A COMPARATIVE ANALYSIS OF DEEP NEURAL NETWORK FOR BRAIN TUMOR DETECTION

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ABSTRACT - The rise of powerful technologies in medicine has revolutionized disease detection, classification, and identification. This has significantly streamlined diagnosis, providing healthcare professionals with invaluable tools to improve patient outcomes. Identifying brain tumors poses a substantial challenge in the medical realm, as early detection is crucial for selecting optimal treatment approaches and enhancing patient survival rates. However, manually detecting tumors for cancer diagnosis using data from clinical instruments is a time-consuming task, with the accuracy heavily reliant on the expertise of radiologists. To address this issue, this paper proposes methods for automating the detection process, thereby enabling radiologists to arrive at conclusions more swiftly and efficiently. These methods are based on pretrained network models, such as ResNet and its variants, renowned for their effectiveness in various computer vision tasks. ResNet-152 stands out as a powerful tool for Brain tumor detection, with its ability to significantly automate the process. By leveraging techniques from deep learning and machine learning, such as neural networks, this approach enhances disease identification processes, assisting healthcare professionals in delivering timely and accurate diagnoses[1].

Keywords: Neural Network, Mahine learning, Deep learning, Disease identification, ResNet.

I. INTRODUCTION

A tumor is defined as an abnormal mass caused by the uncontrolled proliferation of cells within living organisms. These growths can vary greatly in terms of type, size, location, and cellular behavior within the human body. When such growths develop within the brain, they are referred to as brain tumors, representing a substantial portion—between 85% to 95% of all primary tumors of the Central Nervous System (CNS). Due to their potential lethality, early detection and diagnosis are critical. There is sometimes the doctor might diagnosis patient to having a benign tumor is not cancer instant of the malignant and hence advanced systems supporting machine learning should be used to help with early detection machine learning [11]. Brain tumor classification and detection can be achieved through various methods, including Magnetic Resonance Imaging (MRI) scans, Spinal taps, and Biopsies. Deep learning (DL) technology has emerged as a powerful tool, offering a vast array of pre-trained classification models like Alexnet, VGGnet [9], Googlenet [10], Squeezenet [7], ResNet [8], and Xception [6].In[1], Deepa P L. and [4] Rajat Mehrotra et al. have discussed brain tumor classification systems utilizing models like ResNet-152 and comparative approaches based on transfer learning techniques, respectively, achieving high accuracies. One ResNet model that stands out for being especially accurate is ResNet-152.

II. AIMS AND OBJECTIVE

a) Aim

This effort aims to develop and assess a web-based platform that will provide a comprehensive and easy-to-use comparison of several deep neural network designs about their efficacy and accuracy for brain tumor identification using medical imaging data. It will also guarantee that the site is easily navigable for a broad spectrum of users, such as students, medical professionals, and researchers.

b) Objective

- To ensure that application can process uploaded medical images using each of these architectures independently and deliver results effectively. In less quantity of data, we can achieve more accuracy.
- An interactive feature for users to visually compare the outcomes of different neural networks.
- Implement measures for introducing the web-based application to academic communities, medical

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institutions, and potential stakeholders to garner feedback and enhance its relevance and utility.

III. LITERATURE SURVEY

Paper 1: Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network

This work describes an automated brain tumor classification tool leveraging MRI data. The system utilizes a Squeeze and Excitation ResNet model, built upon a Convolutional Neural Network (CNN) architecture. To ensure consistent analysis across tissue types, we implemented preprocessing steps like zero-centering and intensity normalization. The effectiveness of our proposed CNN model was evaluated through comparisons with publicly available brain tumor datasets. Experimental results demonstrate an overall accuracy rate of 89.93% without data augmentation. Incorporating data augmentation further improved accuracies to 98.67%, 91.81%, and 91.03% for Glioma, Meningioma, and Pituitary tumor classification, respectively, yielding an overall accuracy of 93.83% . Notably, the proposed approach exhibits promising enhancements in sensitivity and specificity compared to existing state-of-the-art methods[5].

Paper 2: Image Segmentation and Classification Using CNN Model To detect Brain Tumors

Brain tumors are traditionally diagnosed through biopsies, which are invasive surgical procedures. Techniques like enhancement and machine learning, including Convolutional Neural Networks (CNNs), offer a promising alternative for non-invasive tumor diagnosis using Magnetic Resonance Imaging (MRI). This paper proposes a novel, lightweight CNN architecture for brain tumor segmentation and classification, focusing on three tumor types. The network design is simpler than existing pre-trained models, allowing for faster processing. We evaluated the network's performance and generalizability using contrast-enhanced T1-weighted MRI scans and a subject-specific 10-fold cross-validation technique. Notably, record-oriented cross-validation on the expanded dataset achieved the best accuracy of 96.56%. [3].

Paper 3:Transfer Learning for Automatic Brain Tumor Classification Using MRI Images

Brain tumors are a leading cause of death globally. Classifying and segmenting them using traditional medical image processing methods is complex and challenging. Manual classification with human assistance can be prone to errors due to the variability and similarity between tumors and healthy tissues. Deep learning techniques have emerged as a promising approach to improve the accuracy of brain tumor detection and classification in MRI scans.

This paper proposes a deep learning model for brain tumor classification in MRI images leveraging a Convolutional Neural Network (CNN) with transfer learning. We evaluated several CNN architectures, including ResNet, Xception, and MobileNet-V2. Notably, MobileNet-V2 achieved the best performance, reaching an accuracy of 98.24% and an F1-score of 98.42%. [2].

IV. EXISTING SYSTEM

There are various methodologies utilizing deep learning technology that exist for the detection and categorization of brain cancers. Additionally readily available are pre-trained categorization models like Inception, Xception, ResNet, Squeezenet, VGGnet, Alexnet, and Googlenet. ResNet-101 correctly identified the tumor location into three different categories: pituitary tumor, glioma, and meningioma, with an accuracy percentage of 93.83%. Benign and malignant brain tumors are distinguished using a comparative approach that relies on transfer learning algorithms. Five distinct deep learning models—AlexNet, GoogleNet, ResNet-50, ResNet101, and SqueezeNet—have been employed[1].

V. COMPARATIVE STUDY

Sr. No.	Author	Paper Title	Publication	Technology	Purpose
1.	Deepa P L, Narain Ponraj and Sreena V G	A Comparative Analysis Of Deep Neural Network For Brain Tumor Detection	Researchgate ,2019	ResNet	This paper proposes methods for automating the detection process, thereby enabling radiologists to arrive at conclusions more swiftly and efficiently.
2	Palash Ghosal, Lokesh Nandanwar, Swati Kanchan, Ashok Bhadra	Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network	IEEE,2019	ResNet	There is a machine learning technology that uses MRI data to automatically classify brain tumors.
3	Rachid Benlamri, Mohamed Arbane, Youcef Brik, Mohamed Djerioui	Transfer Learning for Automatic Brain Tumor Classification Using MRI Images	IEEE,2021	CNN	This deep learning model leverages a convolutional neural network (CNN) and transfer learning to classify brain tumors in MRI images.

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4.	Shadi M S Hilles, Noor S. Saleh	Image Segmentation and Classification Using CNN Model To detect Brain Tumors	IEEE,2021	CNN	An architecture for segmenting and classifying brain tumors using three tumor types.

Table 1: Comparative Study

VI. PROBLEM STATEMENT

Brain tumors represent intracranial solid neoplasms originating from abnormal and uncontrolled cell division, predominantly within the brain but also affecting lymphatic tissue, blood vessels, and cranial nerves. To improve patient survival rates and prognoses, brain tumors must be detected promptly and precisely. Diagnosing brain tumors relies heavily on imaging techniques like magnetic Resonance imaging (MRI) and computed tomography (CT) scans. However, manually interpreting these images is time-consuming and prone to human error. Recent advancements in Deep Neural Networks (DNNs) offer a promising solution: automating brain tumor detection from medical scans. This automation could speed up diagnosis times and increase accuracy[1].

VII. PROPOSED SYSTEM

The transfer learning approach is used to develop the suggested network design. Out of all the models mentioned above, the final three layers are swapped out and retrained to handle the two classes, tumor and normal. The retrained network is evaluated and validated using MRI data after training. In this scenario, the networks are distinguishing between input data that has a tumor and data that does not. Thus, the network is functioning as a classifier for two classes. As a result, we are able to identify a tumor location in a certain photograph. Better classification accuracy is achieved by the ResNet without adding to the network model's complexity. 11722 MRI pictures that were downloaded from the Oasis Dataset and the BRATS2017 challenge comprised the dataset that we used. Each image has been resized to fit one input layer of the corresponding network. 10% of the photographs are used for validation, 80% are used for training, and 10% are used for testing[1].

VIII. ALGORITHM

1. Load necessary libraries

import tkinter, cv2, np, matplotlib.pyplot,

2. Function for user brain tumor detection

def user_detect(request):

gui ← BrainTumorDetectionGUI()

3. Preprocess input image for ResNet

def preprocess_image(img_path):

img ← image.load_img(img_path, target_size←(224, 224))

img_array ← image.img_to_array(img)

img_array ← np.expand_dims(img_array, axis←0)

4. User model training and testing

def user_training(request):

from .AlgoProcess import modelTraining

acc, loss ← modelTraining.StartTraining()

X_train←X_train.reshape(X_train.shape[0], number_pix)
X_test←X_test.reshape(X_test.shape[0], number_pix)
X_train←X_train/224

X_test←X_test/224

5. Start model training and get accuracy and loss metrics

acc, loss ← modelTraining.StartTraining()

6. Load trained ResNet-152 model

model ← ResNet152(weights←'imagenet')

7. Predict tumor using ResNet

def predict_tumor(img_path):

preprocessed_img ← preprocess_image(img_path)

preds ← model.predict(preprocessed_img)

decoded_preds ← decode_predictions(preds, top←1)[0]

return decoded_preds[0][1], decoded_preds[0][2]

8. Evaluate the model

loss, accuracy ← model.evaluate(X_test, y_test)

print("Test Loss:", loss)

print("Test Accuracy:", accuracy)

XI. MATHEMATICAL MODEL

1. AlexNet

With a noteworthy degree of accuracy, it is the first deep network to be able to classify some objects in the ImageNet dataset Five convolutional layers make up this network. One of the pioneers in computer vision is the 1deep convolutional neural network design. Many fully connected layers, pooling layers, and convolutional layers make up this structure.

Let Y be the output, and X be the input image (prediction). The result of the i-th layer, denoted as $Z^{[i]}$, is computed as

$$Z^{[i]} = f^{[i]}(Z^{[i-1]}, W^{[i]}, b^{[i]})$$

Where $f^{[i]}$ is the activation function, $W^{[i]}$ is the weight matrix, and $b[i]$ is the bias vector.

2. GoogLeNet / Inception

Another well-known two deep neural network design is GoogLeNet, sometimes occasionaly called as Inception v1.It introduced the concept of inception modules, which consist of many convolutional layers running concurrently at different filter sizes. The foundation of GoogLeNet is the theory that most deep network activations are either superfluous (zero value) or unnecessary due to the correlation between them[10].

Here's the mathematical model of GoogLeNet:

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Let Y be the output, and X be the input image (prediction). The result of the i-th inception module, denoted as $Z^{[i]}$, is computed as:

$$Z^{[i]} = W^{[i]} * Z^{[i-1]} + b^{[i]}$$

3. Resnet-152

According to what has been said thus far, deepening the layer of the network is necessary to boost accuracy, provided that over-fitting continues. However, adding layers alone is insufficient to increase the depth of the network. Because of the issue with vanishing gradients—where gradients are re-propagated to the previous layer—deep networks are challenging to implement. Repeated repetition might lead the gradient to become extremely small. One particular version of ResNet with 152 layers is called ResNet-152. Though it has a deeper network structure than the standard ResNet architecture, its mathematical approach allows it to capture more complicated properties. The mathematical model of ResNet-152 can be created by assembling multiple ResNet blocks, each with 15 convolutional layers, batch normalization, activation functions (like ReLU), and skip connections.[1].

$$Y = F_{\text{ResNet-152}}(X)$$

where $F_{\text{ResNet-152}}$ represents the entire ResNet-152 model.

X. SYSTEM ARCHITECTURE

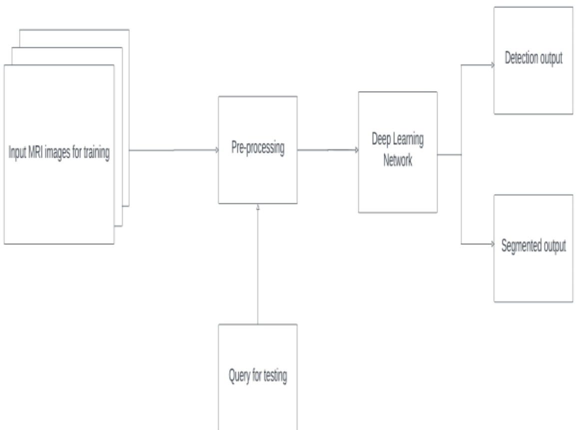

Fig.1: System Architecture

The system architecture utilizes methods from deep learning and machine learning to automate brain tumor detection, aiding medical professionals in providing prompt and precise diagnoses. Pre-trained models like ResNet and its variations offer a significant advantage in brain tumor detection from MRI scans. These models leverage existing knowledge gained from vast image datasets, allowing the system to learn and detect tumor patterns more effectively. This architecture aims to streamline diagnostics, enhance patient outcomes, and assist healthcare providers in addressing brain cancer more effectively.

XI. ADVANTAGES

- Benchmarking ResNet's performance against other DNN designs in brain tumor detection tasks is possible through comparative analysis. This gives important information on how well ResNet works by indicating whether it matches, surpasses, or falls short of other models.
- By means of comparative analysis, scientists can ascertain whether ResNet is the best DNN architecture out of the ones taken into consideration for the identification of brain tumors. ResNet can be reliably chosen for additional study or clinical use if it continuously exhibits better performance.
- By contrasting ResNet with other DNN architectures, researchers can learn more about the advantages and disadvantages of this particular architecture 1 for the identification of brain tumors. This understanding can serve as the roadmap for future modifications or additions intended to improve ResNet's functioning.

X. DESIGN DETAILS

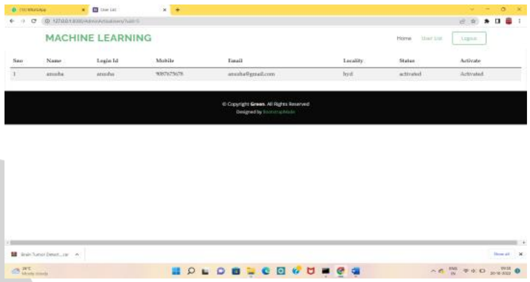

Fig 2: Result

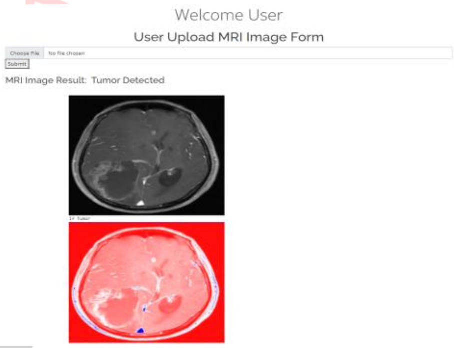

Fig 3: Result

XI. CONCLUSION

Thus, we have tried to implement the paper "A Comparative Analysis of Deep Neural Networks for Brain Tumor Detection", Deepa P L, Narain Ponraj and Sreena V G, a comparison of many ResNet versions ResNet-50, ResNet-101, and ResNet-152 was suggested. The transfer learning approach changes all of the networks by replacing the last three layers of the existing models. Everyone then goes through retraining to determine whether or not they are qualified to detect brain cancers. The results suggest that the ResNet-152 model that was retrained outperforms the others. Utilizing these networks, it becomes feasible to automate the identification of various types of brain tumors.

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