Brain Tumor Detection Using deep neural network

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***Abstract*—This thesis investigates the application of deep neural networks (DNNs) for brain tumor detection using some scan data taken through magnetic resonance imaging (MRI) process. By leveraging the capabilities of DNNs in learning intricate patterns from raw data, we develop a methodology that involves preprocessing MRI scans, extracting features by applying convolutional neural networks (CNNs), and training the model on a comprehensive dataset comprising various tumor types and disease stages. The trained DNN demonstrates high accuracy in distinguishing between tumor and non-tumor regions, as well as differentiating between tumor subtypes based on histological characteristics. Performance evaluation metrics including sensitivity, specificity, precision, and accuracy highlight the effectiveness of the developed model, showcasing its superiority over existing techniques in terms of detection accuracy and computational efficiency. The proposed framework exhibits robustness to variations in imaging protocols and tumor heterogeneity, making it suitable for real-world clinical applications. Overall, this thesis presents a novel deep learning-based approach for accurate and automated brain tumor detection and classification from MRI scans, offering a reliable solution to assist radiologists in early diagnosis and treatment planning, thereby contributing to improved patient care and outcomes in neuro-oncology.**

***Index Terms*- DNNs, Preprocessing, CNNs, Sensitivity, Specificity, Precision, Accuracy**

I. INTRODUCTION

The detection and classification of brain tumors represent pivotal tasks in the field of medical imaging, as they are instrumental in facilitating early diagnosis and formulating optimal treatment strategies. With the advent of sophisticated deep learning techniques, particularly Convolutional Neural Networks (CNNs), remarkable strides have been achieved in automating the detection process from magnetic resonance imaging (MRI) scans. This thesis embarks on a comprehensive exploration of the potential of CNN algorithms for the accurate detection of brain tumors.

Brain tumors pose a significant global health challenge, exhibiting a wide spectrum of types and characteristics that necessitate tailored treatment approaches based on factors such as tumor type, size, and location. Traditional methods of tumor detection heavily rely on manual interpretation by expert radiologists, a process that is inherently time-consuming, subjective, and prone to human error. The burgeoning volume of medical imaging data further exacerbates the need for efficient automated techniques to swiftly and accurately analyze these images, thereby facilitating timely diagnosis and intervention.

Against this backdrop, the primary objective of this thesis is to delve into the effectiveness of CNN algorithms in accurately detecting and classifying brain tumors from MRI images. To achieve this goal, a multifaceted approach is adopted, encompassing the design and implementation of diverse CNN architectures tailored to the intricacies of brain tumor detection. Furthermore, the preprocessing and augmentation of MRI datasets are meticulously orchestrated to ensure optimal model performance. Subsequent phases involve rigorous model training and fine-tuning, followed by a comprehensive evaluation of performance metrics to gauge the efficacy and reliability of the CNN-based approach.

In addition to assessing the standalone performance of CNN algorithms, this thesis endeavors to undertake a comparative analysis with traditional tumor detection methodologies to discern the comparative strengths and weaknesses. Furthermore, an in-depth investigation is conducted to elucidate the impact of various factors, such as dataset characteristics, imaging protocols, and model architectures, on the overall performance of the CNN-based detection framework.

The structure of this thesis is meticulously organized into distinct sections, including an expansive Introduction that delineates the research context and objectives, a thorough Literature Review that synthesizes existing knowledge and research findings in the field, a detailed Methodology section elucidating the experimental design and technical approach, a comprehensive Experimental Setup outlining the datasets, tools, and techniques employed, an extensive Results and Discussion section presenting the findings and their implications, a conclusive Conclusion and Future Work section summarizing the key insights and delineating avenues for future research, and a meticulously curated References section documenting the sources and scholarly contributions underpinning this thesis. Through this structured approach, this thesis endeavors to provide a comprehensive and insightful exploration of the application of CNN algorithms for brain tumor detection, contributing to advancements in the field of medical imaging and ultimately enhancing patient care and outcomes in neuro-oncology.

II. LITERATURE REVIEW

Brain tumors represent an especially malignant form of cancer that can lead to substantial complications within the body. Consequently, identifying a brain tumor early and with precision can substantially enhance the likelihood of survival. However, distinguishing between various types of tumors poses a challenging task. Hence, creating an effective tumor representation through an optimization algorithm is essential for successful identification of brain tumors. This research explores ten existing methods for detecting brain tumors, drawing inspiration from the limitations of each approach to develop a novel strategy for brain tumor detection.

Almufareh et al. [1] proposed an automated brain tumor segmentation and classification system using a YOLO-based deep learning framework. Their study, utilizing BraTS 2015 and BraTS 2017 datasets, achieved impressive accuracies of 98% with a 3D CNN and 96% with BrainMRNet, both CNN-based networks. However, they observed variability in results due to differences in train-test ratios and datasets. This highlights the potential of CNN-based models for brain tumor analysis but underscores the importance of standardized training procedures to ensure consistent performance.

Raju et al. [2] presented an assessment of 3D MRI image segmentation and classification for brain tumor detection using ConvLSTM at the 2023 IEEE 5th International Conference. Their study, utilizing the BraTS 2020 dataset, achieved an accuracy of 91.50% with ConvLSTM. However, the authors noted a limitation in the model's performance enhancement potential, suggesting an expansion of datasets to address this issue.

Santos (2023) [3] employed a deep learning approach utilizing the VGG-16 model for brain tumor detection. The study, conducted on sample MRI images, yielded an approximate accuracy of 88% using CNN and VGG-16. However, Santos highlighted the limitation of requiring further research to evaluate the model's generalizability.

Hasan et al. [4] explored the process of applying Convolutional Neural Networks (CNNs) to find out automated classification of brain tumors. Their study, utilizing brain tumor MRI images, achieved a notable accuracy of 96% with CNN. However, they acknowledged a limitation due to the small size of the dataset, suggesting the need for larger datasets in future research.

Haque et al. [5] (2023) proposed enhancing the performance of brain tumor detection on MRI images using a combination of DCGAN-based data augmentation and the Vision Transformer (ViT) approach. Their study, conducted on brain MRI images, achieved an impressive accuracy of 98% with the ViT model. However, the authors noted a limitation, emphasizing the necessity of a large dataset to further improve the model's performance.

Gupta's [6] study focuses on brain tumor classification using 3D CNN and BrainMRNet on BraTS 2015 and BraTS 2017 datasets, achieving accuracies of 98% and 96%, respectively. However, limitations include potential variability in results based on the train-test ratio and dataset. Almufareh et al. explore automated brain tumor segmentation using CNN models on the same datasets, achieving 91.29% accuracy initially, which slightly decreases to 79.79% with additional techniques. They note a limitation regarding result variance depending on the train-test ratio and dataset, highlighting the need for robust methodologies in medical imaging applications.

Saeedi et al.'s [7] study investigates MRI-based brain tumor detection by applying 2D CNN and machine learning techniques on a dataset comprising glioma, pituitary gland tumor, and no-tumor healthy brain images. Their approach achieves 96.48% accuracy with 2D CNN and 86% accuracy with MLC(NN). However, a limitation is noted regarding the longer execution time for the proposed 2D CNN method.

Zhou et al.'s [8] study focuses on automatic segmentation of brain tumors in MRI images using a U-Net-based network structure. The dataset utilized includes BraTS MRI images encompassing Flair, T2, T1, and T1C sequences. The methodology involves employing Fuzzy C-means (FCM) and Fully Convolutional Neural Network (FCN) techniques. However, a limitation of the study is the absence of specific quantitative results provided.

Villalpando-Vargas et al. [10] present a study on brain tumor detection using deep learning techniques applied to brain MRI images. The dataset is resized to (224, 224) and fed into the VGG16 model. The study employs Support Vector Machine (SVM) and Naive-Bayes (NB) methods for classification. Results indicate an SVM accuracy of 0.89, precision of 0.90, recall of 0.90, and F1 score of 0.89, while NB achieves an accuracy of 0.83, precision of 0.83, recall of 0.84, and F1 score of 0.83. However, a limitation of the study is the absence of information regarding computational resources and training duration.

Villalpando-Vargasa et al. [11] investigate brain tumor detection using deep learning on brain MRI images. They preprocess the dataset by resizing it to (224, 224) before applying the VGG16 model. Employing Support Vector Machine and Naive-Bayes technique, their study reports SVM achieving an accuracy of 89% with precision, recall, and F1 score all at 90%, while NB achieves an accuracy of 83% with precision, recall, and F1 score all at 83%. However, a limitation of their work is the absence of information regarding computational resources and training duration.

III. METHODOLOGY

Our proposed methodology, used a deep neural network and a distinguished model, CNN using the PyTorch framework to classify and detect the brain tumor. We analyzed medical images(MRI) to find the pattern. The annotation of the original data was provided with the dataset: that, the extracted features we fed and trained the mode.

Data preprocessing:

We split the data into two halves of traindataset test-dataset for training and testing of distribution of 80% and 20% respectively. Then resize each image into a width and height of 256 pixels. // Data augmentation is done by horizontal and vertical flips of probability of .5 and random rotation of -30 to 30 degrees.

Data is normalized using mean value of (0.485, 0.456, 0.406) and std value of (0.229, 0.224, 0.225) for each color channel (Red, Green, and Blue) in the image. The normalization is performed channel-wise, meaning that the mean and standard deviation values are applied independently to each color channel.

Proposed methodology using CNN:

Convolutional Neural Networks have come up as a powerful tool in the field of medical science and have shown a great future in aiding medical science in detection and prevention. Over the years many researchers have built models to detect the tumor more effectively. There are various models to operate for this work but we chose CNN for its sparsity and ability to perform better.

TABLE I
SAMPLE TABLE

Author	Model	Dataset	Result	Limitation
Almufareh	3D CNN	BraTS 2015 BraTS 2017	98% Accuracy	Variance in result depending on train-test ratio and dataset
Raju K.S., Arvind S., Chegoni R.	ConvLSTM	BraTS 2020	91.50% Accuracy	Model can enhance its performance by expanding datasets.
Santos D.	CNN, VGG-16	Sample MRI Images	Approximately 88% Accuracy	Needs more research to assess the model's generalizability
Hasan K, Hossain R. B.	CNN	Brain tumor MRI image	96% Accuracy	Small dataset
Haque, M.M	ViT model	Brain MRI Images	96% Accuracy	Require a large dataset
M. Gupta	CNN	Glioma, Meningioma images	91.29% Accuracy	complex models
S. Saeedi	2D CNN	pituitary,gland tumor images	96.48% Accuracy	High execution time
Runwei Zhou	K-means clustering	BraTS	95% Accuracy	does not provide specific quantitative results
Omar Villalpando	CNN	Brain MRI Images	89% Accuracy	Absence of information on computational resources
Marwa Elseddik	CNN	Brain images with tumors	98.67% Accuracy	computational efficiency

Model architecture:

to detect brain tumor, a four-layer Convolutional Neural Network has been used and applied in this work. This complete model consists of sparse networks providing us with more efficient results. Below there is a proposed methodology with a description.

There are four convolutional layers with initial filters of 8 and a kernel size of 3. In the Second convolutional layer with 2*initial filters and a kernel size of 3. In the next two layers, the kernel size remains the same but the initial filters were multiplied by 4 and 8 respectively. As an activation function, reLU was used in each layer for getting better convergence performance.

For progressively reducing the spatial size of the spatial dimensions, there is a max-pooling layer, size of (2,2) with a kernel size of 2 and a stride of 2 was used after each convolutional layer. Dealing with such image datasets also entails the risk of overfitting, and the Max Pooling layer effectively addresses this concern.

Then there were two fully connected layers employed as fc1-1 and fc1-2 represented the dense layers with input features and output features. Before passing output to fully connected layers outputs are flattened.Dropout is used to control the output properly at the rate of 20%.

In the final layer, the softmax activation function is used for classification. The output provides a probability.The sample input images of the proposed work are given in Figure 2 below.

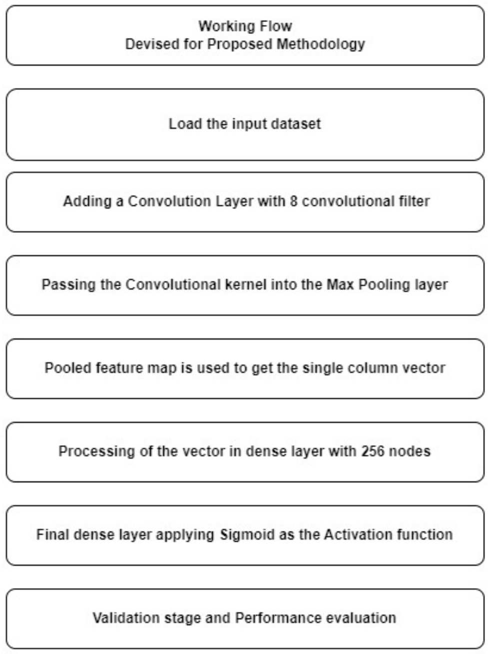

Fig. 1. Fig: Methodology

IV. DATASET

In this thesis paper, we investigate a dataset comprising 4600 unique images, each with specific attributes crucial for medical sector of image analysis, particularly in the sector to detect brain tumor and classification. The dataset includes images categorized into two classes: tumor and normal, with a distribution of approximately 55% for tumor images and 45% for normal images. This balanced class distribution ensures that the dataset is representative of both tumor and normal brain scans, which is essential for training and evaluating machine learning models effectively. The images in the dataset are primarily stored in two different file formats: JPEG and TIFF. JPEG format constitutes the majority of the dataset, accounting for 98% of the images, while the remaining 2% of images are stored in TIFF format. Understanding the distribution of file formats is crucial for data preprocessing and ensures compatibility with various image processing and analysis tools. Furthermore, the dataset includes images encoded in two different color modes: RGB (Red, Green, Blue) and grayscale (L). The vast majority of images (97%) are encoded in RGB color mode, providing detailed color information essential for analyzing image features and patterns. On the other hand, a smaller proportion of images (3%) are encoded in grayscale mode, where each pixel value represents the intensity of light without color information. This diversity in color modes enriches the dataset and enables researchers to explore various image processing techniques suitable for different color representations.

Lastly, the dataset includes images with diverse spatial dimensions or shapes, represented by tuples indicating height, width, and number of color channels (e.g., (512, 512, 3)). The most common spatial dimension is (512, 512, 3), accounting for 19% of the images, followed by (225, 225, 3) representing 8% of the dataset. Understanding the distribution of image shapes is crucial for designing neural network architectures and ensuring compatibility with input dimensions required by the models. The sample input as images of our proposed work are given in Figure 2 below.

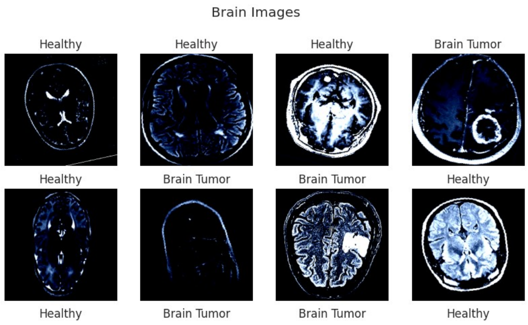

Fig. 2. Sample Input

TABLE II
SAMPLE TABLE

Image	class/label	format/file format	colormode	image dimensions
	tumor:55%	**JPEG: 98%**	RGB: 97%	**(512, 512, 3): 19%**
4600 unique values	normal:45%	**TIFF: 2%**	L: 3%	**(225, 225, 3): 8%**
		Other (18) :0%	Other (7) :0%	**Other (3352):73%**

V. EXPERIMENTAL RESULT

The suggested methodology consisting of five layers yielded highly satisfactory outcomes in classifying brain tumors. The five-layer CNN model for our research involves convolution, max pooling, flattening, and two dense layers. Data augmentation was implemented to diversify the dataset, and the CNN's translation invariance contributed to its strong performance. Remarkably, we achieved an accuracy of 97.87%, which is notable given the relatively sparse nature of the CNN model.

TABLE III
PERFORMANCE OF THE PROPOSED CNN MODEL

Precision	Recall	F1 score	Accuracy (%)
0.98	**0.96**	0.97	**0.97**

VI. RESULT ANALYSIS

In a binary classification, factors like the True Positive, True Negative, False Positive, and False Negative terms are commonly used terms to evaluate the performance of a classification model.

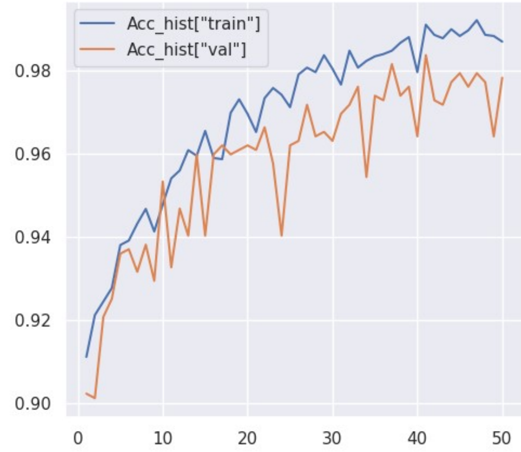

Fig. 3. Sample Input

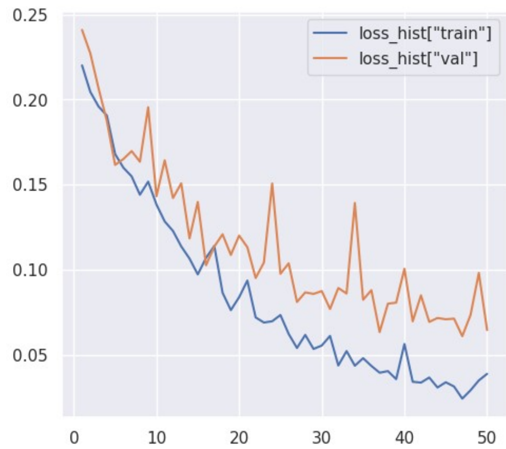

Fig. 4. Sample Input

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity/Recall(TPR) = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity(FPR) = \frac{TN}{TN + FP} \quad (3)$$

$$Precision(PPV) = \frac{TP}{TP + FP} \quad (4)$$

Our true positive rate is about 53.53% which means the model correctly predicted the positive class(tumor) of 53.53%. The true Negative rate is about 43.76% which means the model correctly predicted the negative class(healthy condition) Furthermore the false negative and false positive class rates are about 1.63% and 1.09% which means the model misclassifies these cases. In terms of false negatives, the actual class is the healthy state but the model predicted tumor cell. Similarly, in the case of the false positive the actual class is the non-healthy state but the model predicted the healthy state

VII. LIMITATIONS AND FUTURE WORKS

As a nobel work, there are a lot process that can be taken up by using this data. So we have some future thoughts to add in this work.

Limitations:

One limitation of this thesis is the potential presence of data imbalance in the brain tumor datasets used for training the deep neural network (DNN) models. Imbalanced datasets, where one class (e.g., tumor) is significantly underrepresented compared to others (e.g., non-tumor), can lead to biased model performance and reduced generalization ability. Addressing data imbalance through techniques such as data augmentation or resampling methods could mitigate this limitation.
Another limitation is the inherent lack of interpretability of deep learning models, particularly in the context of medical image analysis. DNN models are often considered as "black-box" models, making it challenging to interpret and understand the underlying factors influencing model predictions. Incorporating techniques for model interpretability, such as attention mechanisms or visualization methods, could enhance the transparency and trustworthiness of the developed brain tumor detection models.

Future Works:

A potential avenue for future work is the integration of multi-modal imaging data, such as combining magnetic resonance imaging (MRI) with other imaging modalities like positron emission tomography (PET) or computed tomography (CT). Exploring fusion techniques and architectures capable of leveraging complementary information from different modalities could enhance the accuracy and reliability of brain tumor detection models.
Further research could focus on conducting extensive clinical validation studies to assess the real-world performance and clinical utility of the developed DNN models for brain tumor detection. Collaborating with healthcare institutions to deploy and evaluate the models in clinical practice, while addressing practical considerations such as integration with existing medical systems and regulatory compliance, could facilitate their adoption and impact in clinical settings.
To overcome the limitations of interpretability and explainability, future research could explore the development of interpretable deep learning models for brain tumor detection. This could involve incorporating attention mechanisms, feature visualization techniques, or designing model architectures that prioritize transparency and interpretability without compromising performance.
Addressing the limitations related to data availability and quality, future work could focus on developing advanced data augmentation and synthesis techniques tailored specifically for medical imaging datasets. This could involve generating synthetic data to augment existing datasets, simulating variations in imaging protocols, and incorporating domain-specific knowledge to improve model robustness.

VIII. CONCLUSION

Medical images are complex to understand and are diversified. Also expensive to always go to a doctor includes hassle as well. Image processing places a vital role in the field of medical science. For brain tumors, we use the deep neural network(CNN) to determine and classify them. And produced an astonishing accuracy of 97%. Handling a larger dataset poses a greater challenge in this domain, and our intention is to construct a dataset specific to our country. This endeavor will accelerate the scope of our work.

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