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Comparative Evaluation for Brain Tumor Detection Using Inception-V3 Architecture

V. Kavitha*[1], K. Ulagapriya[2]

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Abstract: Over the last decade, researchers have been focusing on magnetic resonance imaging (MRI) to detect brain tumors. However, existing methods that involve medical image feature extraction is not sufficient to solve this issue. To tackle this problem, a new model has been proposed, employing the Inception-v3 convolutional neural network. By extracting and categorising various features, this model can help identify s brain tumors earlier. The proposed model is built on Inception-v3 and utilizes loss functions and the Adam Optimizer to optimize its hyperparameters. It also employs a softmax classifier to classify the images into different classes. The results indicate that the Inception-v3 algorithm achieved an impressive training data accuracy of 99.02% and a validation data accuracy of 89%.

Keywords: *Deep Learning, Softmax, ReLU Activation, VGG-16.*

1. Introduction

Medical advancements have significantly improved the services provided by medical practitioners to patients. Artificial intelligence has played a crucial role in expanding their capacity to serve more patients [1]. Global data from the World Health Organization indicates that cardiovascular diseases are the leading cause of death [2]. Among the dangerous diseases worldwide, brain tumors are of great concern. Magnetic Resonance Imaging (MRI) has proven to be a safe and effective method for assessing brain tumor conditions [3]. Currently, researchers are actively developing novel methods and techniques to facilitate faster and easier diagnoses of brain tumors using MRI images [4-5].

The manual diagnosis process can be highly complex, leading to significant time and cost implications. To address this issue, computer-aided diagnosis tools have become increasingly prevalent. Recently, several automated brain tumor detection tools have been developed, falling into two categories: supervised and unsupervised methods [6]. Generally, supervised methods outperform unsupervised methods in brain tumor detection tasks. However, many major techniques rely on segmentation. In this chapter, we will introduce a deep learning method that can effectively classify various tasks involved in the brain tumor detection process. Deep learning techniques are extensively utilized in the medical field for separating the brin tumor images [7] and identifying various types of cancer [8].

Deep learning utilizes machine learning techniques to enhance image classification accuracy. The primary aim of this research is to develop novel approach that can increase the accuracy of the proposed system. Deep learning is focused on enhancing image classification accuracy, and its popularity has grown due to its ability to predict text and image content effectively. It excels at processing large datasets to yield valuable results. In medical imaging, deep learning can be utilized to identify disease-affected regions in images. Moreover, besides image classification, deep learning has various applications, such as object recognition and activity monitoring [9]. The accuracy of deep learning models relies on the dataset and the training mechanism employed to develop them. One approach is transfer learning, which involves utilizing features from larger datasets to train smaller ones [10].

The paper aims to develop a method for detecting brain tumors using magnetic resonance imaging. Section 2 focuses on the development of deep learning techniques for detecting brain tumors. Section 3 talks about the brain tumor dataset's properties. Section 4 covers the Inception v3 and convolutional neural network models. Section 5 presents the analysis of the accuracy of the method. Section 6 wraps up the investigation.

2. Literature Survey

Mechanisms for machine learning are crucial in various fields, such as medical diagnosis and preventive medicine. Only a small amount of research has been conducted on the use of magnetic resonance imaging (MRI) to detect brain tumors. Most of the investigations focused on the traditional methods for handling MRI images. Others investigated the use of deep learning techniques for detecting brain tumors.

The authors introduced a Convolutional Neural Network (CNN) framework [11] aimed at identifying different types

[1] *Research Scholar, Computer Science and Engineering, Vels Institute of Science Technology, and advanced studies*
[2] *Associate professor, Computer science and Engineering, Vels Institute of science technology and advanced studies*
** Corresponding Author Email: kavithareddy.velagalapalli@gmail.com*

of datasets of brain tumor including GoogleNet, and VGGNet. Their proposed algorithm can effectively identify regions of interest in brain tumor images and undergo fine-tuning for improved classification. The authors achieved an impressive 97.8% accuracy in classifying images using the VGGNet framework. Another method for image classification using deep learning is proposed in [12]. This approach involves feature extraction followed by the classification process. The authors developed a n-fold model for classification of images and the automated models outperformed manual models. Furthermore, in [13], a capsule network is utilized to enhance the accuracy of classifying brain tumor MR images. The researchers claimed an 86.5% improvement in accuracy.

The authors in [14] introduced a Neural Network model for brain image classification. They developed various models for different classifications, featuring a Max Pool layer and 64 hidden neurons. The model achieved an accuracy of 98.5% during the training phase and 84% during the validation phase. In [15], the authors used the Gabor filter and 2D-DWT for image classification, achieving 92% accuracy by incorporating backpropagation neural networks. For tumor region retrieval from image datasets, the authors of [16] proposed a neural network-based classification model. They implemented various techniques to enhance the model's accuracy and tested it against two datasets, achieving a 90.6% accuracy. The model also automatically graded the tumor region based on dataset grades. On the other hand, in [17], the authors proposed automatic method for grading gliomas and identifies regions of interest, achieving an accuracy of 92.9%. A hybrid approach combining genetic algorithms with neural networks was developed by the authors in [18] for brain image classification. The proposed system achieved a 90.9% accuracy in classifying images from the Pituitary, Meningioma, and Glioma groups. Using a real-time dataset from US hospitals, the authors of [19] employed a deep learning approach for image classification and achieved an accuracy of 92.8%. In [20], the authors trained their system on CNN models and considered existing models to classify images, resulting in an accuracy of nearly 97%.

3. Brain Tumor Dataset

The dataset collection contains 3064 images which are T1-weighted for brain tumors [25], including Meningioma, Glioma, and pituitary tumors. The images have a resolution as low as 512×512. To train the images, we used the Inception-V3 model and measured classification accuracy, comparing it with ResNet-50 and VGG16. The dataset is divided into three different classes for training, testing, and validation phases. The training phase is dedicated to algorithm training, while the testing and validation phases are used to evaluate the model. Figure 1 displays a sample image dataset.

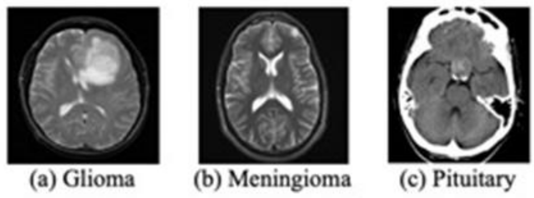

Fig. 1. Various types of brain magnetic resonance images.

4. Proposed Inception-V3 Model

The proposed architecture consists of interconnected pre-training process represented by various layers. Figure 2 illustrates the pre-processing mechanism. Deep learning and hyperparameters are utilized in the model for tumor prediction. The system benefits from the Adam Optimizer and the loss function, which aid in generating an optimal algorithm by minimizing prediction errors. The Adam Optimizer further enhances the model's efficiency.

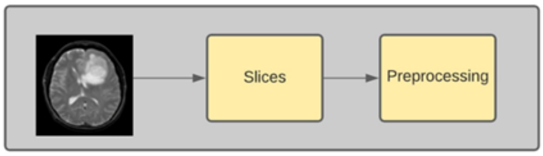

Fig. 2 (i) Pre-processing Mechanism

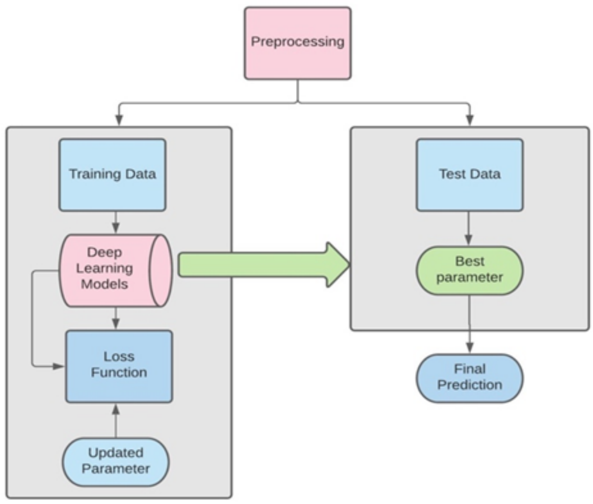

Fig. 2. (ii) Three phases for Proposed model

4.1. Pretrained Module in Deep Learning

Inception-V3 is illustrated in Figure 3 which is a pre-trained network based on GoogleNet's implementation [21]. It consists of 11 inception modules, incorporating activation layers, convolution layers, Max pooling layers, and Normalization layers. Each module provides a list of features extracted from input images, which are then concatenated to form a classification tree for the datasets. Inception-V3 removes inception modules from the bottom layers and concatenates them with features from the top. Global average pooling feature is the last module in the

Inception-V3 model which is extracted from the images. A dropout layer follows the global average pooling layer to further extract image features. The outputs of the dropout layer are then passed to the softmax classifier for image classification.

4.1.1. Activation Function

The activation function used in the Inception V3 is Rectified Linear Unit (ReLU) activation function. This function transforms the input weights into the output [22]. The ReLU activation function is used in the hidden layer of the CNN, and its representation in the convolution layer is given by Eq. 1.

$$f(x) = \max(0, x) \tag{1}$$

In the ReLU activation function, for an input value x, if x is greater than or equal to 0, the output is set to 0, and if x is less than 0, the output becomes 1. Consequently, when the input value is 0, the neuron is considered dead and not considered.

4.1.2. Loss Function

The error between the predicted value and true labelled value is calculated by the cross-entropy loss function and it is commonly employed to minimize the error. In this study, the cross-entropy loss function was employed to calculate the error [23]. It was used for classifying the MR images, and the proposed model considered the multiclass entropy. The multi-class entropy is represented by Eq. 2.

$$L(X_i, Y_i) = -\sum_{j=1}^{c} y_{ij} * \log(p_{ij}) \tag{2}$$

where X_i = input value, $Y_i = (y_{i1}, y_{i2}, \ldots y_{ic})$.

$$y_{i,j} = \begin{cases} 1, & i \in j \\ 0, & otherwise \end{cases} \tag{3}$$

$$p_{i,j} = f(x_i) \tag{4}$$

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4.1.3. Optimization Mechanism

Adaptive Moment Estimation (Adam) was introduced in deep learning as an optimization technique to minimize the loss [24]. The Adam optimizer combines the methods of RMSprop and stochastic Gradient Descent. Equation 5 illustrates the SGD method [25].

$$K = K - \eta \times dK$$

$$g = g - \eta \times dg \tag{5}$$

In the given context, dg shows all epoch bias derivatives dK shows the weight derivatives.

Eq. 6 demonstrates the SGD with Z, where the GMM β which lies between 0 to 1.

$$Z_{dK} = \beta \times Z_{dK} + (1-\beta) \times dK$$
$$Z_{dg} = \beta \times Z_{dg} + (1-\beta) \times dg \tag{6}$$

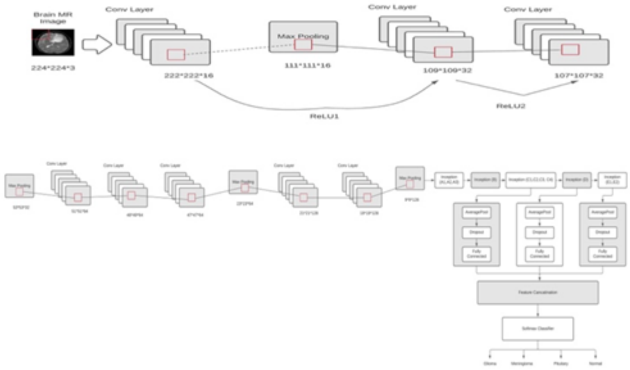

Fig. 3. Architecture for Inception-V3

4.2. ResNet50 Model

Microsoft developed the ResNet50 model [27] in 2015. It is a CNN model that has 26 million parameters and 50 layers. The ResNet learning process in is processed using residuals from the input layers. The ResNet50 model is shown in Figure 5, and it features a skip link to send information across multiple layers. This research work compared the performance of the pre-trained model with the proposed model.

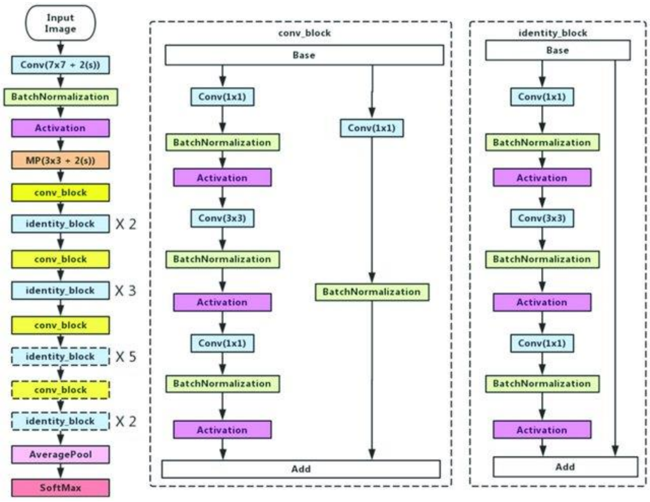

Fig. 4. ResNet 50 Pretrained model [27]

4.3. VGG-16 Architecture

It was utilized in our study to address the issue of overfitting. It features 16 convolution layers and 3 x 3 filters and 224 x 224 x 3 input size. The network topology features a maximum pooling layer of size 2 x 2 and a fully connected pair at the top. VGG-16 pretrained model is shown is Figure 5 [26].

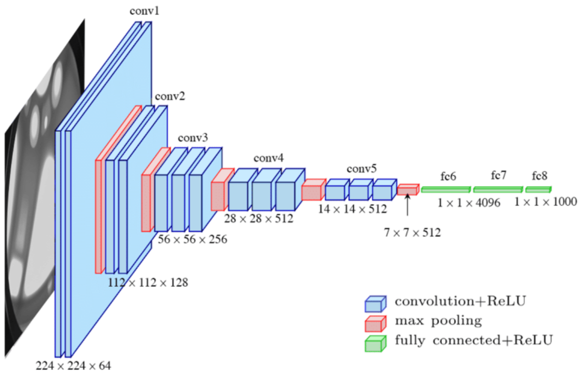

Fig. 5 VGG-16 Pretrained Model [26]

5. Results Evaluation

The proposed model performance was assessed using multiple parameters, including accuracy, precision, recall, and F1-score. Eqs.7 to 10 represent the proposed model parameter measurements.

$$A = \frac{T_p + T_N}{T_P + F_N + F_P + T_N} \tag{7}$$

$$P = \frac{T_p}{T_P + F_P} \tag{8}$$

$$R = \frac{T_p}{T_P + F_N} \tag{9}$$

$$F1 = 2 \times \frac{P \times R}{P + R} \tag{10}$$

In the given context, Fp shows the false positive, Tp shows the true positive, FN shows the false negative and TN shows the true negative.

The proposed model is trained using several hyperparameters listed in Table 1. The proposed architecture utilizes Keras and TensorFlow for model training. The training data constitutes 80% of the dataset, while 20% is reserved for testing and evaluation. The ground truth labels are used to calculate the evaluation metric.

Table 1 Model Training Hyper Parameters

Parameter	Value
Optimizer	Adaptive Moment Estimation
Classifier	Softmax
Number of Epochs	20
Loss Function	Multi class cross function
Learning Rate	0.0001
Batch Size	30

Table 2 displays the different scores of blocks in the Inception-v3 model, which are utilized to classify brain tumor images. These features are extracted from the bottom layer of Inception-v3 and then passed on to the classifier.

Table 2 Proposed Model Parameter scores

Blocks	Classes	F1-Score	Recall (R)	Precision(P)
Inception-C	Normal	100.00	100.00	100.00
	Meningioma	98.00	96.00	99.00
	Pituitary	98.00	100.00	97.00
	Glioma	99.00	98.00	98.00
Inception-D	Normal	100.00	100.00	100.00
	Meningioma	97.00	98.00	97.00
	Pituitary	97.00	98.00	97.00
	Glioma	99.00	99.00	100.00
Inception-E	Normal	100.00	100.00	100.00
	Meningioma	98.00	97.00	100.00
	Pituitary	99.00	99.00	98.00
	Glioma	99.00	98.00	100.00

Table 3 presents a comparison of the accuracy between the proposed and VGG-16 algorithms. The Inception-v3 CNN framework achieved an accuracy of 99.02%, whereas the VGG-16 and ResNet50 models achieved 90.45% and 91.07% accuracy, respectively. Figures 6 to 8 display the training and validation accuracy of ResNet-50, Inception-v3 and VGG-16.

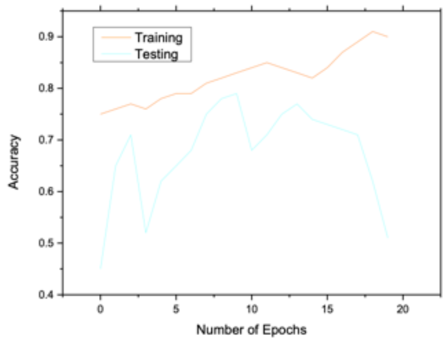

Fig. 6. ResNet-50 prediction Accuracy

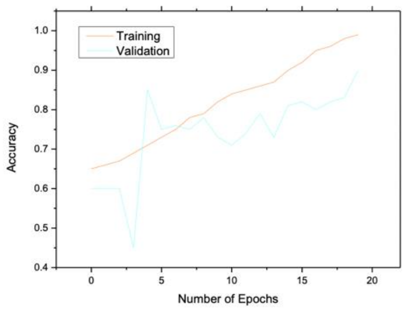

Fig. 7. Proposed Inception-V3 prediction Accuracy

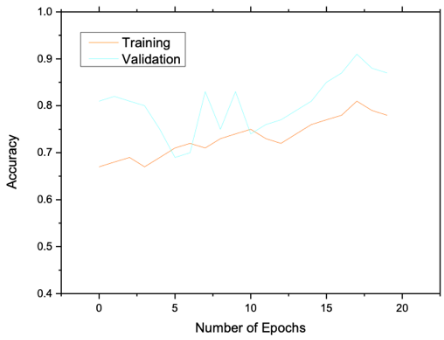

Fig. 8. VGG-16 prediction Accuracy

Figure 9 illustrates the Region of Convergence for both existing and proposed models. The proposed model demonstrated excellent performance for different types of brain tumors (0,1,2,3), particularly for the pituitary, Glioma, and Meningioma classes.

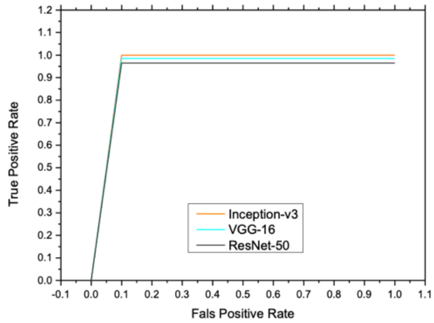

Fig. 9. Existing and Proposed Models ROC plot

Table 3 Accuracy of proposed and existing algorithms

Model	Accuracy
CNN	84.27
CapsNet	86.58
DWT-Gabor	89.90
ResNet-50	91.07
VGG-16	90.45
Proposed model	99.02

6. Conclusion

The paper describes a method for using deep learning techniques in MR images to detect brain tumors. The paper proposes a method that involves modifying the Inception-V3 architecture. This involves removing some of the foundation modules and merging the features of the top modules into the classification framework. The last module, which is the inception, is then concatenated using the global average pooling. The proposed model then forwards the extracted features from the connected layer to the classifier, which can classify the images into different classes. The proposed architecture is built on a deep learning model that is trained using Keras and TensorFlow. The proposed model was able to achieve a 99.02% accuracy rate, which is better than the ResNet-50 and VGG-16 models. The authors then plan to integrate the Inception-V3 framework with the DenseNet model in the future.

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Author contributions

V Kavitha: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Validation., Field study, Visualization, Investigation, Writing. **K Ulagapriya**: Reviewing and Editing

Conflicts of interest

The authors declare no conflicts of interest.

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