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# 2D ENCODING CONVOLUTION NEURAL NETWORK ALGORITHM FOR BRAIN TUMOR PREDICTION

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**Abstract**

In contemporary times, biomedical imaging plays a pivotal role in addressing various patient-related concerns. It serves as a vital tool for enhancing the diagnosis and treatment of a wide array of medical conditions. Within the realm of medical image analysis, the examination of brain images takes precedence. Brain imaging, particularly through techniques like MRI, offers valuable insights crucial for surgical procedures, radiotherapy, treatment planning, and stereotactic neurosurgery. To facilitate the accurate identification of cancerous cells within the brain using MRI, deep learning and image classification techniques have been deployed. These technologies have paved the way for the development of automated tumor detection methods, which not only save valuable time for radiologists but also consistently deliver proven

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levels of accuracy. In contrast, the conventional approach to defect detection in magnetic resonance brain images relies on manual human inspection, a method rendered impractical due to the sheer volume of data This paper outlines an approach aimed at detecting and classifying brain tumors within patient MRI images. Additionally, it conducts a performance comparison of Convolutional Neural Network (CNN) models in this context.

**Keywords:** Deep Learning, Magnetic Resonance Image (MRI), Convolutional Neural Network (CNN) .

## I Introduction

Brain tumors is one of the most formidable challenges in the realm of medical science. Achieving a precise and efficient diagnosis is of paramount importance, particularly during the early stages of tumor development [1]. The standard approach for assessing the grade of a brain tumor involves histological grading, which relies on a stereotactic biopsy examination. However, this process is intricately complex due to several factors, including limited illumination in imaging modalities, the vast amount of data to be processed, and the intricate and variable nature of tumors. These tumors can take on unstructured shapes, vary in size, and appear unpredictably within the brain [2].

In recent times, the medical diagnostic applications field has witnessed a burgeoning interest in automated disease detection through machine learning, especially in medical imaging. This has assumed significant importance in the context of brain tumor detection in MRI scans, providing indispensable insights into anomalous tissues, which are instrumental in planning treatment strategies [3]. Existing literature has underlined the potential of automated detection and diagnosis of diseases via medical image analysis. This not only has the capacity to save valuable time for radiologists but also boasts commendable diagnostic accuracy [4]. Furthermore, the prospect of computer algorithms offering robust and quantitative measurements of tumor characteristics holds immense promise. Such automated measurements could play a pivotal role In the clinical handling of brain tumors, it helps to relieve physicians from the burdensome responsibility of manually delineating tumors [5].

Machine learning-based approaches, notably Deep Convolutional Neural Networks (Deep ConvNets), have emerged as pivotal tools in simplifying disease diagnosis across radiology and various other clinical disciplines. These techniques offer a promising alternative to traditional surgical biopsies for brain tumor detection [6]. In this specific project, the focus revolves around the detection and classification of brain tumors. The study also entails a comparative analysis of outcomes pertaining to both binary and multi-class classification of brain tumors, with and without the integration of Transfer Learning. Transfer Learning entails the utilization of pre-trained Keras models such as VGG16 and EfficientNet within the framework of Convolutional Neural Networks (CNN) [7].

**II Related Works**

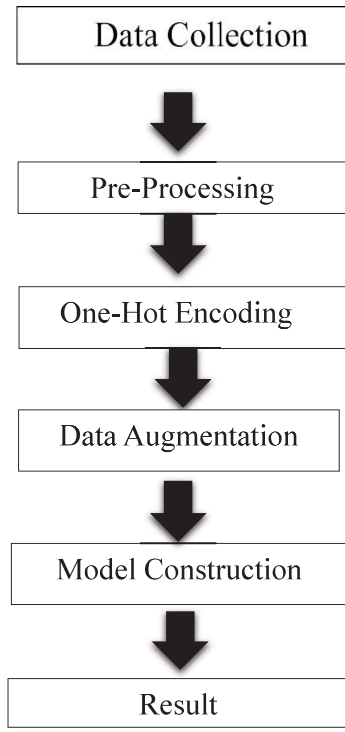
This classification technique plays a crucial role in brain tumor detection. It utilizes both Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) classifiers to identify the presence of tumors and delineate their regions, presenting a neural network-based approach [8]. Another machine learning method aims to ascertain whether an MRI brain image contains a tumor and determine its stage [9]. Moreover, a machine learning approach is employed to detect and categorize brain tumors using patient MRI images, with a focus on evaluating the performance of two distinct algorithms: Support Vector Machine (SVM) and Convolutional Neural Network (CNN)

[10]. In addition to this, MRI scans of the brain serve as the basis for segmenting brain tissues into various categories, including white matter, gray matter, cerebrospinal fluid (background), and tumor-affected tissues. Support Vector Machine and Convolutional Neural Network models are then utilized to classify the tumor stage as either benign or malignant, involving the development of specialized classification models and networks tailored for this specific task [11].

In another approach for brain tumor detection and categorization, machine learning, in conjunction with the Random Forest technique, is employed to detect and classify tumors as benign or malignant. This method incorporates extensive pre-processing to eliminate irrelevant noise from the MRI images. Remarkably, this system achieves efficient classification of MRI images into those with tumors and those without, all without the need for human intervention. The Random Forest algorithm boasts an impressive accuracy rate of 63% in MRI-based classification [12].

Additionally, the ResNet (Residual Network) architecture is introduced, utilizing skip connections and batch normalization. ResNet presents a unique framework for residual learning, enabling the training of much deeper networks than previously utilized [14-16]. This approach reimagines network layers as residual functions with respect to their input, rather than learning unreferenced functions. Extensive empirical evidence supports the assertion that Optimizing these residual networks is a more straightforward process. and can achieve increased precision with significantly greater depth [17]. In a rigorous evaluation on the ImageNet dataset, ResNet models with depths of up to 152 layers are found to be eight times deeper than VGG networks while maintaining lower complexity [18-19]. Furthermore, an ensemble of these residual networks achieves a remarkable error rate of 3.57% on the ImageNet test set [20].

**III. PROPOSED SYSTEM ARCHITECTURE**




## 1. Data collection

The dataset comprises MRI brain images in .jpg format and is sourced from an online Kaggle dataset. It consists of a total of 7,022 images, with 5,023 images depicting brain tumors and 2,310 images representing healthy brain scans. This dataset is a combination of two separate datasets, including **figshare Br35H.**

These 7,022 images are Categorizing into four clear classes: Glioma tumor, Meningioma tumor, absence of tumor, and pituitary tumor. The category of "no tumor" images is derived from the Br35H dataset. Among these images, there are 5,023 images showing tumor-affected brains, and 2,310 images featuring non-tumorous brains. These images come in various shapes and have been resized to a standardized size of 240 x 240 pixels, with the skulls stripped from the images.

The dataset is structured into two primary directories, with one dedicated to training and the other intended for testing purposes. The ‘train’ folder encompasses four sub-folders corresponding to the different classes: Glioma tumor, Meningioma tumor, absence of tumor, and pituitary tumor. Within these sub-folders, there are 1,321 images of Glioma cases, 1,339 images of Meningioma cases, 1,595 images of non-tumorous cases, and 1,457 images of Pituitary cases.

In the ‘test’ folder, you’ll find brain images categorized into the same four classes: Glioma tumor, Meningioma tumor, absence of tumor, and pituitary tumor. This folder contains 300 images of Glioma cases, 306 images of Meningioma cases, 405 images of non-tumorous cases, and 300 images of Pituitary Tumor cases. All these images are stored in .jpg format and adhere to a uniform size of 240 x 240 pixels, with skull stripping applied.

**2. Pre-Processing**

MRI images are collected and stored in the system. During the image pre-processing stage, it’s essential to address any artifacts present in the images before proceeding with feature measurement and analysis. On this module the records are taken from the online source. In addition, the image is resized and normalized for future use. First save the paths of each of our class folders by means of maintaining variables (glioma, meningioma, pituitary, and no_tumor) and append the route of every magnificence our train directory.

- Subsequent, get entry to all of the documents inside a particular elegance folder by the use of os.listdir.
- qdm is a development bar to allow visualize how lots us for loop has accomplished.
- Examine pix using cv2.imread and then crop them the usage of our crop_image function with plot=fake considering

- cv2.resize will resize the image to (240, 240).
- cv2.write will keep the image.

### 3. One -Hot Encoding

One-Hot Encoding is a method employed for representing categorical variables as binary vectors. It involves assigning a unique integer value to each specific category within the variable. Then, each integer value is transformed into a binary vector, where all values are set to zero except for the index corresponding to the integer, which is marked with a 1. In the context of One-Hot Encoding, each distinct category gets its own binary vector, where it is represented as either 1 or 0. The length of these vectors is determined by the total number of categories or classes that the model needs to classify. Consequently, the number of variables in a particular column will now reflect how frequently that variable appears in the vector, making it a useful technique for handling categorical data in machine learning.

### 4. Data Augmentation

Image augmentation is a technique that generates additional training images by applying various processing methods or combining multiple processing techniques. The Image Data Generator is a tool used for this purpose, and it also automates the labeling of data within individual class folders. This simplifies the organization of data for use in neural networks. In this way facts are without problems equipped to be exceeded to the neural network. Declare a datagen and specify rotation_range, widthshift_range, horizontal_flip. It is necessary to set shuffle=False for test_data. When set to False, statistics is sorted in alphanumeric order whilst default is set to True, which shuffles the records, causing y_test and y_test to be within the incorrect order therefore affecting our accuracy_score.

## 5. Model Construction

Several pre-trained models with weights on the ImageNet dataset are available for image classification. These models include Xception, VGG16, VGG19, ResNet, ResNet2, ResNet50, Inceptionv2, Inceptionv3, MobileNet, MobileNetv2, DenseNet, AlexNet, GoogleNet, and more. For the implementation of Transfer Learning in this mission, selected VGG16 and EfficientNetB2 as out samples. Transfer Learning without a doubt down-load the weights from EfficientNetB2 and VGG16 model, prefer to use very own layer as a closing layer so use *include_top = False*. After downloading the EfficientNetB2 and VGG16 Weights. Then observe the GlobalAveragePooling2D. X is the output layer of observe two Dense layers with 1024 Neurons and the Activation feature is Relu. And one extra Dense layer with the 512 Neurons and identical Activation feature Relu. Eventually, one more layer that's Prediction layer with two Neurons because of the reality need to classify between two classes and upload *Softmax* Activation feature that's for possibility Distribution

### GlobalaveragePooling2D:

Designed to alternate absolutely related layers. It takes the common of every function map and feed the ensuing vector without delay into the softmax layer. Dense as output layer with activation softmax in view that is a multi-class classification problem.

## 6. Algorithm

1. Begin by importing the necessary libraries and packages.
2. Import the dataset containing images related to glioma, meningioma, no tumor, and pituitary cases.
3. Resize all the images to a consistent size of 256x256 pixels.

4. Normalize the pixel values in the images to ensure uniformity.
5. Split the dataset into two portions: one for training and the other for testing.
6. Create a sequential model for neural network architecture.
7. Compile the model with the chosen optimization and loss functions.
8. Train the model using the training dataset.
9. Assess the model's effectiveness by testing it with the evaluation images.
10. Apply the model to identify the existence of tumors in the supplied MRI images.
11. Visualize and compare the training and test accuracy using a graphical plot.

## IV. RESULTS AND DISCUSSION

The model has been developed using Google Colab, and it operates on a dataset comprising 7,022 human brain images categorized into four distinct classes. The dataset has been split into a training set, accounting for 75% of the data, and a testing set, which makes up the remaining 25%. This proposed system gives precise identification of the presence of a brain tumor. The CNN Transfer learning is used to detect the tumor. The result of implementation is displayed in the form of input images. Input has been upload using the upload button and then clicking the predict button that shows the patients have tumor or not and what type of tumor. The First model EfficientNetB2 which patient had tumor or not. The accuracy of the model is 82.23%. The Second model VGG16 which patient had tumor or not. The accuracy of the model is 41.12%. Mostly this model is successful in predicting a tumor or not based upon the features provided in the data and the training.

TABLE 1 TWO MODEL COMPARISION

| **MODEL** | **ACCURACY** |
|---|---|
| EFFICIENTNETB2 | 82.23% |
| VGG16 | 41.12% |

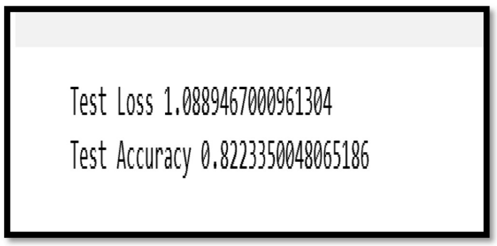



**Figure 1 Accuracy and loss**

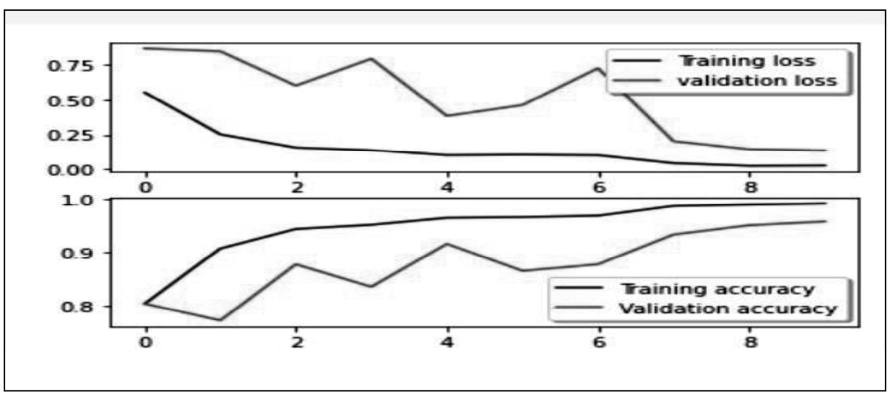



**Figure2 EfficientNetB2**

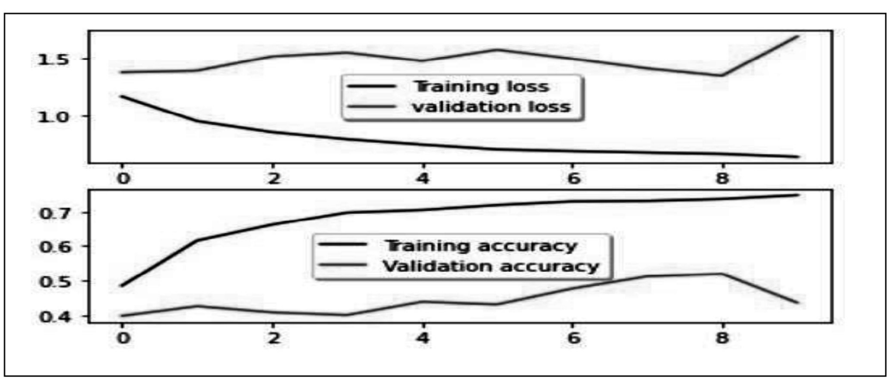



**Figure 3 VGG16**

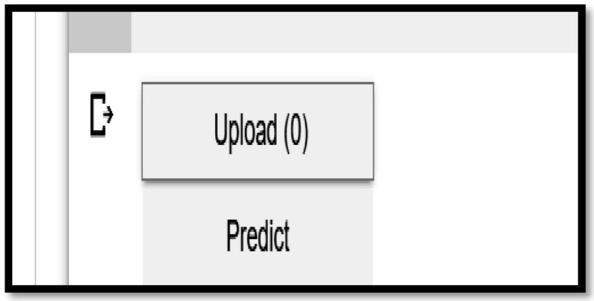



**Figure 4 Upload the MRI Image**

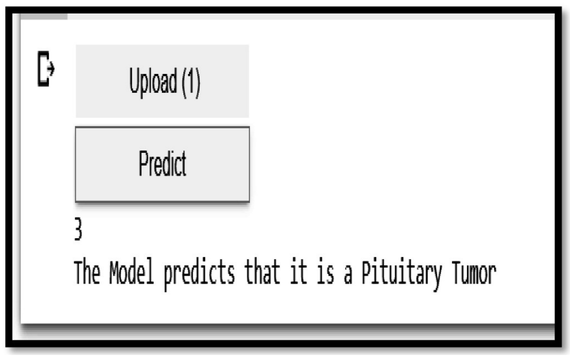



**Figure 5 Model predicts the tumor**

## V. CONCLUSION

Algorithms for studying and classifying medical pictures have won an excellent stage of attention these days. The experiments found in this work show that when preprocessing MRI pictures, transfer learning EfficientNetB2 turned into the high-quality. VGG16 did very well but the accuracy was very low. The dataset divided into 75% for training and 25% for testing. Moreover, the strategies of overall performance measuring metrics which includes accuracy and prediction.

Two models are used in this project one is EfficientnteB2, it gives the highest accuracy 82.23% compared to the Second model VGG16, it gives the lowest accuracy 41.12%. A far higher accuracy can be performed by using gaining a higher dataset with high-decision pictures taken directly from the MRI scanner. Probabilities over-fitting the dataset are higher when training the version from scratch instead of the usage of pre-trained Keras.

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