

Comparative Analysis of Hybrid VGG16-LSTM and VGG19-LSTM Models for Brain Tumor detection in MRI images

Introduction

The brain, a highly complex structure within the human body, operates through the coordinated activity of billions of cells[1]. When cell proliferation goes unchecked, it leads to the formation of an abnormal mass of cells either in or around the brain, giving rise to a brain tumor[2]. On the other hand, brain tumor detection from MRI images is a critical process in the diagnosis and treatment of brain tumors. MRI scans are widely recognized as a standard diagnostic tool for this purpose, providing detailed information about the brain's soft tissue[3,4]. Doctors must identify brain tumors, so it's critical to identify the various types of tumors as precisely as possible. However, manual identification takes a lot of time and can be challenging for doctors. Therefore, Doctors can benefit from an automated method that accurately detects brain tumors.

Recent advancements in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL) have significantly improved the accuracy and efficiency of brain tumor detection from MRI images[5,6]. Moreover, the development of CNN models and transfer learning techniques have revolutionized the detection of brain tumors from MRI images. The utilization of Convolutional Neural Networks (CNNs) in conjunction with transfer learning for brain tumor detection using MRI images is a prominent area of research. Transfer learning, as applied in this context, involves pre-training a CNN on a large dataset and then fine-tuning it on MRI images to detect brain tumors, which can lead to improved performance even with limited medical imaging data [7,8]. Another approach which hybrid models of deep learning models can improve the performance for detecting brain tumors from MRI images accurately[9]. These models leverage the strengths of multiple deep-learning architectures to improve the accuracy and reliability of brain tumor classification from medical imaging data[10]. Another algorithm mainly used for Natural Language processing tasks is Long Short Term Memory(LSTM)[11]. According to our research, most of the studies used CNN or transfer learning techniques to classify brain tumors from MRI images but only a few of them used LSTM[12]. Moreover, another gap we have found is that most of the studies validate their model in only one dataset.

To fill the existing gaps, we utilized six deep learning models through transfer learning techniques. Additionally, we introduced two hybrid models, namely VGG19-LSTM and VGG16-LSTM. Subsequently, we evaluated the performance of all models by validating them with two publicly accessible datasets. So, our main contributions will be:

- We will employ six pre-trained deep-learning models across two datasets. To the best of our knowledge, only one dataset for brain tumor detection has been used by previous researchers to accurately detect brain tumors from MRI Images.
- We will propose two hybrid deep learning models, which combine a pre-trained model with LSTM, aiming to enhance accuracy. Subsequently, we will conduct a comparative analysis with other models.
- By leveraging LSTM, we aim to explore its efficient utilization in brain tumor detection, striving for high-performance outcomes.

Literature review

Recurrent neural networks are reviewed in this paper with an emphasis on LSTM cells and network structures [13]. In reviewing LSTM and its variants, the paper emphasizes how important it is for managing long-term dependencies in sequential data analysis, as well as how many applications it has. As a result, LSTM has become a central topic in deep learning research. Despite its efficacy, LSTM networks may incur computational costs and encounter vanishing/exploding gradient issues.

The suggested hybrid Convolutional Neural Network (CNN) achieves an accuracy of 98.73% in brain tumor detection from 2D MRI scans, showing improved performance [15]. Brain tumors can be found more quickly and accurately by applying machine learning and deep learning algorithms to MRI scans. This allows patients to receive timely and correct therapy. The hybrid CNN has a high accuracy rate, but its computational complexity might make it difficult to use in contexts with limited resources.

In classifying brain tumor datasets, this study examines the effectiveness of CNN models, such as VGG-16, VGG-19, and Inception-V3. Accuracy rates range from 97.2% to 98.95%, with the maximum accuracy being achieved by the VGG-19 and AQO optimizer [16]. The findings highlight the critical role that deep learning—and CNN models in particular—plays in improving medical diagnosis by effectively classifying huge datasets and possibly cutting down on diagnostic time and errors. There may be difficulties in scaling the method for crowdsourced data gathering and analysis in many healthcare disciplines, necessitating additional research for the best possible implementation.

In addition to highlighting the value of machine learning and data mining techniques in healthcare, this paper presents an automatic method for the detection and classification of brain tumors using Convolutional Neural Networks (CNN), stressing the significance of image segmentation in MRI for accurate diagnosis.[17]. The proposed method combines CNN and data mining to improve brain tumor detection, classification, and segmentation accuracy by extracting patterns from healthcare data.

Implementing CNN-based segmentation and classification approaches may face challenges in generalizing across different datasets and dealing with computational complexity.

To detect brain tumors from medical images, this work presents a novel approach that combines feature extraction and CNN. It outperforms conventional CNN models and achieves a high accuracy of 99.12% on test data, improving the accuracy of medical diagnosis [18]. The technique successfully integrates CNN and feature extraction to increase the accuracy of brain tumor identification, resulting in better patient treatment results and medical diagnosis. Despite its great accuracy, there may be some drawbacks, such as the need for more extensive dataset validation and the need to take computational resources into account for practical medical applications.

This research provides two machine learning-based methods based on shape features for the classification of brain tumors, using the Multi-Layer Perceptron algorithm to achieve a maximum precision of almost 95% on a dataset of 174 brain MR images[19]. The work demonstrates how form data taken from MRI scans may be used to achieve high-precision brain tumor classification using machine learning methods, specifically the Multi-Layer Perceptron. Larger datasets may be required, and adding more features—like texture and intensity—to improve classification accuracy may be one way to overcome these restrictions.

This study presents a machine learning-based brain tumor identification system that extracts texture features using a grey-level co-occurrence matrix. On a dataset of 212 brain MRI images, the system achieves 98.6% accuracy with multi-layer perceptrons and 91.6% accuracy with Naive Bayes [20]. The research highlights how texture-based information taken from MRI images can be used to identify brain tumors with high accuracy. Multi-layer perceptrons and Naive Bayes in particular are effective in this regard. Some drawbacks could be the requirement for bigger datasets and the addition of more intensity-based characteristics in order to improve detection precision.

In order to help future researchers advance the field of brain tumor research, this study offers a critical examination of recent deep learning algorithms for the identification and classification of brain tumors using MRI data. It also includes insights and comparisons[22]. For deep learning experts interested in this field, the work makes a significant contribution by methodically examining and evaluating deep learning techniques used in brain tumor identification and categorization from 2015 to 2020. The study's timeline (2015–2020) and possible bias towards deep learning, which could cause it to ignore alternate approaches or more recent developments, are potential weaknesses.

Two deep learning models for brain abnormality identification and tumor grade classification are presented in this study. These models outperform earlier literature studies with high prediction accuracies of 97.8% and 100% for dataset 1 and dataset 2, respectively [23]. By utilizing extensive data augmentation techniques and introducing

unique deep learning architectures customized for varying image data sizes, the study considerably improves brain tumor detection accuracy over previous studies. Further validation across various datasets and consideration of computational resource requirements for real-world implementation are two potential limits.

In order to diagnose brain tumors, the study introduces a novel technique that combines feature extraction and CNN. It performs better than conventional CNN methods and achieves high accuracy levels of up to 99.12% on test data [25]. The paper makes a contribution by presenting a useful technique for CNN feature extraction and brain tumor identification, improving diagnostic precision and supporting patient treatment choices. Potential drawbacks could include the method's dependency on a single dataset and the requirement for additional validation across a variety of datasets to gauge the robustness and generalizability of the suggested approach.

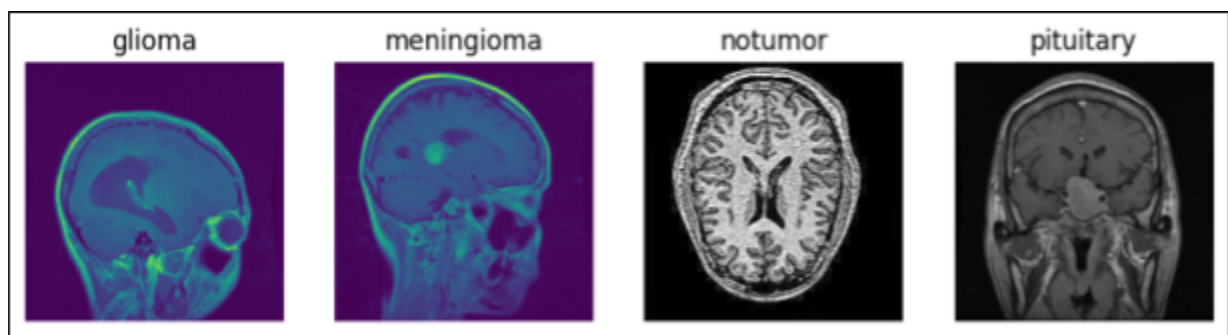
In comparison to current brain tumor detection and segmentation techniques, the study presents a novel Hierarchical Deep Learning-Based Brain Tumor Classifier that uses CNN. It achieves superior accuracy (92.13%) and a misclassification rate (7.87%), promising improved clinical support in brain tumor diagnosis and classification [26]. An important limitation of the system's efficacy in clinical settings could be its inability to reliably classify rare or complex tumor forms.

Methodology

Dataset Description: In our research, we used two datasets to validate our work. The first dataset that we used consists of about 7023 images of human brain MRI scans classified into 4 categories: glioma, meningioma, no tumor, and pituitary.

Table:1 - Dataset distribution Brain MRI dataset

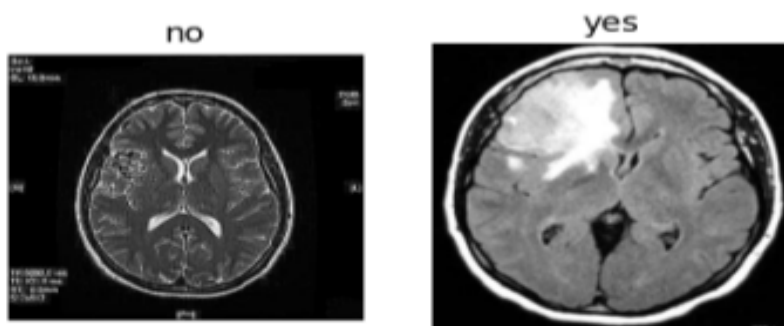
Class Name	No of Images
Glioma	1621
Meningioma	1645
Notumor	2000
Pituitary	1757



The second dataset that we used consists of about 1500 images of human brain MRI scans classified into 2 categories: yes and no.

Table:2 - Dataset distribution Br35H dataset

Class Name	No of Images
Yes	1500
No	1500



Data-preprocessing

Model Description :

Vgg16:

VGG-16 consists of 16 convolutional layers and is very appealing because of its very uniform Architecture. Similar to AlexNet, it has only 3x3 convolutions, but lots of filters. In our work, we used VGG16-based architecture tailored for brain tumor classification tasks. We leveraged the VGG16 convolutional base as a feature extractor, with its layers frozen to prevent overfitting. Additionally, a flattened layer followed by two fully connected layers with 4096 neurons in each layer was introduced. Moreover, the Relu activation function was used in each dense layer. Finally, we incorporated an output layer with softmax activation for classification.

Vgg19: The VGG19 model is a deep convolutional neural network with 19 layers. It includes 16 convolution layers, 3 fully connected layers, 5 MaxPool layers, and 1 SoftMax layer. The architecture is characterized by small receptive fields using 3x3 convolution filters. VGG19 was trained on the ImageNet dataset containing over a million images. It is designed for image classification, known for its simplicity and depth.

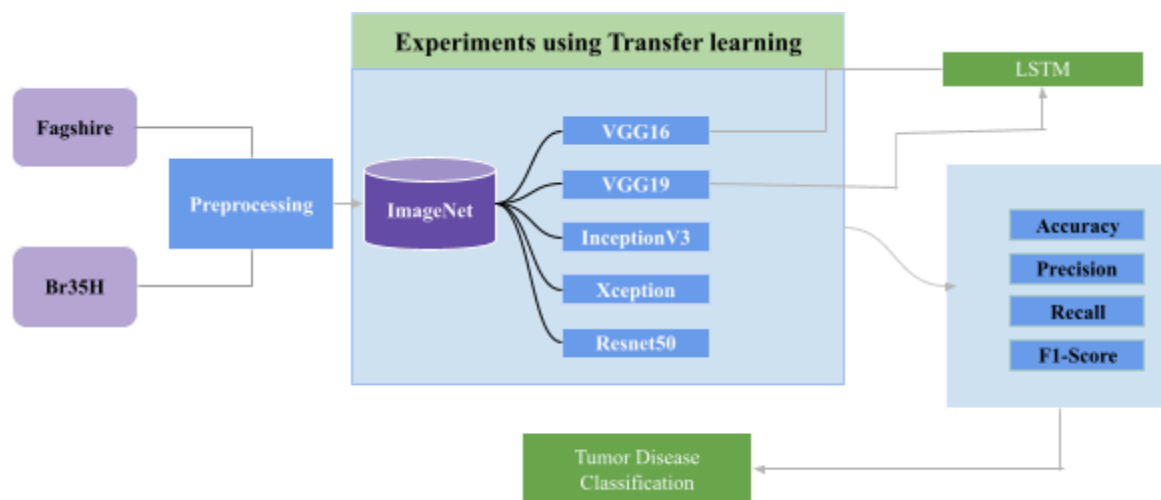
Inception V3: The Inception V3 model is a deep convolutional neural network with 48 layers. It features a combination of convolution layers, pooling layers, and fully connected layers, along with Inception modules to optimize the architecture. The model includes 11 Inception modules, 5 MaxPool layers, 2 AveragePool layers, and 1 SoftMax layer. Inception V3 was trained on the ImageNet dataset containing over a million images. It is designed for image classification and recognition tasks, emphasizing efficiency and accuracy.

Xception: The Xception model is a deep convolutional neural network with 71 layers. It consists of depthwise separable and regular convolution layers, with 14 modules containing residual connections. The architecture includes 36 convolution layers, 1 fully connected layer, multiple MaxPool layers, and 1 SoftMax layer. Xception was trained on the ImageNet dataset, which has over a million images. It is designed for image classification, enhancing performance by optimizing computational efficiency.

Resnet50: The ResNet50 model is a deep convolutional neural network with 50 layers. It includes convolution layers and identity shortcut connections to form residual blocks. The architecture comprises 48 convolution layers, 1 MaxPool layer, 1 AveragePool layer, and 1

SoftMax layer. ResNet50 was trained on the ImageNet dataset containing over a million images. It is designed for image classification, known for its ability to mitigate the vanishing gradient problem through residual learning.

LSTM: The LSTM model, or Long Short-Term Memory, is a type of recurrent neural network (RNN) designed to handle sequential data. It consists of multiple LSTM units, each containing a cell state and three gates: input, output, and forget gates. This architecture allows it to capture long-term dependencies and mitigate the vanishing gradient problem. LSTM models are trained on various datasets, often for tasks like language modeling, time series prediction, and speech recognition. They are designed for sequence learning, excelling in retaining information over long sequences.



Experimental Results

Accuracy: Accuracy is a metric that measures how frequently a machine learning model makes correct predictions. The ratio of correctly predicted observations to total observations produces an accuracy value.

$$Accuracy = \frac{Total\ Instances}{True\ Positive + True\ Negative}$$

Precision: Precision tells us the fraction of predicted positive results that are true positives. Precision is the number of True Positives divided by the number of True Positives and False Positives.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The proportion of actual positive cases that the model accurately predicted is measured by the recall. It evaluates the model's ability to find every relevant case.

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

F1-score: The harmonic mean of precision and recall is the F1-Score. It is helpful when dealing with imbalanced datasets since it strikes a balance between precision and recall.

$$F1 - score = \frac{2(Precision * Recall)}{Precision + Recall}$$

Experiments on Dataset 1

Architecture					Accuracy		
Vgg16					98.17%		
	Vgg19				96.67%		
	Inception V3				97.33%		
	Xception				85.83%		
	Resnet50				92.83%		
	VGG16-LSTM				97.5%		
	VGG19-LSTM				97.67%		
Model name	Class	Precision	Recall		F1 - score	Specificity	

Vgg16	Yes	98.01	98.33	98.17	98.00
	No	98.33	98.00	98.16	98.33
Vgg19	Yes	97.62	95.67	96.63	
	No	95.75	97.67	96.70	
Inception V3	Yes	96.10	98.67	97.37	96.00
	No	98.63	96.00	97.30	98.67
Xception	Yes	84.13	88.33	86.18	
	No	87.72	83.33	85.47	
Resnet50	Yes	91.05	95.00	92.99	90.67
	No	94.77	90.67	92.67	95.00
VGG16-LSTM	Yes	95.82	99.33	97.55	95.67
	No	99.31	95.67	97.45	99.33
VGG19-LSTM	Yes	97.35	98.00	97.67	97.33
	No	97.99	97.33	97.66	98.00

Model name	Class	TP	TN	FP	FN
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Vgg16	Yes	294	295	5	6
	No	295	294	6	5
Vgg19	Yes	293	287	13	7
	No	287	293	7	13
InceptionV3	Yes	296	288	12	4
	No	288	296	4	12
Xception	Yes	250	265	50	35
	No	265	250	35	50
Resnet50	Yes	285	272	28	15
	No	272	285	15	28
Vgg16- LSTM	Yes	298	287	13	2
	No	287	298	2	13
Vgg19-LSTM	Yes	294	292	8	6
	No	292	294	6	8

Experiments on Dataset-2:

Architecture	Accuracy
Vgg16	86.88%
Vgg19	89.40%
Inception V3	85.20%
Xception	73.61%
Resnet50	81.31%
Vgg16 - LSTM	91.00%
Vgg19 - LSTM	87.11%

Model name	Class	Precision	Recall	F1 - score	Specificity
Vgg16	Glioma	73.88	93.33	82.47	93.97
	Meningioma	87.88	56.86	69.05	93.73

	Notumor	95.34	96.05	95.69	94.26
	Pituitary	90.80	98.67	94.57	99.60
Vgg19	Glioma	87.85	84.33	86.05	93.77
	Meningioma	84.56	75.16	79.58	94.13
	Notumor	91.84	97.28	94.48	98.34
	Pituitary	91.61	98.33	94.86	97.92
Inception V3	Glioma	95.85	61.67	75.05	61.62
	Meningioma	64.85	89.22	75.10	85.27
	Notumor	95.34	96.05	95.69	97.1
	Pituitary	93.43	90.00	91.68	98.12
Xception	Glioma	73.26	66.67	69.81	92.78
	Meningioma	60.40	49.35	54.32	90.15
	Notumor	81.31	82.72	82.01	91.50
	Pituitary	74.20	93.00	82.54	90.41
Resnet50	Glioma	81.21	76.33	78.69	94.76
	Meningioma	65.03	65.03	65.03	89.35
	Notumor	88.26	92.84	90.49	94.48
	Pituitary	88.22	87.33	87.77	96.54
Vgg16 LSTM	Glioma	89.06	78.67	83.54	97.13
	Meningioma	81.71	87.58	84.54	94.03
	Notumor	97.06	97.78	97.42	98.68
	Pituitary	94.52	97.67	96.07	98.32
Vgg19 LSTM	Glioma	89.47	73.67	80.80	97.43
	Meningioma	72.94	81.05	76.78	90.85
	Notumor	91.98	96.30	94.09	96.25

	Pituitary	94.33	94.33	94.33	98.32
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Model name	Class	TP	TN	FP	FN
Vgg16	Glioma	263	950	61	37
	Meningioma	222	942	63	84
	Notumor	394	854	52	11
	Pituitary	252	1007	4	48
Vgg19	Glioma	268	948	63	32
	Meningioma	238	946	59	68
	Notumor	368	891	15	37
	Pituitary	279	990	21	21
Inception V3	Glioma	185	1003	8	115
	Meningioma	273	857	148	33
	Notumor	389	887	19	16
	Pituitary	270	992	19	30
Xception	Glioma	200	938	73	100
	Meningioma	151	906	99	155
	Notumor	335	829	77	70
	Pituitary	279	914	97	21
Resnet50	Glioma	229	958	53	71
	Meningioma	199	898	107	107
	Notumor	376	856	50	29
	Pituitary	262	976	35	38
Vgg16 LSTM	Glioma	236	982	29	64
	Meningioma	268	945	60	38
	Notumor	396	894	12	9
	Pituitary	293	994	17	7

Vgg19 - LSTM	Glioma	221	985	26	79
	Meningioma	248	913	92	58
	Notumor	390	872	34	15
	Pituitary	283	994	17	17

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