Advanced Brain Tumor Diagnosis: MRI Image Classification with Deep Learning Technology

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ABSTRACT

Currently several diseases are epidemic in Bangladesh, one of them is brain tumor. This disease usually affects people of any age. It usually spreads slowly in the human brain. Although initially it is small, as time goes by it does not look terrible, and the shape of the head becomes distorted. If the disease continues for a long time and without specific treatment, it often does not turn into cancer. Because the tumor affects the brain, it is called a brain tumor. Using machine learning and various image processing techniques, this paper proposes to automate brain tumor diagnosis. This dataset consists of images of brain tumor patients, non-brain tumors, and a total of 4 types of brain tumors. In this paper we have used the Customize CNN Algorithm, through which we have used the 7 architectures of CNN. The 7 custom CNN methods we used are VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3 and DenseNet201. Here we can see that accuracy of VGG19 is 0.75, accuracy of MobileNetV2 is 0.88, accuracy of MobileNetV3 is 0.97, accuracy of EfficientNet B0 is 0.99, accuracy of EfficientNet B3 is 0. 99, Inception V3 is 0.86, and DenseNet201's accuracy is 0.90. From all the methods it can be seen that EfficientNet B0 and EfficientNet B3 method has obtained the highest accuracy i.e., 0.99. The lowest accuracy i.e., 0.75 was obtained using the VGG19 model.

Keywords— Deep learning, MRI Image, Brain Tumor, Image Processing, .

INTRODUCTION

Every year, brain tumors, whether primary or metastatic (secondary), harm around 190,000 people globally. There are many trends among brain tumor patients, despite the fact that the precise cause of these tumors is unknown. No matter how old they are, it might affect anyone. It was first discovered that the tumor region had a decreased mortality risk [1].

Due to technological improvement, every day, a significant quantity of magnetic resonance (MR) pictures are generated. These images are used to keep track of people's physical health. On the other hand, studying them for specialists is a difficult work because it helps with the patient's medical judgment's diagnosis and therapy. In other words, illness diagnosis and therapy often begin with medical picture analysis. Medical image analysis has become a fascinating field as a result, playing a big part in modern therapeutic applications. It is challenging to diagnose a brain tumor early, which is why further study is needed [2]. The exact identification of stroke lesions and brain tumors is challenging in medical imaging because it has a big influence on clinical diagnosis. A brain tumor is an abnormal cell that develops in or near the brain and alters the structure and behavior of the brain. Brain tumors are the world's biggest cause of mortality and have increased more than threefold over the past three decades, according to National Brain Tumor Foundation (NBTF) study reports [3]. Due to these diseases, Our bodies are prone to experiencing a variety of physical symptoms, such as involuntary movements of body parts, speech delay or blurred vision, loss of appetite, nausea and vomiting, lack of focus, memory loss or disorientation, neck pain or stiffness, seizures, and hearing impairment has to be many babies need help a few years after birth.

In this research, we developed data science models to accurately diagnose brain tumors, saving doctors' time and expediting patient recovery. Our aim is to assist underprivileged people by employing deep learning and machine learning models for diagnosing various illnesses, including brain tumors. Filling doctor vacancies and increasing technology dependency in the medical sector can further alleviate these issues.

LITERATURE REVIEW

A. Sasi Kumar et al. [1] present a study utilizing deep learning to diagnose brain diseases like Alzheimer's and tumors, based on image datasets. Using 257 datasets, they employ LSTM models with RNN and CNN neural network classifiers for classification and prediction. A. A. Dehkordi et al. [2] utilize an advanced Convolutional Neural Network for brain MRI analysis to distinguish tumor tissues using the BRATS 2015 and brain image datasets, achieving 97.4% accuracy, 96.0% sensitivity, 98.6% specificity, 98.4% accuracy, and a 96.6% F1-score. Z. Al-Azzwi et al. [3] developed a computer-based system for classifying brain images into normal and abnormal categories using Stacked Ensemble Deep Learning Methods. Utilizing VGG19, Inception v3, and ResNet 10 models on Kaggle datasets, they achieved 96.6% accuracy in binary classification. V.P.G. Pushpa Rathi et al. [4] present a deep learning approach for detecting and classifying brain diseases using three modules: segmentation, feature extraction, and classification. Their technique, applied to image-based datasets categorized as tumor or non-tumor, outperforms previous methods with results of 1, 0.85, and 0.94. P. Gorla et al. [5] present a hybrid approach for brain tumor detection and classification using MRI images, incorporating noise filtering and skull detection. The dataset includes 100 images (25 normal, 75 abnormal), achieving a 96.63% accuracy on both training and test sets. R. Mathew et al. [6] present a study on brain tumor detection using Wavelet Transform for feature extraction and noise removal, and SVM for classification. They achieved an 87% accuracy rate on image-based datasets, with key steps including feature extraction, classification, and segmentation. J. Naik et al. [7] present a method for brain tumor detection using Decision Tree (DT) classification, achieving 100% accuracy. The study involves pre-processing, association rule mining, and feature extraction. DT outperforms the Naive Bayesian algorithm in accuracy, based on image-based datasets. Shubhashis Kumar Shil et al. [8] improved and analyzed a Brain Tumor Detection and Classification algorithm using SVM. Their study classified brain tumor images into normal and abnormal categories, achieving 99.33% accuracy, 99.17% sensitivity, and 100% specificity with 100 normal and 180 abnormal images. M. O. Khairandish et al. [9] utilized Hybrid CNN-SVM Threshold Segmentation to detect and classify benign and malignant brain tumors from MRI images, focusing on tumor orientation, size, and location for disease diagnosis. Their approach achieved 98.4959% accuracy using BRATS 2015 dataset and various classification methods including RELM, DCNN, DNN, DWA, kNN, and CNN. J. Amin et al. [10] propose a research paper focusing on Brain Tumor Detection and Classification using a Distinctive Approach. They analyze brain tumors based on shape, texture, and severity using image datasets including local, RIDER brain image, and Harvard datasets. Their method achieves high accuracy (97.1%), AUC (0.98), sensitivity (91.9%), and specificity (98.0%) with algorithms like Linear, Cubic, and Gaussian. S. Chauhan et al. [11] developed a method using image-based data mining techniques to detect and classify brain tumors from MRI scans. They achieved an 86.6% classification accuracy using the IBkLG algorithm in WEKA 3.9, focusing on tumor orientation, size, and location for diagnosis. M. Gurbina et al. [12] utilize Support Vector Machines and Wavelet Transforms to classify brain images computationally. They achieve 92%, 91%, and 99% accuracy using Binary Linear Classification, Binary Kernel Classification, and Binary SVM, respectively, for image-based disease prediction.

RESEARCH METHODOLOGY

Design Approach

We present an approach using Convolutional Neural Networks (CNNs) to compare brain tumor images systematically. Our method involves analyzing and classifying a dataset sourced from Kaggle, comprising 5712 original images categorized into 4 classes. This research aims to integrate traditional

histopathological analysis with advanced deep learning techniques, enhancing early and precise brain tumor detection for improved patient outcomes. Detailed sections will cover data collection, preprocessing, model training, and evaluation, emphasizing reproducibility, interpretability, and comparative analysis with other methods. The study procedure follows multiple steps outlined in Figure 1.

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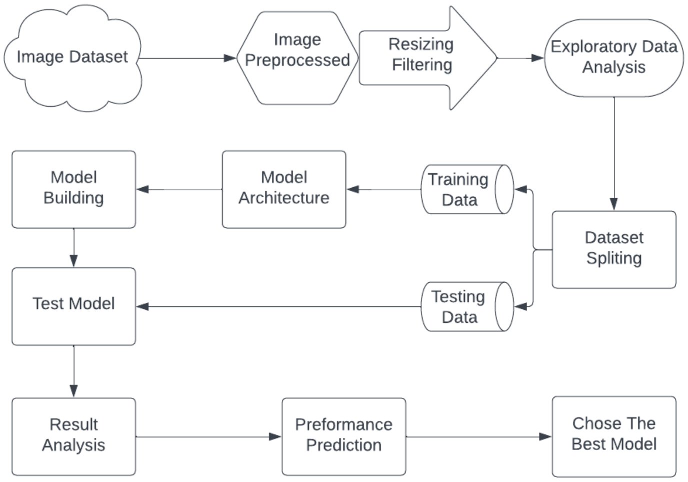

Fig. 1. Architecture of Working Process

Dataset Description

The data set we used was about brain tumor. The data set consisted of several images of brain tumor that we could analyze. The total number of pictures there was 5712. A total of 5712 images were divided into four categories. The four categories are Glioma, Meningioma, No tumor and Pituitary. The number of pictures divided into Glioma category was 1321, the number of pictures divided into Meningioma category was 1339, the number of pictures divided into No tumor category was 1595, the number of pictures divided into Pituitary category was 1457. The training dataset, testing dataset, and validation dataset are the three sections that make up our dataset. Training 70% data taken, testing data set 20% data taken and validation dataset 10%.

Table 1

Classifiers Description

SL	Class Name	No of Data	Description
01	Glioma	1321	Here are 1321 images of Glioma disease. We collected images to predict glioma disease.
02	Meningioma	1339	Here are 1339 images of Meningioma disease. We collected images to predict glioma disease.
03	Notumor	1595	Here are 1595 images of Notumor disease. We collected images to predict glioma disease.
04	Pituitary	1457	Here are 1457 images of Pituitary disease. We collected images to predict glioma disease.

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Fig. 2. Class wise Separate Image

Data Preprocessing

- Grayscale preprocessing converts color images to single-channel grayscale, enhancing computational efficiency and focusing on intensity variations for analysis.
- Histogram Equalization is a method used in image processing to improve contrast by redistributing pixel intensities, enhancing details in both dark and bright areas of an image.
- Noise reduction preprocessing technique involves filtering out unwanted distortions or random variations from data to enhance signal clarity and improve accuracy in analysis or classification tasks.

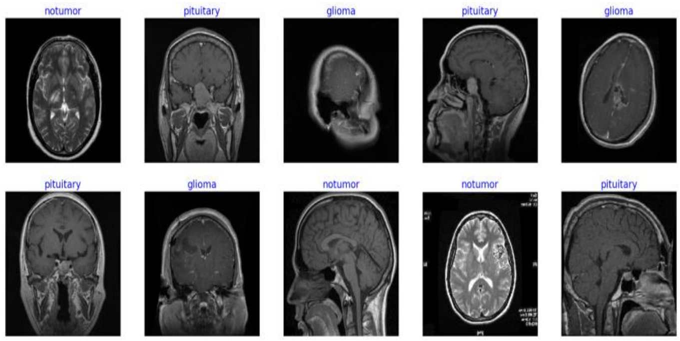

Fig. 4. Preprocessed Images

EXPERIMENTAL RESULTD AND DISCUSSION

VGG19

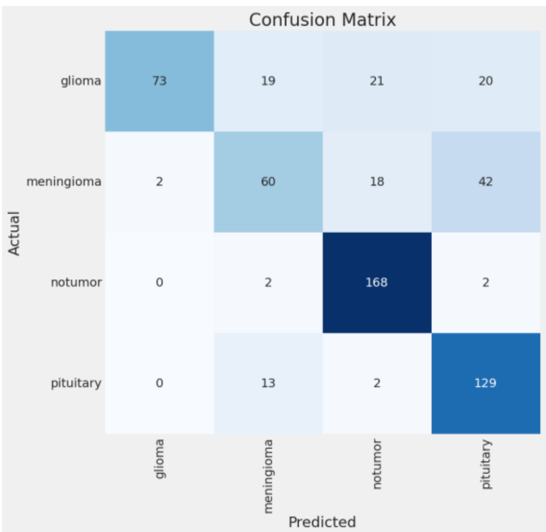

Fig. 3. Confusion Matrix for VGG19

Table 2

Classification Report Of Vgg19

Classes	Precision	Recall	F1_Score	Support
Glioma	0.97	0.55	0.70	300
Meningioma	0.64	0.49	0.56	306
Notumor	0.80	0.98	0.88	405
Pituitary	0.67	0.90	0.77	300
Accuracy			0.75	1311
Macro Avg	0. 77	0. 73	0. 73	1311
Weighted Avg	0. 77	0. 75	0. 74	1311

MonileNet V2

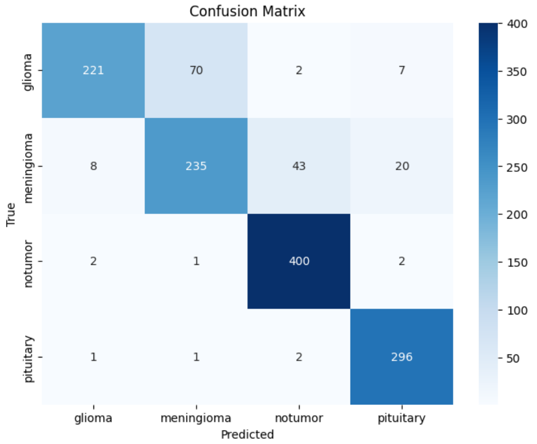

Fig. 4. Confusion Matrix for MobileNet V2

Table 3

Classification Report Of Mobilenet V2

Classes	Precision	Recall	F1_Score	Support
Glioma	0.95	0.74	0.83	300
Meningioma	0.77	0.77	0.77	306
Notumor	0.89	0.99	0.94	405
Pituitary	0.91	0.99	0.95	300
Accuracy			0.88	1311

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Macro Avg	0. 88	0. 87	0. 87	1311
Weighted Avg	0. 88	0. 88	0. 88	1311

MobileNet V3

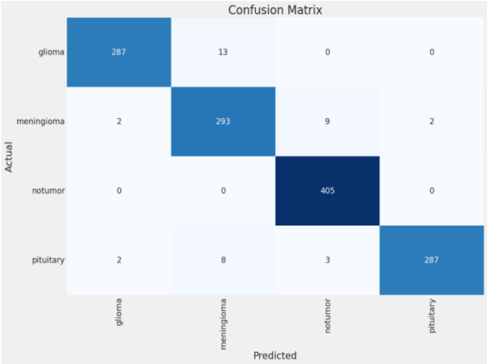

Fig. 5. Confusion Matrix for MobileNet V3

Table 4

Classification Report Of Mobilenet V3

Classes	Precision	Recall	F1_Score	Support
Glioma	0.98	0.95	0.97	300
Meningioma	0.93	0.95	0.94	306
Notumor	0.97	1.00	0.98	405
Pituitary	0.99	0.95	0.97	300
Accuracy			0.97	1311
Macro Avg	0. 97	0. 96	0. 96	1311
Weighted Avg	0. 97	0. 97	0. 97	1311

EfficientNet B0

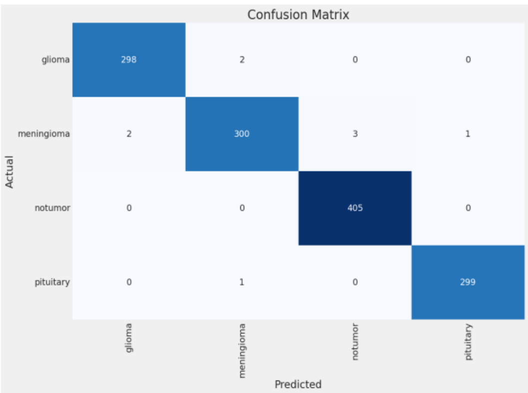

Fig. 6. Confusion Matrix for EfficientNet B0

Table 5

Classification Report Of Efficientnet B0

Classes	Precision	Recall	F1_Score	Support
Glioma	0.99	0.99	0.99	300
Meningioma	0.99	0.98	0.98	306
Notumor	0.99	1.00	0.99	405
Pituitary	0.99	0.99	0.99	300
Accuracy			0.99	1311
Macro Avg	0.99	0.99	0.99	1311
Weighted Avg	0.99	0.99	0.99	1311

EfficientNet B3

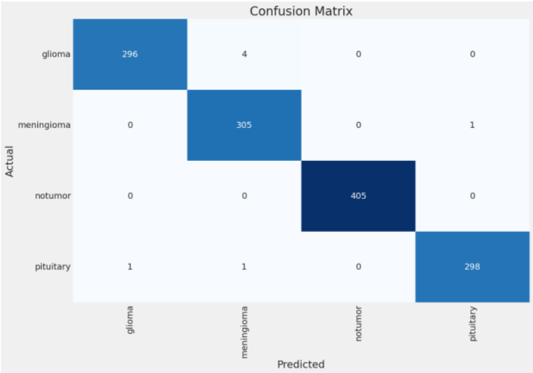

Fig. 7. Confusion Matrix for EfficientNet B3

Table 6

Classification Report Of Efficientnet B3

Classes	Precision	Recall	F1_Score	Support
Glioma	0.99	0.98	0.99	300
Meningioma	0.98	0.99	0.99	306
Notumor	1.00	1.00	1.00	405
Pituitary	0.99	0.99	0.99	300
Accuracy			0.99	1311
Macro Avg	0.99	0.99	0.99	1311

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Weighted Avg	0.99	0.99	0.99	1311

Inception V3

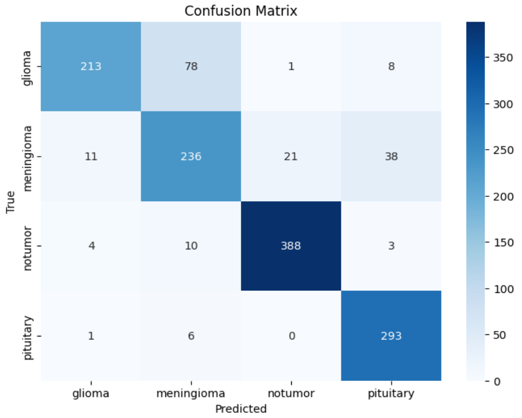

Fig. 8. Confusion Matrix for Inception V3

Table 7

Classification Report Of Inception V3

Classes	Precision	Recall	F1_Score	Support
Glioma	0.93	0.71	0.81	300
Meningioma	0.72	0.77	0.74	306
Notumor	0.95	0.96	0.95	405
Pituitary	0.86	0.98	0.91	300
Accuracy			0.86	1311
Macro Avg	0.86	0.85	0.85	1311
Weighted Avg	0.93	0.71	0.81	300

DenseNet 201

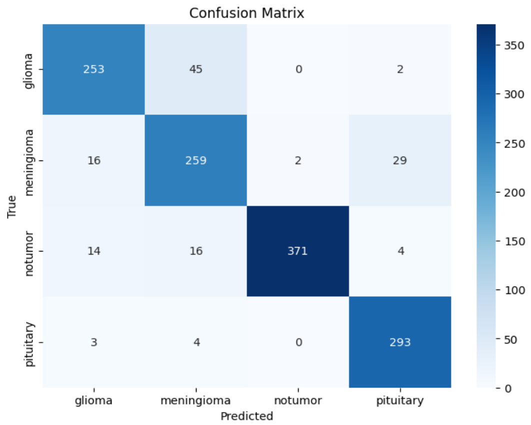

Fig. 9. Confusion Matrix for DenseNet 201

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Table 8

Classification Report Of Densenet 201

Classes	Precision	Recall	F1_Score	Support
Glioma	0.88	0.84	0.86	300
Meningioma	0.80	0.85	0.82	306
Notumor	0.99	0.92	0.95	405
Pituitary	0.89	0.98	0.93	300
Accuracy			0.90	1311
Macro Avg	0.89	0.90	0.89	1311
Weighted Avg	0.90	0.90	0.90	1311

Overall Classification Report

Here the Customize CNN algorithm is used. 7 architectures of the Customize CNN algorithm are used. The 7 methods of Customize CNN we used are VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3 and DenseNet201. Here we can see that the accuracy of VGG19 is 0.75, the accuracy of MobileNetV2 is 0.88, the accuracy of MobileNetV3 is 0.97, the accuracy of EfficientNet B0 is 0.99, the accuracy of EfficientNet B3 is 0. 99, the accuracy of Inception V3 is 0.86, and the accuracy of DenseNet201 is 0.90. Among these architectures, 2 models of MobileNet namely MobileNetV2 and MobileNetV3 are used, whose accuracy is 0.88 and 0.97 respectively. Among these architectures, 2 models of EfficientNet namely EfficientNet B0 and EfficientNet B3 have been used, whose accuracy is 0.99 and 0.99 respectively. The DenseNet201 architecture also gave good results, with an accuracy of 0.90. It can be seen from all the methods that the highest results are obtained in EfficientNet B0 and EfficientNet B3 methods, whose accuracy is 0.99. The lowest results were obtained using the VGG19 model, with an accuracy of 0.75.

Table 9

Classifiers Description

Model	Accuracy	Precision	Recall	F1-score
VGG19	0.75	0.77	0.73	0.73
MobileNetV2	0.88	0.88	0.88	0.87
MobileNetV3	0.97	0.97	0.96	0.96
EfficientNet B0	0.99	0.99	0.99	0.99
EfficientNet B3	0.99	0.99	0.99	0.99

Inception V3	0.86	0.87	0.86	0.86
DenseNet201	0.90	0.90	0.89	0.89

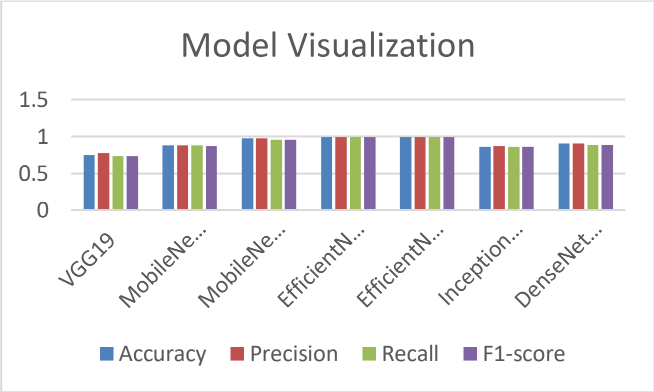

Fig. 10. Overall Model Visualization

DISCUSSION

Health is paramount for happiness, with the brain being crucial for human existence and daily functions. Proper brain function ensures normal life activities like movement, essential for survival. Just as the body requires nutritious food for optimal organ function, neglecting brain health can lead to debilitating consequences. Our project employs artificial intelligence and deep learning, specifically using 7 CNN architectures—VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3, and DenseNet201—to detect brain tumors and diseases. Among these, EfficientNet B0 and B3 showed the highest accuracies, while VGG19 had the lowest. These methods not only diagnose diseases but also save time for both patients and doctors, offering crucial awareness and treatment options for better healthcare management and disease prevention.

CONCLUSION

Early detection and treatment are crucial for managing brain tumor diseases effectively. Proper dietary habits, including balanced nutrition and avoiding excessive non-vegetarian and sugary foods, play a significant role in prevention. Scientific advancements, particularly through artificial intelligence and deep learning in our project, offer promising results for diagnosing various types of brain tumors. Utilizing customized CNN algorithms such as VGG19, MobileNetV2, MobileNetV3, EfficientNet B0, EfficientNet B3, Inception V3, and DenseNet201, we found that EfficientNet B0 and B3 achieved the highest accuracies, underscoring their effectiveness in clinical applications compared to other models like VGG19.

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