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Deep learning frameworks for brain tumor detection

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***bstract—* One of the abnormalities of the brain that can develop is a brain tumor. Every year, thousands of people get diagnosed with a brain tumor. One of the most commonly used bio-imaging techniques for assessing brain tumors at the clinical level is MRI-assisted brain scanning. With the help of 2D-MRI images,The objective of the work that has been proposed is to compare two deep learning architectures (DLAs) that will facilitate the independent diagnosis of brain tumours. This study suggests using the VGG-19 and ResNet50 as the DLAs to find brain tumors.**

Keywords—: brain tumor; brain MRI images; VGG-19, Deep Learning, ResNet50

I. INTRODUCTION

One of the fundamental organs in humans is the brain, and it is this organ that evaluates the comprehensive physiological movements that are being transmitted from other sensory sections of the body and then takes whatever corrective actions are required. If an infection or illness develops in the brain, normal brain functions are severely disrupted. Should a problem in the brain remain unidentified and untreated for an extended period of time, it can result in a wide range of problems, including death..

Primary brain tumour (benign tumour) and secondary brain tumour are the two main categories for brain tumours (malignant tumor). Gliomas are a type of brain tumour that is a benign tumour and grows slowly in the brain. It comes from astrocytes, which are brain cells that are not neurons. Primary tumours are often less aggressive, but because of the pressure they put on the brain, the brain becomes dysfunctional. Secondary tumours are more aggressive and spread into adjacent tissues more quickly. Secondary brain tumours develop from other body parts. These tumours are caused by metastatic cancer cells that have spread to various body parts, such as the brain and lungs. A secondary brain tumour is extremely cancerous. Lung, kidney, bladder, and other cancers are the primary causes of secondary brain tumours.

Uncontrolled cell growth (UCG) in a crucial brain area, congenital abnormalities, and accidental head trauma are all potential exacerbators of a normal brain's condition. These are only a few of the potential causes. These are all examples of conditions that can cause deviations in the brain. An irregularity will produce a different difficulties across the physiological system, and an abnormality in the brain that is left untreated will also lead to a number of serious disorders. An anomaly in the brain caused by UCG is a significant risk factor, and if the growth is not treated,It's a surefire recipe for brain cancer, one of the many deadly diseases that are on the rise around the world. According to the report published by the WHO in 2016, the rankings and classifications of brain tumors are well covered in the research carried out by Louis et al (WHO).

To protect people from the harmful effects of these conditions, numerous awareness campaigns have been started in recent years. On the other hand, the vast majority of people are already suffering from an advanced form of brain cancer due to a wide array of unavoidable causes, such as modern ways of living, dietary habits, genetic factors, and the natural progression of age. If brain cancer is found at an early stage, there is a potential treatment that will be utilised to speed up recovery. This treatment is only available if the disease is diagnosed. At the clinical level, single- or multi-channel EEG signals, in addition to a variety of imaging modalities for the brain, can be used to determine whether brain tumours are present. In contrast to the signal-assisted method, the image-assisted method is able to provide information that is far more significant in nature.

Using image recording techniques like computed tomography (CT) and magnetic resonance imaging (MRI), it is common practise to assess the acquired three-dimensional (3D) and two-dimensional (2D) pictures of the brain to look for anomalies. This can be done to look for abnormalities in the brain. This is because CT and MRI can produce images in multiple dimensions at once. As a result, imaging procedures are widely preferred in the majority of clinical-level detection. A brain tumour is more easier to see on an MRI of the brain than it is on a CT scan, and this is one reason why MRI is increasingly favoured over CT as technology advances.Magnetic resonance imaging scans are frequently advised in preference to other diagnostic techniques for the diagnosis of a number of brain illnesses, including brain tumours.

II. STATE OF THE ART (LITERATURE SURVEY)

According to this study, a customised VGG19 network that uses both hand-crafted and deep MRI scan features can be used to identify brain tumours. The method generated accuracy of 96.08% and an AUC of 0.99 on a dataset of 306 MRI images, demonstrating that the VGG19 network may perform better for this job when deep and handmade features are mixed [1].

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The authors' proposed convolutional neural network (CNN)-based deep learning method for detecting brain tumours uses this technology. The network receives input from MRI images, and after a number of convolutional and pooling layers, moves on to fully linked layers for classification. The proposed method was evaluated on a dataset of 150 MRI scans, and it generated accuracy and sensitivity results of 98.7% and 97.1%, respectively. The results indicate that the suggested CNN-based strategy has promise as a brain cancer identification tool [2]The authors advocate using convolutional neural networks (CNNs), a deep learning approach, to precisely identify brain tumours. The network receives input from MRI images, and after a number of convolutional and pooling layers, moves on to fully linked layers for classification [3].

A novel deep learning framework for the detection of lung abnormalities utilising a mix of chest X-ray and lung CT scan images is presented in the study by Bhandary A. While deep learning techniques have been used to detect lung problems in a number of studies, the proposed framework stands out for its unique approach and the demonstrated efficacy in detecting various types of lung abnormalities[4].

The study makes a foundation with the purpose of providing doctors with reliable brain picture analysis and therapy planning based on early diagnosis. Utilizing a convolutional neural network (CNN), the framework for classification, correctly identified brain tumours using a set of brain Magnetic resonance imaging scans with an accuracy of 97.14 percent.The paper was published in Neural Computing and Applications in 2020 [5].

This study evaluated their suggested method using a dataset of 20 MRI images, indicating that the proposed method can be an effective tool for segmenting brain regions in medical images. The paper was published in Current Medical Imaging in 2016 [6].

The CNN model in this work, which was trained and tested using a dataset of brain MRI images, classified brain tumours.The study demonstrates that deep learning can be an effective tool for analyzing big data in medical imaging and improving the accuracy of brain tumor detection[7].

The study's proposed method was tested using a dataset of EEG signals from epileptic patients, and it had an average detection accuracy of 91.6%. The research demonstrates that the suggested technique can be a useful instrument for identifying interictal spike activity. in EEG signals, which can aid in the diagnosis and treatment of epilepsy. The paper was published in Australasian Physical & Engineering Sciences in Medicine in 2017 [8].

This study uses a dataset of MRI images to train and test their deep transfer learning model, which achieved an accuracy of 97.9% for brain abnormality classification. The study demonstrates that transfer learning can be an effective tool for automated medical image analysis, especially when the amount of labeled data is limited. The paper was published in Cognitive Systems Research in 2019[9].

This study uses a dataset of MRI images to train and test their deep learning model, which got an accuracy of 99.6% for brain tumour detection and 97.7% for tumor segmentation.The work shows that deep learning can be a useful technique for precise and automated brain tumour detection and segmentation in medical pictures, which can help with brain tumour diagnosis and therapy [10].

The paper by presents a deep learning-based approach for the classification of brain tumor MRI images using a ResNet50 architecture. While the approach shows promising results, further research is needed to explore other deep learning architectures and advanced techniques for preprocessing and feature extraction[11].

The paper by Aslantas and Tanrikulu (2020) presents an automatic brain tumor dectection approach by VGG19 model. While numerous studies have explored the use of deep learning techniques for the identification of brain tumor MRI images, this paper demonstrates the effectiveness of using the VGG19 specifically for this task. Further research can explore ditional deep learning architectures or sophisticated techniques for preprocessing and feature extraction to improve brain tumour classification performance[12].

Zhang have proposed a promising approach for brain tumor classification using deep learning. Their method outperformed several state-of-the-art methods and can potentially assist clinicians in diagnosing and treating brain tumors. Further research is needed to evaluate the generalizability of the proposed method and to optimize its performancep[13].

Deep learning has been proposed by Zhu as a promising method for categorising and identifying brain cancers. The recommended approach achieved high accuracy and outperformed other state-of-the-art methodologies. The method might aid in the detection and management of brain tumours by medical personnel. More research is needed to evaluate the recommended method's generalizability and improve its performance[14].

Results of feature selection, segmentation, and detection of brain tumours using Sharif's proposed ADNN approach on MRI images are positive. The technique successfully identified brain tumours and has the potential to aid medical professionals in making diagnosis and developing treatment plans. To determine how generalizable and effective the recommended technique is, however, further research is needed[15].

Nadeem's overview and taxonomy of deep learning-based approaches for brain cancer analysis are invaluable resources for scientists and medical professionals working in this field. The study focuses on how deep learning-based approaches could improve the efficacy and accuracy of brain cancer analysis. Additional research is necessary to address the challenges and limitations of these tactics and evaluate how effectively they function in clinical situations. The suggested directions for future study could act as a guide for creating deep learning-based brain tumour analysis[16].

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III. Proposed Work

Numerous different DLAs, both standard and customised, are proposed throughout the research literature as potential methods for locating anomalies in medical imaging. Constructing, training, testing, and validating the architecture in order to meet the requirements of a particular test are some of the many complex steps involved in the creation of a new DLA from the initial concept. As a consequence of this, the majority of previous efforts to address a disease detection problem have consisted of modifying the validated DLAs that can already be found in the literature. Before selecting and putting an architecture into action, it is essential to have a solid understanding of its structure, as well as the degree of effort involved in putting it into action, the initial tweaking, and the validation procedures.

In this particular research project, the identification of brain tumours from the studied MRI material is carried out with the use of the VGG-19 and ResNet50 Deep Learning Architectures. Because the experiments conducted for this investigation have shown that ResNet50 outperforms VGG19 on several image classification benchmarks, especially on larger and more complex datasets. However, VGG19 can still perform well and may be a better choice for smaller datasets or when computational resources are limited. So we have used them achieve greater results

Figure 1 depicts the VGG19 that was regarded for use in this investigation and ultimately utilised.Principal component analysis (PCA) is a deep and meticulous feature used to sort and serially integrate images. It is then used for training, testing, and validating the classification component that divides the input images into yes and no cancer classes.

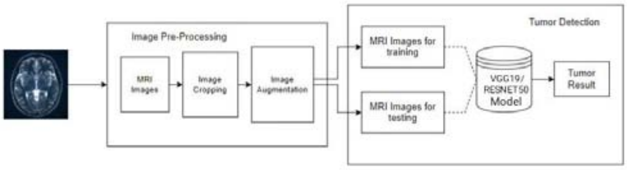

Fig.1.Strucrture of the customized VGG19 network

Fig 1. describes the structure of the VGG19 network; it was mainly divided into image pre-processing and algorithm analysis

The success of such an established system for making diagnoses is largely based on the database that is considered for each medical evaluation procedure in accordance with the problem that must be resolved. The widely recognised benchmark photos served as the basis for the majority of the images that were utilised in the brain tumour detection competition. The image dataset that was utilised for this study is displayed in Figure 2, which can be found here.

The glioma images connected to the skull portion are used for this evaluation. In order to validate the proposed Deep Learning Architecture, Proscans Ltd. clinical-grade Magnetic resonance imaging are also taken into account.This strategy contributed to the vast number of test photos for the tumour classifications YES and NO.

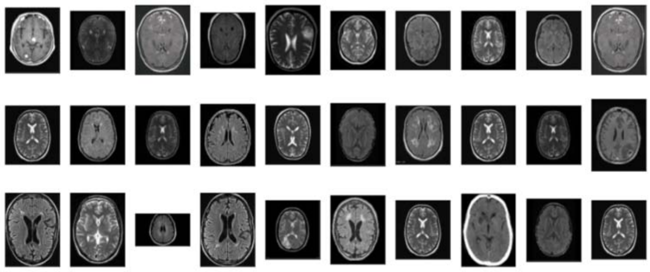

Fig. 2. Sample test images

Fig 2. describes the MRI images which was taken for testing from original dataset

Feature extraction is the primary stage in ML and DL techniques that helps extract important information from a picture based on its structure and texture characteristics.The implemented classifier units are trained, examined, and validated based on these traits.

Calculating the key performance metrics is often how classifier performance is evaluated. The performance of the classifier in this work will be evaluated using specific performance metrics.

Visual Geometry Group 19 (VGG19)

One of the first deep convolutional neural networks, VGG19, was able to perform at the cutting edge on the difficult ImageNet dataset, which consists of more than a million photos divided into 1000 different classes. The popularity of deep learning for computer vision problems was aided by the performance of VGG19 on this dataset.

In contrast to larger filters with a longer stride, the architecture of VGG19 is built on the idea of using smaller filters (3x3) with a stride of 1. This improves performance by enabling the network to record more precise characteristics at each layer.

VGG19 has been utilised for transfer learning, where further computer vision tasks are launched using the network's pre-trained weights, in addition to its success on image classification tasks. Performance on a variety of tasks, such as object detection, segmentation, and even natural language processing, has improved as a result.

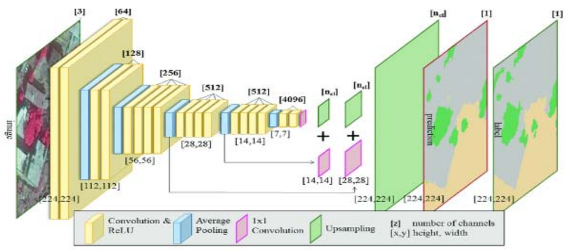

Fig. VGG19 Architecture

Fig 3. describes the different layers of VGG19 architecture

Residual Network 50 (ResNet50)

Microsoft Research presented ResNet50, a deep convolutional neural network design, in 2015. The architecture has 50 layers, including 1 fully linked layer and 49 convolutional layers.

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The introduction of residual connections, also referred to as skip connections, which allow data to escape specific network levels, is the main innovation of ResNet50. As a result, the network can be trained more successfully and the vanishing gradient problem that might arise in very deep networks is lessened.

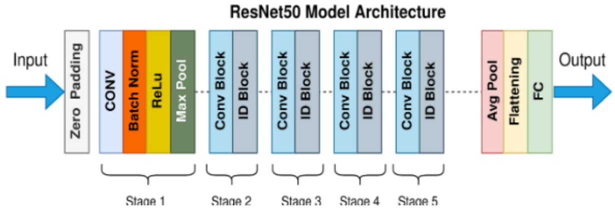

Fig4. RESNET50 Architecture

Fig 4. describes the steps present in RESNET50 model architecture

$$Accuracy = ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = PRE = \frac{TP}{TP + FP}$$

$$Sensitivity = SEN = \frac{TP}{TP + FN}$$

$$Specificity = SPE = \frac{TN}{TN + FP}$$

$$F1 - score = F1S = \frac{2TP}{2TP + FN + FP}$$

$$Negative\ Predictive\ Value = NPV = \frac{TN}{TN + FN}$$

IV. Implementation

In this part of the paper, the findings of the experiments and any subsequent commentary on those results are included. Matlab is used to conduct the research on a workstation equipped with an Intel i7 processor, 12 gigabytes of random access memory (RAM), and two gigabytes of dedicated video RAM. During this stage of the procedure, an initial value is designated for each DLA, as can be seen in the table below.

The epoch size is 15, the iteration size is 150, the number of iterations that occur in each epoch is 50, the update frequency is once every 5 iterations, the learning error rate is 1e-5, and the termination criterion is either the best validation or the maximum number of iterations. The epoch size is 15, the iteration size is 150, the number of iterations that occur in each epoch is 50, and the iteration size

First, images taken from a dataset that contained MRI slices were rendered into a visual representation. The photographs are all various sizes, so I have to crop the picture before I can use it. On the other hand, the model's input can be a picture with dimensions of (224*224*3). You will need to resize the image in order to accomplish this. Simply resizing an image without paying attention to the results can result in severe image distortion. Therefore, crop the image first, and then proceed to resize it. Problems with distortion will be reduced to a minimum as a result. Finding the image contours in order to crop them is accomplished with the help of the OpenCV library. The process of cropping an image consists of four steps.

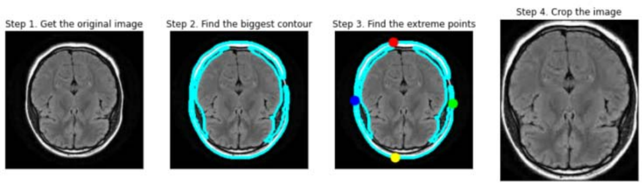

Fig. 5. Steps to Visualize how cropping works

Fig 5. describes the visualization of steps involved in cropping of images

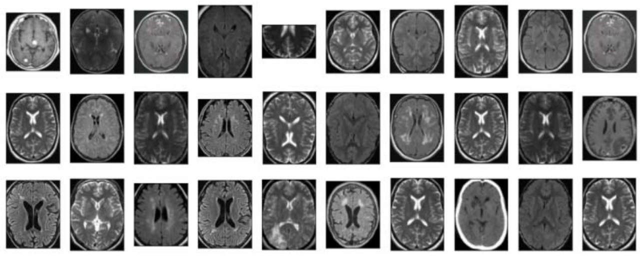
Fig. 6. Images After being cropped

Fig 6. describes the visualization of images after being cropped

After an image has been cropped, it should be resized so that it does not suffer from significant distortion or artifacts caused by resizing, and it should then be enlarged so that more photographs can be saved..

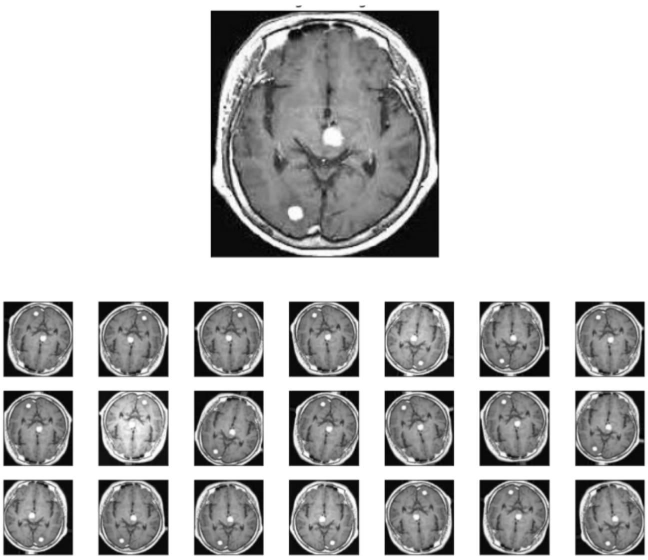
Fig. 7. Images After Augmentation

Fig 7. describes the visualization of images from augmentation of original image, In that augmentation describes the creation of duplication of images from original image

V. Results discussion

These datasets were gathered from Kaggle and contain a total of 3,070 images, of which 2000 were used for the training phase and 70 were used for the testing operation. Accuracy of 94% is achieved while using the selected VGG19 as the benchmark for performance.

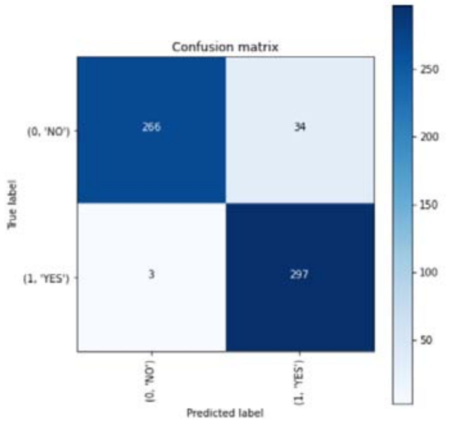

Fig..8 Validation of Dataset

Fig 8. describes the confusion matrix of the given dataset.By using this diagram we can calculate accuracy,precision and few other metrics

Furthermore we have used few performance metrics on the datasets. We got 94 as a accuracy score, 94.12 as a precision score, 94 as a Recall score, 93.99 as a F1 score for VGG19. Whereas we got 93.5 as a accuracy score, 93.76 as a precision score, 93.5 as a Recall score, 93.49 as a F1 score for ResNet50.

TABLE.1.Performance comparison of VGG19 and ResNet50.

Model	TP	FP	TN	FN	Acc	Pre	Recall	F1 score
VGG19	294	6	287	13	0.94	0.94125	0.94	0.93995
RESNET50	300	0	291	9	0.935	0.9376	0.935	0.9349

Table 1. describes the comparison of different metrics for two ifferent algorithms

TABLE.2 .Performance comparison of VGG19 and ResNet50 with Large and Small Datasets.

Algorithm	Dataset	Accuracy	Precision	Recall	F1-score
VGG19	Large	90.98	91.45	91.00	91.22
	Small	94.00	94.12	94.00	93.99
ResNet50	Large	93.50	93.76	93.50	93.49
	Small	89.99	90.50	90.35	90.42

Table 2. describes the comparison between VGG19 and ResNet50 where the use of different sized datasets show different performance results which give us a clear idea of what algorithm to use for what datasets.

After the MRI slices had been separated into normal and tumor classes using a DLA, the slices that included tumors were subjected to additional scrutiny by a medical professional. The primary focus of this study was the implementation of a DLA. In order to construct a computerized model that can monitor the spread of ependymal tumors, it is possible to use the results of the system that has been proposed in conjunction with the data that has been obtained clinically.

The following is future research's project scope:

I. Improving the handcrafted quality of the feature vector by taking into account extra texture and form characteristics.

II. Making adjustments to the fully-connected and drop-out layers in order to achieve more accuracy in the categorization.

III. Making enhancements to the method of feature concatenation in order to achieve superior results.

IV. Putting into practice the suggested VGG19 DLA in order to categorize the gliomas as either low or high grade.

V. The development of a neural network model for the propagation of ependymal tumors

VI.Conclusion

The main goal of the suggested study was to find and enhance an acceptable deep-learning architecture that might help with more accurate brain cancer diagnosis using 2D MRI data. This study offered experimental proof that the VGG19 was in fact the cause of the positive outcomes that were noticed. The features were combined to generate the custom VGG used in this work. After then, the accuracy of the classification is increased by taking into account the final feature vector, which is 1x1x1223, as described above. The clinical datasets that were included in this research contained photographs of the brain, and the general findings that were produced using the proposed VGG19 assisted in providing superior outcomes on modality images. The performance was validated ten times over, and it was shown to be accurate in classifying more than 94% of the time.

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