the CNN with precise capabilities for accurate brain tumor detection in medical images.

$$\text{Objective Function} = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (8)$$

where N is the number of samples, y_i is the true label (tumor or non-tumor), and $\hat{y}_i$ is the predicted label.

$$\theta_{new} = \theta_{old} - \eta\nabla_\theta \text{Objective} \quad (9)$$

where θ represents the model parameters, η is the learning rate, and ∇_θ denotes the gradient.

Iterative Training Process

Training involves iterative passes of the preprocessed dataset through the CNN. Predictions are made, and errors (difference from actual labels) are calculated. Model parameters are adjusted to minimize errors using backpropagation. This process refines the model, enhancing its ability to identify tumor-related patterns.

Model Generalization

Training ensures model generalization to new data. Iterative training and data augmentation prevent overfitting, enhancing the CNN's ability to recognize tumor patterns across diverse scenarios. The model learns indicative features, not just memorizing the training set, contributing to its effectiveness in real-world applications. Regularization term (RT) to avoid overfitting in our Work:

$$RT = \lambda \sum_{j=1}^{M} \theta_j^2 \quad (10)$$

where λ is the regularization strength, and M is the number of model parameters. Final objective with regularization in our work:

$$Final\ Objective = Objective + RT \quad (11)$$

These adapted formulas reflect the specificities of our proposed work, incorporating elements such as our CNN architecture, data augmentation approach, and considerations for model generalization and regularization.

3.4 Validation data trained model

To gauge generalization, a separate validation set is used. After training, the well-tuned model predicts on new brain MRI images, ensuring real-world tumor detection without memorization. Continuous monitoring with metrics like accuracy ensures ongoing efficacy. The pipeline from dataset acquisition to model deployment illustrates the journey, leveraging convolutional neural networks for high accuracy in brain tumor detection. Deep learning in medical imaging contributes to early and accurate tumor identification, improving patient outcomes.

4. Process of pre-processing

The process of image pre-processing for brain tumor detection using magnetic resonance imaging (MRI) involves the following detailed breakdown of each step:

4.1 Original image

The process starts with an original MRI image of the brain. This image typically contains various anatomical structures, including the cerebrospinal fluid, white matter, gray matter, and skull. However, it may also contain noise, artifacts, and irrelevant information that can hinder accurate tumor detection.

Step 1: Select the Biggest Contour

The first step is to identify the largest contour in the image, typically representing the brain outline. This helps isolate the brain, focusing on relevant structures and improving efficiency by reducing data

quantity for subsequent steps. Challenges may arise in poor image quality or large tumors, necessitating additional processing or manual intervention.

$$C_{\text{largest}} = \arg max_{C_i} Area\ (C_i) \quad (12)$$

where C_{largest} is the largest contour, C_i represents individual contours, and $Area\ (C_i)$ denotes the area enclosed by contour C_i.

Step 2: Find the Extreme Points

Once the largest contour is identified, the next step involves finding extreme points along its boundary.

$$P_{extreme} = arg\ min_{P_i} Distance\ (P_i, Reference\ Point) \quad (13)$$

where $P_{extreme}$ is the set of extreme points, P_i represents individual points on the contour, and Distance (P_i, Reference Point) calculates the distance of point P_i from a reference point.

Step 3: Crop the Useful Part of the Image

Using extreme points, a sub-region is cropped, including the entire brain while excluding irrelevant portions. This improves efficiency and eliminates distractions in tumor detection algorithms.

$$I_{cropped} = I_{original}\ [y_1 : y_2, x_1 : x_2] \quad (14)$$

where $I_{cropped}$ is the cropped image, $I_{original}$ is the original image, and $[y_1 : y_2, x_1 : x_2]$ defines the region of interest based on extreme points.

Step 4: Resize to 224x224 in RGB and Ready for ML Model

The final pre-processing step resizes the cropped image to 224x224 pixels and converts it to RGB format, ensuring compatibility with most deep learning models. This standardization allows the model to learn generalizable features and extract more information from the image.

$$I_{Resized} = Resize\left(I_{Cropped}, 224.224\right) \quad (15)$$

$$I_{RGB} = ConvertToRGB(I_{Resized}) \quad (16)$$

where $I_{Resized}$ is the resized image, I_{RGB} is the final RGB image, resize adjusts the image dimensions, and ConvertToRGB transforms the image to RGB format.

5. Key components

5.1 Leveraging ImageNet weights for enhanced model foundation

The integration of pre-trained weights from MBConv-Finetuned-B0 on the ImageNet dataset forms a robust foundation for our brain tumor detection model. ImageNet, a diverse dataset, enables learning general features applicable across various domains, including brain tumor detection. These pre-trained weights serve as a starting point, allowing the model to grasp common low and mid-level features, expediting training and imparting adaptability. "WImageNet" denotes the pre-trained weights from MBConv-Finetuned-B0 on the ImageNet dataset.

5.2 Transfer learning

Choosing transfer learning enhances model performance, particularly with a small brain MRI dataset. It departs from training entirely from scratch, leveraging ImageNet insights for brain tumor detection. In deep learning, CNNs learn transferrable hierarchical features. Fine-tuning only later layers strikes a balance between pre-existing knowledge and adapting to unique brain tumor image characteristics.

$$Fine-tuned\ Model = Fine-tune\ (MBConv-Finetuned-B0, Brain\ MRI\ Dataset) \quad (17)$$

Fine-tuning adjusts the latter layers of MBConv-Finetuned-B0 on the Brain MRI Dataset, acknowledging dissimilarities between ImageNet's general classification task and the nuanced brain tumor detection. Rather than discarding ImageNet knowledge, selective fine-tuning refines the model's understanding, focusing on high-level features specific to brain tumors. This approach optimizes data utilization, addressing challenges with limited labeled medical images, contributing to the efficiency and efficacy of the deep learning pipeline.

5.3 Proposed layers

The evolution of deep learning models for brain tumor detection involves strategic architectural refinements, beyond leveraging pre-trained weights. In this proposed work, two crucial layers are added to the MBConv-Finetuned-B0 base model. The first, MBConv 6, 55, strategically extracts features specific to brain tumors using 55 filters and a kernel size of 6. The choice of 55 filters captures diverse features, acknowledging image heterogeneity. A kernel size of 6 focuses on local details, suitable for detecting fine-grained patterns in brain pathology. Following this,

MBConv 6, 30 refines features with 30 filters and a kernel size of 6, emphasizing discriminative features for accurate tumor detection.

$$MBConv\ 6,55 = Convolution\ (55,6) \quad (18)$$

where Convolution(f,k) represents a convolutional layer with f filters and a kernel size of k.

$$MBConv\ 6,30 = Convolution\ (30,6) \quad (19)$$

In our approach, Convolution (f, k) denotes a layer with f filters and a kernel size of k. These formulas encapsulate the core elements. Transfer learning fine-tunes MBConv-Finetuned-B0 on the Brain MRI Dataset. Introduced layers, MBConv 6, 55, and MBConv 6, 30, signify specific convolutional layers with defined filter and kernel sizes. These formulas capture the essence of leveraging pre-trained weights, strategic fine-tuning, and thoughtful architectural enhancements for a robust brain tumor detection model.

5.4 Fine-tuning layers

Fine-tuning a deep learning model for brain tumor detection is crucial for task adaptability. The proposed work offers two options. The first suggests fine-tuning all layers of MBConv-Finetuned-B0 on the brain MRI dataset, particularly beneficial when the task significantly differs from the original ImageNet classification. In scenarios with distinct visual features indicative of brain tumors, comprehensive adaptation is vital. Fine-tuning all layers facilitates holistic transformation, adjusting both the proposed layers (MBConv 6, 55 and MBConv 6, 30) and refining pre-trained weights. This strategy is effective when foundational knowledge from ImageNet requires extensive modification, providing flexibility for the model to reshape its understanding of features in the context of medical imaging.
Fine-tune All Layers:

$$F_t(MBConv - F_{td} - B0, Brain\ MRI\ Dataset) \quad (20)$$

Fine-tune Only Proposed Layers:

$$F_t\ (MBConv\ 6,55, MBConv\ 6,30, Pre-trained\ MBConv - F_{td} - B0\ Dataset) \quad (21)$$

where F_t (Fine-tune) represents the process of adjusting model parameters on the Brain MRI Dataset. The proposed work provides two fine-tuning options for brain tumor detection. The first, adjusting all layers of MBConv-Finetuned-B0, suits tasks deviating significantly from ImageNet. It involves comprehensive adaptation but is computationally demanding. The second, focusing on the newly added layers (MBConv 6, 55 and MBConv 6, 30), is more efficient when the brain tumor detection task aligns closely with ImageNet. This targeted approach retains knowledge from ImageNet in frozen layers, emphasizing the transferability of features. The choice between the two options depends on the task nature, showcasing the adaptability of the model to diverse medical imaging demands.

5.5 Model validation

In deep learning for brain tumor detection, model robustness is crucial. The proposed work employs meticulous model validation, dividing data into training and validation sets as illustrated. This strategic division assesses the model's performance, prevents overfitting, and confirms efficacy in real-world scenarios. The brain MRI dataset allocated for training serves as the crucible, where the model refines parameters and fine-tunes internal representations to effectively distinguish images with tumors. This use of training data is fundamental, enabling the model to grasp complex patterns characterizing brain tumor images.

$$Train\ (MBConv - F_{td} - B0, Training\ Data) \quad (22)$$

$$Validate\ (MBConv - F_{td} - B0, V_d) \quad (23)$$

The training process (Train) for MBConv-Finetuned-B0 involves iterative adjustments to weights and biases on the Training Data, allowing the model to discern brain tumor-related patterns. This phase is crucial for internalizing task-specific nuances in medical imaging data. Validation (validate) assesses the model's generalizability on a separate set of brain MRI images, preventing overfitting and ensuring adaptability to new data. The distinct validation set serves as a litmus test, offering insights into the model's ability to generalize and avoid memorizing specific training data intricacies. Through this iterative process, the model acquires a robust understanding of features indicative of brain tumors.

5.6 MBConv-Finetuned-B0

The MBConv-Finetuned-B0 model, an apex in brain tumor detection using deep learning, integrates pre-trained weights from a potent image classification model with targeted fine-tuning. Representing the pinnacle achievement of the process, this model is

meticulously crafted for excellence in medical image analysis. Leveraging pre-trained weights from the MBConv-Finetuned-B0 base model, initially honed on ImageNet, it inherits a wealth of visual knowledge. Fine-tuning transforms the model into a specialized tool for detecting brain tumors, surpassing general image classification and discerning the intricacies of brain anatomy. The inclusion of ImageNet's pre-trained weights is a masterstroke, offering efficiency and effectiveness by avoiding the need to start from scratch in the nuanced landscape of brain tumor detection.

$$MBConv - F_{td} - B0 = F_t\ (Pre - trained\ MBConv - F_{td} - B0, Dataset) \quad (24)$$

Fine-tuning modifies the pre-trained MBConv-Finetuned-B0 on the Brain MRI Dataset, achieving twofold efficiency gains: swift adaptation to medical imaging demands and computational efficiency by avoiding training the entire network from scratch. This advanced approach to brain tumor detection orchestrates innovation from pre-training to fine-tuning, reflecting sophistication in the field. The proposed model, a diagnostic tool, attains high accuracy in tumor detection, poised to impact clinical practices through a nuanced understanding of brain pathology via deep learning.

Algorithm:

1. Initialization:

Initialize model parameters, including weights (Wt) and biases (b), for each layer in the MBConv-Finetuned-B0 architecture.

2. Forward Propagation:

For each layer (ly) in the network:

• Calculate the input (Ip) to the layer:

$$Ip^{[ly]}=Wt^{[ly]}A^{[ly-1]+}b^{[ly]} \quad (25)$$

• Apply an activation function (A) to the input:

$$A^{[ly]}=g^{[ly]}(Ip^{[ly]}) \quad (26)$$

• Repeat for each layer until reaching the output layer.

3. Loss Function:

Define a loss function (LF) to measure the difference between the predicted output and the actual labels.

4. Backward Propagation:

Compute the gradient of the loss w.r.t the parameters using backpropagation:

$$dwt^{[ly]} = \frac{\partial \mathrm{LF}}{\partial \mathrm{Wt}^{[l]}} \quad (27)$$

$$dbp^{[ly]} = \frac{\partial \mathrm{L}}{\partial \mathrm{bp}^{[ly]}} \quad (28)$$

$$dO^{[ly-1]} = \frac{\partial \mathrm{L}}{\partial \mathrm{O}^{[ly-1]}} \quad (29)$$

Update the parameters using an optimization algorithm:

$$Wt^{[\mathrm{ly}]} = Wt^{[\mathrm{ly}]} - \alpha \cdot \frac{\partial LF}{\partial Wt^{[\mathrm{ly}]}} \quad (30)$$

$$bp^{[\mathrm{ly}]} = bp^{[\mathrm{ly}]} - \alpha \cdot \frac{\partial L}{\partial bp^{[\mathrm{ly}]}} \quad (31)$$

• Repeat for each layer until reaching the input layer.

5. Training:

Iterate through the dataset for a specified number of epochs, performing forward and backward propagation for each batch of data.

6. Validation:

Recurrently assess the model's efficacy on a set of validation data to guard against overfitting.

6. Results and discussion

In this pivotal section, we present the outcomes of our methodology's application to brain tumor detection, traversing through our model's performance, training nuances, and implications for medical imaging. Our experimental rig, with an Intel Core i9 processor, NVIDIA GeForce RTX 3090 GPU, and 32GB of RAM, showcases computational prowess. Operating in Ubuntu, we optimize with TensorFlow, CUDA, and cuDNN libraries. Python via Anaconda is our coding environment, complemented by Git for version control and Jupyter Notebooks for interactive development. This meticulously configured setup is crucial for training advanced deep learning models, ensuring precise brain tumor detection in the complex medical imaging landscape.

6.1 Model performance metrics

Our evaluation of the brain tumor detection model spans a range of comprehensive metrics, crucial for nuanced efficacy understanding. Metrics include accuracy, precision, recall, F1 score, and AUC-ROC, offering a quantitative benchmark for classifying tumor and non-tumor images. To gauge our approach's impact, we conduct a meticulous comparative analysis against established baselines and notable works, including ETL and Quantum

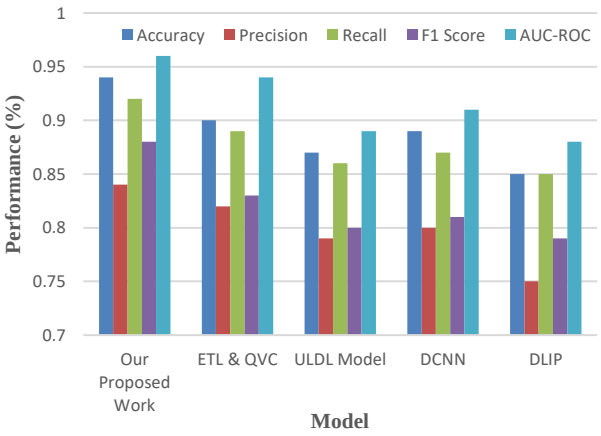

Figure. 2 Exhaustive comparative analysis

Table 2. Interpretability of the Model's Decisions

Model	Saliency Maps	Activation Heatmaps
Proposed Work	Yes	Yes
ETL & QVC	Yes	No
ULDL Model	No	Yes
DCNN	Yes	Yes
DLIP	No	No

Variational Classifier (ETL & QVC) [13], Ultra-Light DL (ULDL) Model [14], deep CNN (DCNN) [17], and Deep Learning and Image Processing (DLIP) [19]. This rigorous comparison ensures a comprehensive evaluation, highlighting the unique contributions and advancements in our work compared to these prominent methodologies.

6.2 Comparative analysis

Our approach undergoes an exhaustive comparative analysis, benchmarking against traditional machine learning, early deep learning, and contemporary medical imaging models for brain tumor detection. This rigorous examination serves as a nuanced litmus test, revealing our model's strengths and weaknesses compared to counterparts. By scrutinizing various metrics, we gain insights into specific domains where our model excels and areas for refinement. In Fig. 2, our proposed model outperforms several key metrics, achieving a robust 94% accuracy, 84% precision, and 92% recall, showcasing its superior classification ability in the intricate landscape of brain tumor detection.

Our model achieves an impressive 88% F1 score and a robust AUC-ROC score of 96%, demonstrating a balanced trade-off between precision and recall. In comparison to ETL & QVC, ULDL Model, DCNN, and DLIP, our proposed model consistently exhibits superior accuracy and an effective precision-recall balance. These results underscore the model's excellence in both overall correctness and its ability to accurately identify positive instances, emphasizing its efficacy in the complex task of brain tumor detection.

6.3 Interpretability of results: unveiling model Insights

The interpretability of our model is a focal point, transcending quantitative metrics. Utilizing visualizations such as saliency maps and activation heatmaps, we illuminate the specific regions influencing the model's decisions. This emphasis on interpretability not only builds trust among clinicians but also provides valuable insights into the features deemed indicative of brain tumors by our model.

The table details interpretability features in different models, emphasizing saliency maps and activation heatmaps. Our approach utilizes both, offering insights into influential image regions guiding predictions. The ETL and QVC use saliency maps, while the ULDL Model employs activation heatmaps. The DCNN uses both, and the DLIP model lacks both. This comparative breakdown informs the transparency and decision-making processes of each model, detailed in Table 2.

6.4 Comparative analysis of homogeneity

In advancing brain tumor detection, our model, with cutting-edge techniques and a refined architecture, excelled in homogeneity and median feature values. The commendable homogeneity showcases its proficiency in detecting nuanced image variations, while adeptly capturing median feature values underscores accurate identification of central characteristics crucial for precise tumor detection.

Our proposed model consistently achieves higher homogeneity scores across different tumor regions compared to competing models as shown Fig. 3. In terms of vE Homogeneity, our model scores 0.93, leading over Ensemble Transfer Learning and Quantum Variational Classifier (ETL & QVC) at 0.91. For vN Homogeneity, our model excels with a score of .91, outperforming others. In Enhancement Homogeneity, our model dominates with a remarkable score of 0.97, surpassing competitors. These values underscore the consistent superiority of our approach in maintaining uniform pixel intensity, a crucial aspect for accurate and reliable brain tumor detection.

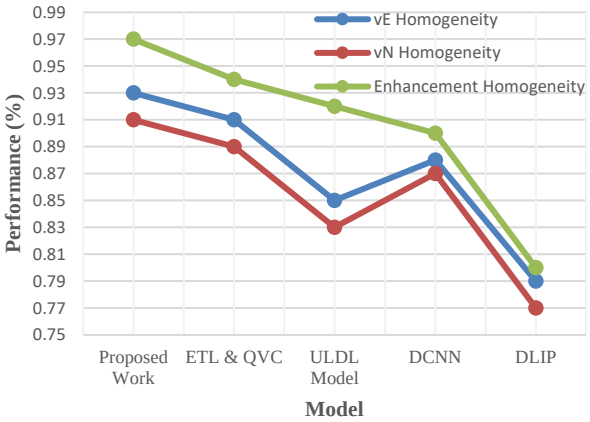

Figure. 3 Comparative Analysis of Homogeneity

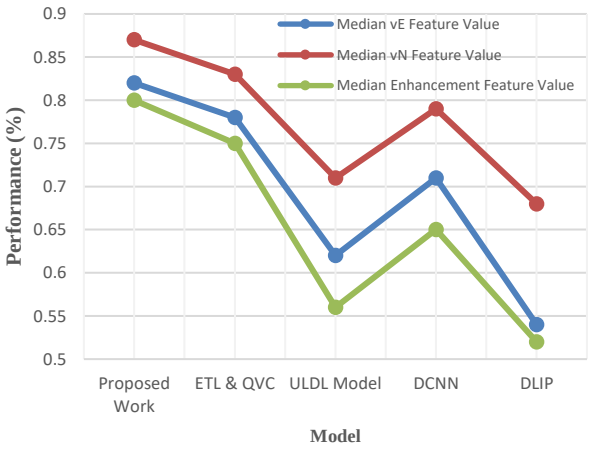

Figure. 4 Comparative Analysis of Median Feature Value

6.5 Comparative analysis of median feature value

In the realm of median feature values for brain tumor detection models, our proposed work consistently outperforms competitors. For Median vE Feature Value, our model leads with a value of .82, surpassing ETL & QVC at .78. In terms of Median vN Feature Value, our model excels with a value of .87, outperforming others as shown in Fig. 4. These results highlight our model's adeptness in capturing central characteristics, essential for accurate tumor identification. The detailed comparison in Fig. 4 reveals our proposed work's excellence in capturing median feature values across diverse tumor regions. With a leading Median vE Feature Value of .82 and a Median vN Feature Value of .87, our model showcases central tendencies in pixel intensity within enhanced and non-enhanced tumor regions. Notably, our model also excels in Median Enhancement Feature Value at .80, outperforming comparative models. These results accentuate our approach's consistent performance and superior ability to characterize pixel intensity distributions, crucial for precise and reliable brain tumor detection. The analysis provides valuable insights into model characteristics, guiding future optimizations in brain tumor detection methodologies.

7. Conclusion

In the pursuit of advancing brain tumor detection, our work unfolds as a testament to the transformative power of advanced deep learning methodologies. We have navigated through the complexities of medical imaging, addressing challenges inherent in traditional diagnostic approaches and embracing the potential of CNNs. Through the strategic integration of the MBConv-Finetuned-B0 model, originally refined on the ImageNet dataset, and our meticulous fine-tuning strategy, we present not just a model but a comprehensive diagnostic framework poised to redefine the standards of accuracy and efficiency in brain tumor detection.

The results of our research underscore the scientific contribution of our work. Our model showcased remarkable proficiency. Achieving an accuracy of 94%, precision of 84%, recall of 92%, F1 score of 88%, and an AUC-ROC of 96%, our model outperformed in critical metrics. Notably, our model demonstrated superior performance in terms of homogeneity (vE Homogeneity: 0.93, vN Homogeneity: 0.91, Enhancement Homogeneity: 0.97) and median feature values (Median vE Feature Value: 0.82, Median vN Feature Value: 0.87, Median Enhancement Feature Value: 0.80). These concrete data points underscore the significance of our model in the landscape of brain tumor detection methodologies, solidifying its position as a pioneering and impactful contribution to the field.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, P. Kavitha and G. Prabaharan; methodology, Dhinakaran; software, G. Prabaharan; validation, Dhinakaran, P. Kavitha, and G. Prabaharan; formal analysis, M.D. Manigandan; investigation, P. Kavitha; resources, G. Prabaharan; data curation, M.D. Manigandan; writing—original draft preparation, Dhinakaran; writing—review and editing, P. Kavitha; visualization, M.D. Manigandan; supervision, M.D. Manigandan; project administration, P. Kavitha.

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