

Enhancing Pre-Trained Transfer Learning Performance Using Automated Brain Tumor Classification

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Abstract. Classification and prediction of brain tumors are essential for the early diagnosis and treatment of brain-related conditions. Broad exploration and strategic enhancements over the long haul bear witness to the need of cerebrum cancer recognition and investigation for any sign framework. Exact cancer recognition is fundamental for this review, thus a productive robotized technique should be executed. To aid in and enhance the classification of brain tumors, numerous segmentation algorithms have been developed. Brain imaging segmentation is a well-known and challenging subfield of medical image processing. A novel automated detection and classification system is suggested by the study. Preprocessing MRI images, segmenting those images, extracting features, and classifying those features are the stages that make up the suggested strategy. In this review, we propose an exchange learning way to deal with precisely characterize mind growths and foresee their threat utilizing progressed profound learning methods. After the features from the MRI scans were extracted, a deep learning model was used to divide the images into gliomas, meningiomas, non-tumors, and pituitary tumors. For grouping, VGG-16 Net pre-prepared models were utilized. To upgrade the VGG-16 Net model's presentation, information expansion strategies are applied to lighten overfitting and further develop speculation. The trained model has remarkable sensitivity and specificity in detecting tumor presence and accurately predicting tumor grades, achieving the highest level of accuracy for brain tumor classification. The suggested VGG-16 Net was able to correctly identify brain tumors on MRI images with 96.17 percent accuracy.

Keywords: Deep learning, a detection model, MRI images, disease prediction, and disease classification.

1 Introduction

The Brain malignant growths present tremendous challenges in the field of clinical assurance and treatment. Early and exact distinguishing proof of frontal cortex malignant growths is

fundamental for feasible treatment organizing and chipping away at grasping outcomes. All through the long haul, clinical imaging techniques play had an imperative effect as a main priority development acknowledgment, and movements in advancement have disturbed how frontal cortex tumors are examined and described [1]. Methods like registered tomography (CT) and attractive reverberation imaging (X-ray) were typically used to locate brain cancers. CT channels gave significant information about the development's region and size at this point regularly coming up short on anticipated that repugnance should perceive different disease types and grades. However, X-ray filters provided unparalleled delicate tissue contrast, enabling a more accurate representation of growth limits and the surrounding tissues of the brain [2]. However, the emotional and time-consuming nature of manual X-ray image interpretation necessitated the use of automated and skilled brain cancer grouping systems.

Recent advances in AI, particularly deep learning calculations, have altered clinical picture examination, including the arrangement of mind cancer. Convolutional brain organizations (CNNs) and other profound learning models, for example, have demonstrated remarkable abilities for extracting complex examples and components from clinical images. CNNs are able to distinguish between typical mind tissues and growth districts by naturally separating significant highlights, enabling precise and automated brain growth characterization [4]. Furthermore, the openness of colossal degree named datasets and overhauls in computational power have empowered the headway of current CNN structures uniquely designed for clinical picture assessment. These advances have enabled scientists to develop robust models capable of accurately identifying various cancer types and growth grades [5].

In addition, the model's speculation has been improved and over fitting has been reduced thanks to the adoption of information increase procedures to address issues arising from limited datasets. The blend of significant learning models with data extension has in a general sense additionally created mind disease request precision and constancy. In addition, the integration of cutting-edge AI models and user-friendly interfaces has resulted in their acceptance in clinical practice [6]. Online applications grant clinical specialists to move X-beam checks effectively and get second psyche disease portrayal results. Such applications empower clinicians with successful devices for early acknowledgment and treatment organizing, provoking better persevering thought and results.

From conventional techniques like CT and X-ray to the cutting-edge profound learning models used in clinical picture examination today, we expect to investigate the development of brain cancer arrangement and forecast methods in this review. We attempt to develop a precise and solid mind growth characterization model by utilizing cutting-edge CNN structures and information increase techniques. This investigation might conceivably change the field of neuroimaging, giving clinical specialists astounding resources for the early assurance and treatment of brain developments, in the end further creating patient perseverance rates and individual fulfilment [7].

The remainder of the article's substance is coordinated as follows. The various methods for recognizing and anticipating the mind cancer location that have been laid out are the subject of investigation in Section 2. In Area 3, the deep learning structure that was used to describe and anticipate a move learning-based brain cancer location is examined. The findings of the work and potential future patterns are the focus of segment 4.

2 Literature Survey

In the past, brain cancer diagnosis was mostly determined by looking at clinical images like CT and X-ray filters. Radiologists genuinely unravelled the photos, perceiving disease regions considering their appearance, size, and region. Nevertheless, these procedures required objectivity and were monotonous. Researchers began looking into computerized brain growth arrangement methods as computational power increased. To distinguish growth areas from healthy cerebrum tissues, picture handling techniques like thresholding, locale development, and component extraction were used. These methodologies showed ensure anyway often combat with complex development shapes and covering tissues [8].

During the 2010s, artificial intelligence estimations particularly support vector machines (SVM) and inconsistent woods, procured conspicuousness for brain malignant growth game plan. These calculations distinguished between normal and growth areas using hand-tailored highlights like surface, force, and shape highlights that were separated from X-ray images. Even though these methods were more precise than traditional approaches, they were constrained by the need for manual element design [9].

This piece of the article is given to a composing evaluation of the multi-portrayal of brain developments using CNN. It is conceivable to investigate the assessment found in the composition from different places. For instance, some researchers have used their own CNN models to conduct cerebrum growth grouping, and other researchers have adopted the exchange learning approach in search of a similar explanation. The goal of these two groups of scientists is similar. The going with researchers has encouraged their own CNN models for the grouping of psyche developments. For instance, Bada and Barjaktarovi[10] fostered a 22-layered CNN designing for brain development type request by utilizing 3064 T1-weighted contrast-further developed X-beam data [11][12]. The cancers were characterized using this design. With an accuracy of 86.56 percent, the proposed model correctly identified the three types of cerebrum cancer: meningioma, glioma, and pituitary [13].

3 Transfer Learning Performance Using Automated Brain Tumor Classification

In this segment, we have utilized VGG-16 exchange learning model for Order and expectation of cerebrum cancer utilizing X-ray pictures. VGG-16 is a profound convolutional brain organization (CNN) engineering proposed by the Visual Calculation Gathering (VGG) at the College of Oxford. During the 2014 Image Net Large Scale Visual Recognition Challenge (ILSVRC), it gained popularity and achieved remarkable success in computer vision tasks, particularly image classification. The levels of the VGG-16 Net architecture are as follows: Convolutional Layers, Activation Function, Pooling Layer, Flatten and Fully Connected Layer, Soft-Max Classifiers, and Input Images for Training and Testing.

Input: The VGG-16 model acknowledges a data picture as its hidden information. Before being handled and delivered to the organization, the image is typically preprocessed to the appropriate size.

Layers Convolutional: 13 convolutional layers are used to process the information picture. Each convolutional layer is at risk for recognizing different low to evident level features in the image. In order to create include maps and convolve over the data, these layers make use of tiny

3x3 channels. VGG-16 employs zero-cushioning to ensure that the component maps' spatial elements remain unchanged following each convolution.

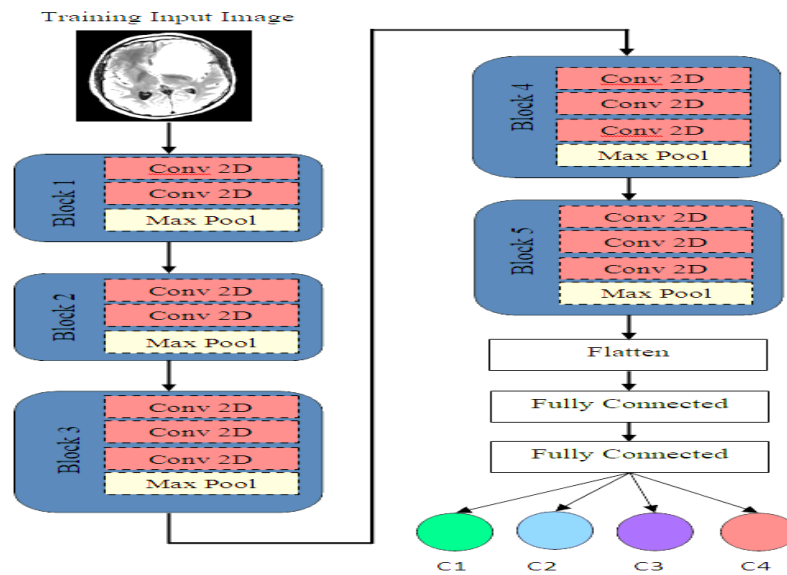


Fig. 1. Architecture of VGG-16 Net Model

Commencement Ability (ReLU): After each convolutional layer, a Changed Direct Unit (ReLU) commencement capacity is applied part wise to introduce non-linearity. The model is able to truly learn complex examples and highlights because ReLU sets typically regrettable pixel values to nothing. ReLU presents non-linearity, which allows the association to learn complex models and makes getting ready more capable appeared differently in relation to customary activation capacities like sigmoid or tanh.

Pooling Layers: Discontinuously, VGG-16 uses max-pooling layers with a 2x2 window and a stage of 2. Max-pooling decreases the spatial parts of the component maps, which reduces computational multifaceted design and further creates translation invariance.

Layers Completely Connected: After a couple convolutional and pooling layers, the spatial parts of the component maps are basically reduced. The smoothed component maps are then passed through three separate layers, or thick layers, that are completely connected to one another.

Classifier Softmax: The last totally related layer is a softmax classifier. It takes the aftereffect of the past layer and makes probabilities for each class. The model's last prediction is considered to be the class with the highest likelihood.

Training: VGG-16 is arranged using back propagation and stochastic point drop (SGD) with force. During preparation, the model determines how to limit the cross-entropy error between the expected class probabilities and the ground-truth marks.

Output: VGG-16 produced a likelihood distribution across all of the dataset's potential classes. It will in general be used for tasks like picture portrayal, where the model predicts the most plausible class for a given data picture.

Depiction of a Dataset: Patients with gliomas, meningiomas, and pituitary tumors were included in the study's cerebrum cancer dataset, which consists of a different set of X-ray images. Glioma, meningioma, notumor, and pituitary cancer tests of varying risk levels are also included in the dataset. Before being incorporated into the model, the X-ray checks are preprocessed and standardized. It has an amount of 4 classes with an amount of 5,650 Alluring Resonation Imaging (X-beam) pictures, with each class including 1350 pictures. In the dark variety plot, the goal for each image is 176 x 208 pixels. Figure 2 shows that the glioma is labeled as c1, the meningioma is labeled as c2, the tumor is labeled as c3, and the pituitary is labeled as c4.

Figure 2 shows a few instances of pictures from the kaggle storehouse dataset in X-ray pictures. Separate preparation and testing sets were made from the dataset. As displayed in Table 1, 70% of the dataset is utilized to prepare the model, 20% of the dataset is utilized to approve the model, while 20% is utilized to test it.

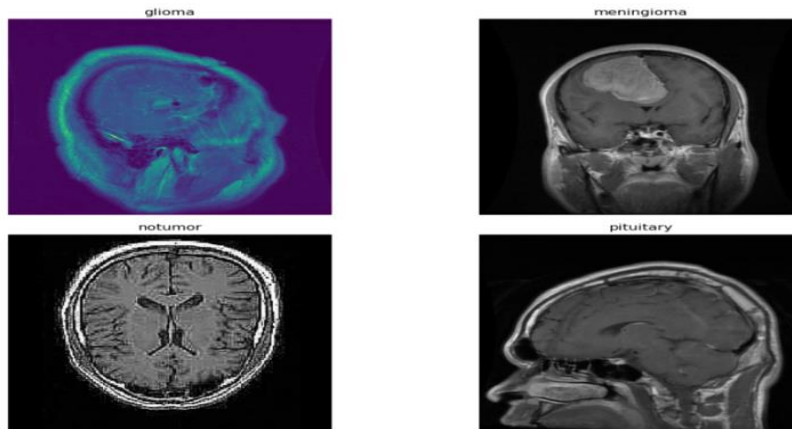


Fig. 2. Sample Brain MRI Images for Brain Tumor Detection

Table 1. Dataset split for brain tumor prediction and classification

S. No .	Disease Type	Training Images	Validation Images	Testing Images	Total No. of Images	Category
1.	Glioma	1000	300	50	1350	C1
2.	Meningioma	1000	300	50	1350	C2
3.	Notumor	1100	405	95	1600	C3
4.	Pituitary	1000	300	50	1350	C4

This section examines the recommended early diagnosis and recognition of Alzheimer's disease in X-ray examinations, as well as the evaluation results, using VGG-16 Net exchange learning methods. The model that was suggested was developed using Python and the Anaconda IDE. This was completed on a PC with a 1TB hard plate drive, 8GB of Slam, and an i5 central processor.

A. Execution Measurements

Measurements of characterization execution are used to assess the viability of a factual or AI model in terms of the ability to classify information into distinct categories or classes. These measurements help break down the model's exactness, accuracy, review, and other fundamental components and reveal how well it is performing.

Accuracy: Out of the total number of cases in the dataset, the exactness metric makes an estimate of the proportion of examples that have been accurately characterized (both genuine positives and genuine negatives).

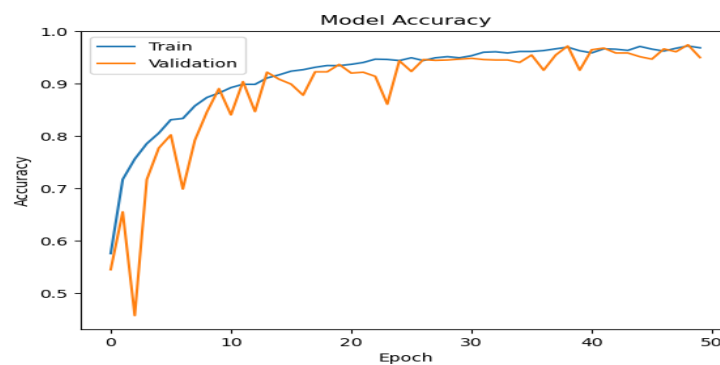
Precision: Accuracy, or positive predictive value, is the percentage of genuine positive expectations among the model's sure forecasts. It demonstrates the model's ability to correctly differentiate positive examples from false positives.

Recall: Audit assesses the degree of authentic positive conjectures out of all certifiable positive events in the dataset. It gives an estimate of the model's capacity to avoid false negatives and each positive example.

F1 Rating: The F1 score is the symphonious mean of exactness and survey and offers a single advantage that changes the two estimations. When you really want to consider both review and accuracy simultaneously, it is helpful.

1. Result Analysis

In this review, we present the exploratory consequences of cerebrum cancer grouping and forecast utilizing a profound learning model. The objective is to assess the model's exhibition in precisely recognizing different cancer types and foreseeing their harm grades. In the experimental setup, the model is trained on a dataset of MRI scans from brain tumors and evaluated on separate validation and test datasets.



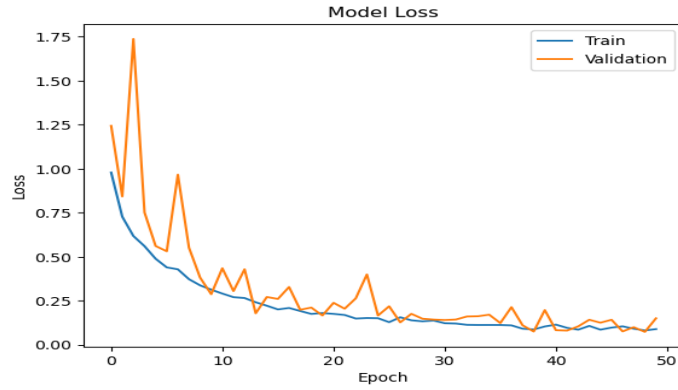


Fig. 3. VGG-16 Net transfer learning accuracy and Loss

Table 2. Performance Comparison of base models

S. No	Model	Accuracy	Precision	Recall	F1-Score
1.	VGG-16 Net	96.17	96.3	96.2	96.2

To begin, we have constructed and examined the VGG-16 Net exchange learning model in order to describe brain cancer in X-ray filters. Based on the data presented in Table 2 and Figure 4, we concluded that the VGG-16 Net method had the highest possible exactness of 96.17 and was the most effective method. Figures 3 depict the standard measurements of prepared precision, approved exactness, prepared shortfall, and approved deficit at 50 ages for a VGG-16 Net exchange learning model. These boundaries are created to provide the data in order to provide an evaluation of the prepared models using a learning rate of 0.00001 and SGD improvement. These boundaries are determined to provide that assessment in order to provide a gauge of the extent to which the preparation models have been overfit. Figure 4 presents a view of the components of some representative of frontal cortex malignant growth pictures.

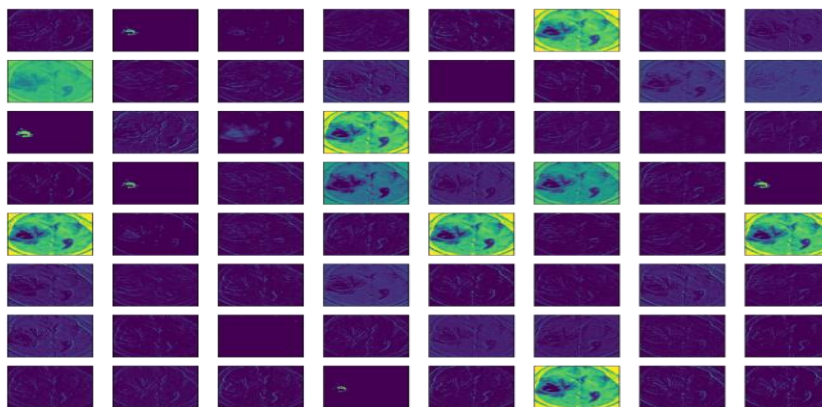


Fig. 4. Feature Visualization of brain tumor disease images

The results of the confusion matrix as well as the predictions made for the illness prediction and classification of brain tumors are depicted in Figures 5 and 6

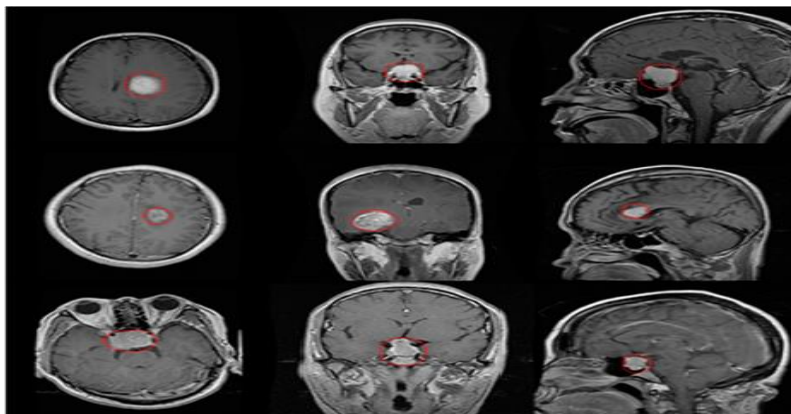


Fig. 5. Brain tumour disease prediction and classification

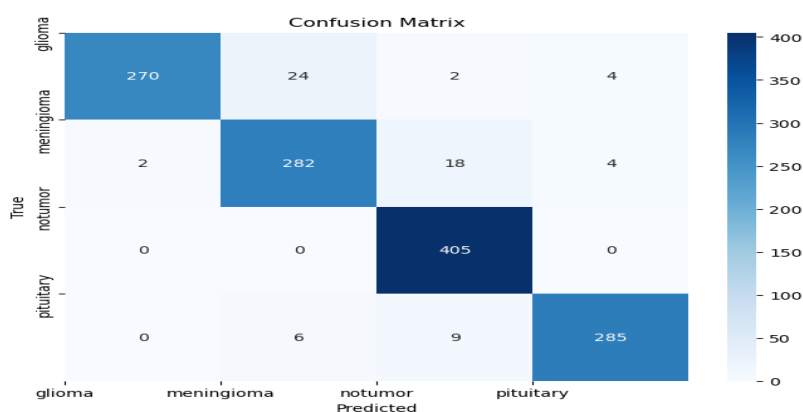


Fig. 6. Confusion matrix of brain tumor images

4 Conclusion

The study of machine learning has moved beyond the realm of feature engineering and into the realm of architectural design as a result of recent advances in deep learning. Using VGG-16 Net transfer learning models, this study offers a method for multi-classifying brain tumors in order to aid in their early detection. To order cerebrum growths in clinical pictures, three strong CNN models are assigned. The detection of brain tumors achieves a high level of accuracy, such as 96.1 percent. Doctors and radiologists can check the accuracy of their preliminary screening for a variety of brain tumors using the CNN models developed in this study.

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