



## A ROBUST APPROACH FOR BRAIN TUMOR DETECTION IN MAGNETIC RESONANCE IMAGES USING FINETUNED EFFICIENT NET

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### ABSTRACT:

A brain tumor is a disorder caused by the growth of abnormal brain cells. The survival rate of a patient affected with a tumor is difficult to determine because they are infrequent and appear in various forms. These tumors can be identified through Magnetic Resonance (MRI) Images, which plays an essential role in determining the tumor site; however, manual detection is a time-consuming and challenging procedure that can cause some errors in results. The adoption of computer-assisted approaches is essential to help in overcoming these constraints. With the advancement of artificial intelligence, deep learning (DL) models are being used in medical imaging to diagnose brain tumors using MR images. In this study, a deep convolution neural network (CNN) EfficientNet-B0 base model is fine-tuned with our proposed layers to efficiently classify and detect brain tumor images. The image enhancement techniques are used by applying various filters to enhance the quality of the images. Data augmentation methods are applied to increase the data samples for better training of our proposed model. The results show that the proposed fine-tuned state-of-the-art EfficientNet-B0 outperforms other CNN models by achieving the highest classification accuracy, precision, recall, and area under curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection. Other DL algorithms such as VGG16, InceptionV3, Exception, ResNet50, and InceptionResNetV2 are used for comparative analysis.

### 1. INTRODUCTION

A brain tumor is a disorder caused by the development of abnormal cells or tissues in the brain [1]. Cells generally reproduce and die in a regular sequence, with each new cell replacing the previous one. However, some cells become abnormal and continue to grow, causing severe damage to the brain functions, and often leading to death. A minimum of 120 multiple types of brain tumors and the central nervous system (CNS) exist. According to the American Cancer Society, 18,600 adults and 3,460 children Under 15 will die due to brain and CNS tumors in 2021. The 5-year survival rate for the patients having brain tumors is only 36%, and the 10-year survival rate is 31% [2]. Furthermore, National Cancer Institute reported 86,010 multiple cases of brain cancer and CNS cancers diagnosed in the United States in 2019. It was predicted that roughly 0.7 million people in the United States suffer from brain tumors. A total of 0.86 million cases were identified, of which 60,800 patients had benign tumors, and 26,170 patients had malignant tumors [3]. World Health Organization reported that 9.6 million people worldwide are estimated to have been diagnosed with cancer in 2018 [4].

One of the most significant aspects of saving a patient's life is early brain tumor diagnosis. The proper examination of brain tumor images is vital in evaluating a patient's condition. The conventional method of detecting brain tumors includes a doctor or radiologist examining magnetic resonance (MR)

images for anomalies and making decisions. However, it is strongly dependent on a doctor's medical expertise; disparities in experience levels and nature of images create extra complexity for diagnosing with naked human eyes [5]. It is challenging for a doctor to interpret these images in a limited period since they contain several abnormalities or noisy data. As the volume of information increases, assessing a massive amount of information gets even more challenging. The manual detection of a brain tumor becomes more time-consuming and costly. Therefore, an automatic computer-aided diagnostic (CAD) system is required to assist doctors and radiologists in the timely detection of these deadly tumors to save precious human lives.

Artificial intelligence (AI) is a field of computer science that aims to give computers human-like intelligence, allowing them to learn, think, and resolve issues when confronted with various information. AI plays an essential role in identifying and diagnosing brain tumors. The discipline of brain tumor surgery is an excellent choice for additional AI integration due to its complicated and elaborate processes. Multiple attempts have been made to establish a highly accurate and reliable approach for brain tumor classification. However, the wide range of shape, texture, and contrast changes across and among individuals remains a difficult challenge to solve. Machine learning (ML) and deep learning (DL), subsets of AI, have recently revolutionized neurosurgical procedures. They consist of data

preprocessing, feature extraction, feature selection, feature reduction, and classification. According to the study [6] because of AI, neurosurgeons can leave the operating room more confident than ever in terms of their patient's brain tumor diagnosis.

Deep learning particularly neural networks, gains substantial importance when it obtains promising results. Convolutional neural networks (CNNs) are remarkable for learning features and providing unlimited precision. Many deep learning applications have been developed, including pattern categorization, object detection, voice recognition, and other decision-making tasks, [7], [8]. In previous studies, traditional ML algorithms such as support vector machines (SVMs), k-nearest neighbor (k-NN), decision trees, and Naive Bayes and DL algorithms, such as custom CNNs, VGG Nets [9], Google Net [10], and Res Nets [11]. Existing approaches have lower precision and recall levels, resulting in low efficiency and requiring more time for image classification, which could delay the patient's treatment

[12]. Deep learning has recently been used in studies to boost the effectiveness of computer-aided medical diagnostics in brain cancer investigation. They play an essential role in the healthcare profession and act as valuable tools in various vital disorders, including brain disease diagnosis and skin cancer image analysis [13], [14]. DL methods based on transfer learning and fine-tuning are preferred and widely used for the classification of Brain tumors. The motivation of this research is to conduct extensive experimentation using deep convolutional neural networks, transfer learning, and fine-tuning to automate the process of brain tumor classification and detection. The primary contributions of our proposed study are:

- A new automated method based on the state-of-the-art EfficientNet-B0 model is fine-tuned with our recommended layers, which can replace conventional invasive brain tumor classification and enhance overall classification accuracy.
- An initial three-step image preprocessing strategy is employed to enhance the low visual quality of the MRI images.
- The data augmentation strategy is utilized to generate better outcomes on small datasets, and the effect of over-fitting phenomena on classification is studied.
- A comparative analysis is conducted regarding the accuracy, weight sizes, and parameters between our proposed model and other state-of-the-art deep CNNs models used in this study. The proposed model outperformed the other CNNs in every aspect.

#### **SCOPE OF THE PROJECT**

The main scope of the project is tumors can be identified through Magnetic Resonance (MRI) Images, which plays an essential role in determining

the tumor site. Using with artificial intelligence, deep learning (DL) models are being used in medical imaging to diagnose brain tumors using MR images. In this study a deep convolution neural network (CNN) EfficientNet-B0 base model is fine-tuned with our proposed layers to efficiently classify and detect brain tumor images.

#### **OBJECTIVE**

We are used to help the healthcare community diagnose such malicious diseases. Although researchers have made various attempts to detect tumors from MRI scans, many deficiencies exist (i.e., low accuracy, big and slow models, and high computational costs). Using with artificial intelligence, deep learning (DL) models are being used in medical imaging to diagnose brain tumors using MR images. Deep learning has recently been used in studies to boost the effectiveness of computer-aided medical diagnostics in brain cancer investigation. They play an essential role in the healthcare profession and act as valuable tools in various vital disorders, including brain disease diagnosis and skin cancer image analysis. Additionally, the more extensive data always remains a challenge in the healthcare domain because researchers cannot openly share medical information due to the privacy concerns of their patients.

#### **EXISTING SYSTEM:**

Image processing plays a major role in neurologists' clinical diagnosis in the medical field. Several types of imagery are used for diagnostics, tumor segmentation, and classification. Magnetic resonance imaging (MRI) is favored among all modalities due to its noninvasive nature and better representation of internal tumor information. Indeed, early diagnosis may increase the chances of being lifesaving. However, the manual dissection and classification of brain tumors based on MRI is vulnerable to error, time-consuming, and formidable task. Consequently, this article presents a deep learning approach to classify brain tumors using an MRI data analysis to assist practitioners. The recommended method comprises three main phases: preprocessing, brain tumor segmentation using k-means clustering, and finally, classify tumors into their respective categories (benign/malignant) using MRI data through a VGG19.

#### **Existing System Disadvantages:**

- It has trouble clustering data where clusters are of varying sizes and density.
- It always try to construct a nice spherical shape around the Centroid. That means, the minute the clusters have a complicated geometric shape, K-means does a poor job in clustering the data.
- Vanishing gradient problem

## 2. LITERATURE SURVEY

Title: American Cancer Society's report on the status of cancer disparities in the United States

Author: F. Islami, C. E. Guerra, A. Minihan, K. R. Yabroff, S. A. Fedewa, K. Sloan, T.L. Wiedt, B. Thomson, R. L. Siegel, N. Nargis, R. A. Winn, L. Lacasse,

Year: 2022.

Description: In this report, the authors provide comprehensive and up-to-date US data on disparities in cancer occurrence, major risk factors, and access to and utilization of preventive measures and screening by sociodemographic characteristics. They also review programs and resources that have reduced cancer disparities and provide policy recommendations to further mitigate these inequalities. The overall cancer death rate is 19% higher among Black males than among White males. Black females also have a 12% higher overall cancer death rate than their White counterparts despite having an 8% lower incidence rate. There are also substantial variations in death rates for specific cancer types and in stage at diagnosis, survival, exposure to risk factors, and receipt of preventive measures and screening by race/ethnicity, socioeconomic status, and geographic location. For example, kidney cancer death rates by sex among American Indian/Alaska Native people are  $\geq 64\%$  higher than the corresponding rates in each of the other racial/ethnic groups, and the 5-year relative survival for all cancers combined is 14% lower among residents of poorer counties than among residents of more affluent counties. Broad and equitable implementation of evidence-based interventions, such as increasing health insurance coverage through Medicaid expansion or other initiatives, could substantially reduce cancer disparities. However, progress will require not only equitable local, state, and federal policies but also broad interdisciplinary engagement to elevate and address fundamental social inequities and longstanding systemic racism.

Title: Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey

Author: K. Muhammad, S. Khan, J. D. Ser, and V. H. C. D. Albuquerque

Year: 2021.

Description: Brain tumor is one of the most dangerous cancers in people of all ages, and its grade recognition is a challenging problem for radiologists in health monitoring and automated diagnosis. Recently, numerous methods based on deep learning have been presented in the literature for brain tumor classification (BTC) in order to assist radiologists for a better diagnostic analysis. In this overview, we present an in-depth review of the surveys published so far and recent deep learning-based methods for BTC. Our survey covers the main

steps of deep learning-based BTC methods, including preprocessing, features extraction, and classification, along with their achievements and limitations. We also investigate the state-of-the-art convolutional neural network models for BTC by performing extensive experiments using transfer learning with and without data augmentation. Furthermore, this overview describes available benchmark data sets used for the evaluation of BTC. Finally, this survey does not only look into the past literature on the topic but also steps on it to delve into the future of this area and enumerates some research directions that should be followed in the future, especially for personalized and smart healthcare.

Title: MRI-based brain tumor classification using ensemble of deep features and machine learning classifiers

Author: J. Kang, Z. Ullah, and J. Gwak.

Year: 2021.

Description: Brain tumor classification plays an important role in clinical diagnosis and effective treatment. In this work, we propose a method for brain tumor classification using an ensemble of deep features and machine learning classifiers. In our proposed framework, we adopt the concept of transfer learning and uses several pre-trained deep convolutional neural networks to extract deep features from brain magnetic resonance (MR) images. The extracted deep features are then evaluated by several machine learning classifiers. The top three deep features which perform well on several machine learning classifiers are selected and concatenated as an ensemble of deep features which is then fed into several machine learning classifiers to predict the final output. To evaluate the different kinds of pre-trained models as a deep feature extractor, machine learning classifiers, and the effectiveness of an ensemble of deep feature for brain tumor classification, we use three different brain magnetic resonance imaging (MRI) datasets that are openly accessible from the web. Experimental results demonstrate that an ensemble of deep features can help improving performance significantly, and in most cases, support vector machine (SVM) with radial basis function (RBF) kernel outperforms other machine learning classifiers, especially for large datasets.

Title: Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification.

Author: A. R. Khan, S. Khan, M. Harouni, R. Abbasi, S. Iqbal, and Z. Mehmood.

Year: 2021.

Description: Image processing plays a major role in neurologists' clinical diagnosis in the medical field. Several types of imagery are used for diagnostics, tumor segmentation, and classification. Magnetic resonance imaging (MRI) is favored among all

modalities due to its noninvasive nature and better representation of internal tumor information. Indeed, early diagnosis may increase the chances of being lifesaving. However, the manual dissection and classification of brain tumors based on MRI is vulnerable to error, time-consuming, and formidable task. Consequently, this article presents a deep learning approach to classify brain tumors using an MRI data analysis to assist practitioners. The recommended method comprises three main phases: preprocessing, brain tumor segmentation using k-means clustering, and finally, classify tumors into their respective categories (benign/malignant) using MRI data through a fine-tuned VGG19 (i.e., 19-layered Visual Geometric Group) model. Moreover, for better classification accuracy, the synthetic data augmentation concept is introduced to increase available data size for classifier training. The proposed approach was evaluated on BraTS 2015 benchmarks data sets through rigorous experiments. The results endorse the effectiveness of the proposed strategy and it achieved better accuracy compared to the previously reported state-of-the-art techniques.

Title: Deep learning guided by ontology for medical images classification using a multimodal fusion.

Author: H. Yahyaoui, F. Ghazouani, and I. R. Farah  
Year: 2021.

Description: Brain tumor is regarded as one of the most perilous diseases, with Glioma being the most prevalent form of primary brain tumor. Brain tumor classification, by playing the part of a treatment guide, makes diagnosis easier by providing acquisition tools for medical imagery providing various modalities that are fused for brain tumor classification. Therefore, to perform this task, existing works fuse either 2D brain MRI image slices or 3D brain images. In this paper, we propose a novel semantic method for MRI brain tumor classification using a multimodal fusion of 2D and 3D MRI images. The proposed method raises two major challenges: the semantic classification and the fusion of 2D and 3D images. It consists of three levels: preprocessing, classification, and fusion. The preprocessing level has a considerable impact on the results. At the classification level, we used two deep learning models and two heterogeneous datasets. The Dense Net model is used to classify 2D brain images into three brain tumor categories (Glioma, Meningioma, and Pituitary tumor). The 3D-CNN model is designed for glioma grading (High/Low-grade glioma) using the 3D brain images. At the fusion level, we used specific-domain ontology to perform the fusion of the output classes. The evaluation of the proposed approach on the test set has shown good results and the classification accuracy rate reached 92.06% and 85% for Dense Net and 3D CNN models respectively and 100% at the fusion level.

## PROPOSED SYSTEM

Deep learning has recently been used in studies to boost the effectiveness of computer-aided medical diagnostics in brain cancer investigation. They play an essential role in the healthcare profession and act as valuable tools in various vital disorders, including brain disease diagnosis and skin cancer image analysis. DL methods based on transfer learning and fine-tuning are preferred and widely used for the classification of Brain tumors.

The motivation of this research is to conduct extensive experimentation using deep convolutional neural networks, transfer learning, and fine-tuning to automate the process of brain tumor classification and detection. A new automated method based on the state-of-the-art EfficientNet-B0 model is fine-tuned with our recommended layers, which can replace conventional invasive brain tumor classification and enhance overall classification accuracy..

### Proposed System Advantages:

- The Efficient Net models achieve both higher accuracy and better efficiency over existing techniques.
- Faster Problem-solving. Increasing the image size or resolution provides more information to the network.

## 2. METHODOLOGY

The main aim of the project is used to identify the brain tumors by using the deep learning (DL). Deep learning models are being used in medical imaging to diagnose brain tumors using MR images. In this study, a deep convolutional neural network (CNN) EfficientNet-B0 base model is fine-tuned with our proposed layers to efficiently classify and detect brain tumor images

### DATASET DESCRIPTION

The dataset contained 3762 MR images, 3060 were used as a subset, and 1500 were labelled as 1 (tumors). The other 1500 scans were labelled as 0 (non-tumor). In order to avoid class dominance, the dataset was equally divided between the two classes, with 80% (2400) of the images going for training and 20% (600) going for validation.

### DATA PREPROCESSING

Preprocessing the images will transform the data into a standard classified format. In the first step, the images were converted to grayscale with a constant pixel resolution of  $224 \times 224$ . Second, the images were blurred using Gaussian blur to reduce noise and increase the output quality. These photos were then processed through a high pass filter, which sharpened the picture and allowed the extraction of more complex features. Image processing techniques like erosion and dilation eliminate pixel intensities in too tiny regions to carry the structuring element. Erosion is the process of removing pixels from the edges of objects. After eroding the white

areas (e.g., tumors), the volume was reduced, while the gaps, especially the holes in the white areas, grew in size. Dilation works opposite to erosion and adds pixels to the edges of structures. After dilation, the white areas increased in size due to extra white pixels on the edges.

**DATA AUGMENTATION**

The effectiveness of most ML and DL models is determined by the quality, amount, and relevance of training data. However, one of the most prevalent problems in applying machine learning in organizations is a lack of data. It is due to the fact that gathering relevant data may be costly and time-consuming in many circumstances. Data augmentation is a series of methods for artificially increasing the quantity of data by producing additional data points from current data. It is a quick and efficient way to expand the dimensionality of training data and improve generalization to new unseen samples by making minor data modifications or deep neural networks to generate additional data samples. Data augmentation is popular in computer vision and natural language processing, signals, and speech domains. In computer vision, the original dataset’s augmentations undergo several image transformations to increase the data samples, which helps better train models and decrease overfitting.

**EXPIREMENTAL SETUP**

The proposed model was deployed on the open-access dataset. The fine-tuned EfficientNet model was implemented in Python using the Keras and TensorFlow frameworks as the foundation. First, we imported the pre-trained EfficientNet-B0 network from Keras and froze the beginning layers of the base model. In the second phase, fine-tuning was performed with our proposed ending layers with the brain tumor MR images, and the complete network was re-trained. The proposed and other CNN models were also compared to validate our experiment.

**PERFORMANCE EVALUATION METRICS**

The confusion matrix (CM) is a standard method representing how well a trained model could predict a given validation dataset. The CM has equivalent rows and columns indicating the actual class and the ground truth labels (i.e., tumors or non-tumors). Similarly, the predicted values represent the number of correct and wrong predictions or classifications for each validation sample. True Positive specifies the number of correctly identified positive samples as positive, whereas True Negatives indicate the number of accurately predicted negatives as negatives. False Positives are predictions in which the image was labelled as positive; however, it was not positive. False Negatives are negative results that appear to be positive.

**TECHNIQUE USED OR ALGORITHM USED**

**EXISTING TECHNIQUE: -**

- **K-Means Clustering & VGG19**

K-means algorithm is vigorous, fast, and simpler to measure. It is an unsupervised learning technique for clusters. K-means algorithm provides a remarkable outcome when data points are well separated from one another. In this approach, initially, “K” centroids are marked randomly or using some heuristic but must be positioned distantly from one another. Then select a data point and assign it to the nearest centroid until no data point is remaining.

VGG19 to classify brain tumors into its respective two classes. Generally, the pre-trained VGG19 model involves 19 layers, 16 are convolutional and 3 fully connected layers. In VGG19, the first and second convolution layers of the group of two layers followed by max-pooling layers, and next eight convolution layers are a group of four layers followed by max-pooling with same filter size, that is,  $3 \times 3$ , the last three are dense layers, contain 4,096 and 1,000 features followed by SoftMax function

**PROPOSED TECHNIQUE USED OR ALGORITHM USED:**

- **Novel: EfficientNet**

The proposed model with multiple layers and pre-trained algorithms will be thoroughly discussed in the subsequent sections. Figure 1 depicts the stages of the brain tumor image preprocessing, augmentations, training, and evaluation. The proposed transfer learning and fine-tuning method are based on DL algorithms that use numerous hyper parameters for training and optimization.

An optimizer is an algorithm that adjusts the neural network biases and learning rate. As a result, it aids in lowering total loss and improving accuracy. A loss function demonstrates how well a specific algorithm matches the given data for ML. With the help of an optimization function, the loss function gradually learns to decrease the prediction error. The binary cross-entropy and Adam optimizer is used here to solve this specific problem.

**SYSTEM ARCHITECTURE**

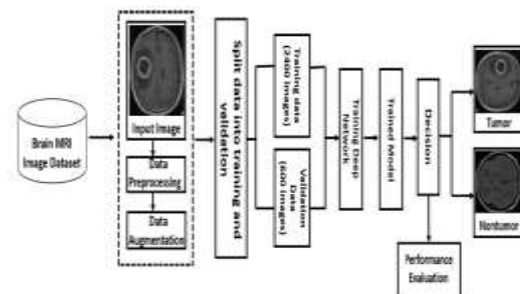


Fig 4.11: System Architecture

**FUTURE ENHANCEMENTS:**

Using CNN models for brain tumor classification and conduct segmentation with reduced time complexity in future approaches. Also, to improve the accuracy of the proposed model, we will

increase the number of MRI scans in the dataset used for this study.

#### CONCLUSION

MR imaging for the detection of brain tumor research has gained significant popularity because of the rising requirement for a practical and accurate evaluation of vast amounts of medical data. Brain tumors are a deadly disease, and manual detection is time-consuming and dependent on the expertise of doctors. An automatic diagnostic system will be required to detect abnormalities in MRI images. Therefore, this study developed an efficient, fine-tuned EfficientNet-B0 based transfer learning architecture to identify brain cancers from MRI scans. The proposed technique achieved the maximum performance in brain tumor detection, with 98.87% validation accuracy. Although this study focused on five other convolutional models and transfer learning designs for brain tumors in the medical imaging field, further research is needed. We will investigate more significant and influential deep CNN models for brain tumor classification and conduct segmentation with reduced time complexity in future approaches. Also, to improve the accuracy of the proposed model, we will increase the number of MRI scans in the dataset used for this study. Furthermore, we will also be applying the proposed approach to other medical images such as x-ray, computed tomography (CT), and ultrasound which may serve as a foundation for future research.

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