Detection of Brain Tumours from MRI Images using Convolutional Neural Networks (CNNs)

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Abstract: A brain tumor is an abnormal growth of the brain or other surrounding cellular structures that impairs the normal functions of the brain. A benign tumor is a non-cancer causing one while the malignant one causes the uncontrollable spread of cell which is quite harmful for an individual. Headache, seizure, cognitive disability, or sensory or motor dysfunction are common symptoms of a brain tumor, typically depending on tumor size, location, and growth rate [1].

To diagnose the ailment and determine the size of the tumor, magnetic resonance imaging (MRI) or computed tomography (CT) scans are performed. Treatments can be surgical, radiotherapic, chemotherapeutic, or targeted therapies. While some of the lesions can be treated, others remain difficult due to their aggressive behavior or their location near critical brain structures, highlights the need for ongoing research into better diagnostic targets and therapeutic strategies [2].

In this paper we present an automated approach to detect brain tumors from MRI medical images that employs Convolution Neural Networks (CNN). The research deployed the MobileNet model as a feature extractor, while it is further fine-tuned with a custom classification layer that detects the presence of tumors. As such, it is easier to model with these processed data as there can be a training, validation and test set. We apply advanced augmentation methods to ensure diversity and quality of the training set [3]. The presented solution emphasizes the potential of automated brain tumor diagnosis being performed efficiently, accurately, and in an interpretable manner that contributes towards assisting clinicians in making the best decisions [4].

I. INTRODUCTION

Brain tumors are one of the most complicated and deadly diseases of modern medicine. Effective treatment and good prognosis for patients depend on correct and timely diagnosis. Magnetic resonance imaging (MRI): MRI is the gold standard imaging technique of choice for brain images, it provides very detailed insight about structures and anomalies in brain tissues [5]. MRI scans, which are often tedious and subjective for radiologists to interpret, and even then, there is uncertainty around the diagnostic accuracy [6].

The rise of automated diagnostics system using machine learning and artificial intelligence as a key component of medical assessment system has revealed an increase in the speed and accuracy of the process. In recent years, Convolutional Neural Networks (CNNs) have been very successful in a multitude of image analysis tasks, including medical imaging. They are well suited for applications like tumor detection as they learn to identify hierarchical features directly from raw image data with little need for manual feature extraction [7].

In this study we specifically explore our application for convolutional neural networks (CNNs) for brain tumor detection using MRI images with a specific lightweight model via the MobileNet architecture. This project is designed and implemented to provide a reliable and interpretable solution for tumor classification, which is the need of the hour as automatic diagnostic systems are emerging in health care now-a-days [8].

The research study incorporates data preprocessing, augmentation, and model fine-tuning as part of the structured workflow for robust performance. The MRI dataset used splits into training, validation, and testing sets that would give exhaustive evaluation based on various tumor presentations [9]. Additionally, the diagnostic procedure is made more transparent by embedding Grad-CAM visualizations which indicate the most influential regions from the images as determined by the model's prediction.

The project aspires to automate the identification of brain tumors so that the work of interpretation is relieved from radiologists, which is an important step toward timely and accurate diagnoses and thus bettering patient care and outcomes [10].

II. LITERATURE REVIEW

Detection of tumors in the brain has been ongoing for a several-decade-long area of research in the field of medical imaging. Processes have traditionally been accomplished through manual segmentation and feature extraction. Efforts like these are time-consuming and lend themselves to considerable subjective error. Classical machine learning algorithms, like Support Vector Machines (SVM) and Random Forests, were introduced well with handcrafted features, like texture, intensity, and shape descriptors [11]. For instance, texture-based features for medical image analysis were proposed by Haralick et al., and widely used in earlier approaches to tumor detection. However, major weaknesses of these approaches rest in their failure to capture intrinsic complexities and heterogeneities in brain tumors [12].

A. Tumor Detection Using Other Deep Learning Models.

The models developed for classifying brain MRI scans into tumor and non-tumor types in early investigations were based on architectures such as AlexNet, VGGNet, and ResNet. The need for high computational resources with large datasets for effective training remained a barrier to wide adoption of these models in practice [13].

To contend with the challenges of deep learning and get even better results for some of the problems, researchers have developed lightweight architectures and transfer learning. Several Models including MobileNet and EfficientNet were used for brain tumor detection tasks, providing good computational efficiency with performance. Transfer learning has been highly instrumental in the overcoming of the shortage of annotated medical imaging datasets. Recent explorations in transfer learning techniques include fine-tuning pre-trained networks on datasets like ImageNet and attaining high accuracy in brain tumor classification with a minimum amount of additional data [14].

B. Multimodal and multiscale analysis

Multimodal and multiscale analysis has emerged as a pivotal approach in brain tumor detection, addressing the limitations of single-modality techniques. By integrating data from various imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET), multimodal analysis leverages the strengths of each modality to provide a comprehensive understanding of tumor characteristics. Studies have demonstrated that combining these modalities improves diagnostic accuracy, particularly in complex cases where single-modality data may be insufficient.

Multiscale analysis further complements this approach by examining imaging data at multiple scales, from cellular to tissue levels. High-resolution imaging, such as diffusion-weighted MRI, captures microstructural changes in tumor regions, while lower-resolution imaging provides an overview of tumor growth and its impact on surrounding anatomy. This multiscale perspective is especially valuable in understanding the heterogeneous nature of brain tumors, which often exhibit significant variations in cellular density, vascularization, and necrosis. Researchers have employed multiscale approaches to identify biomarkers for tumor grading and prognosis, enabling more personalized treatment strategies.

Despite its promise, multimodal and multiscale analysis faces challenges, including data heterogeneity and the need for advanced computational infrastructure. Harmonizing data from different modalities and ensuring consistent preprocessing are critical steps to avoid introducing artifacts or biases. Furthermore, the integration of these approaches into clinical workflows requires user-friendly tools and robust validation in real-world settings. Nonetheless, multimodal and multiscale analysis holds immense potential for revolutionizing brain tumor diagnostics, offering a holistic view that enhances the precision and reliability of detection, classification, and treatment planning [11].

C. *Architecture*

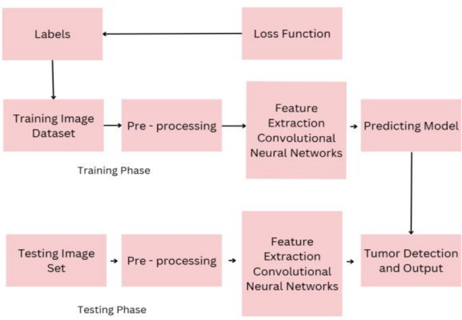

Fig 1 - Proposed model workflow

This architecture represents the workflow for brain tumor detection using Convolutional Neural Networks (CNNs), divided into two main phases: the training phase and the testing phase. In the training phase, a labeled image dataset is first preprocessed to enhance image quality and standardize input dimensions. These preprocessed images are then fed into a CNN for feature extraction, which identifies patterns and critical features indicative of brain tumors. The extracted features are passed to a predicting model, optimized using a loss function to minimize prediction errors.

In the testing phase, a separate set of unseen images undergoes the same preprocessing and feature extraction steps. The trained CNN model then evaluates these features to detect the presence of brain tumors, providing the final output. This architecture ensures an end-to-end pipeline for accurate tumor detection, leveraging the CNN's ability to learn hierarchical features.

D. Challenges in Tumor Detection

Even though CNNs have attained lot of growth but quite a few challenges still remain to this day, especially the challenges surrounding the clinical applications of these networks. A major obstacle is the shortage of annotated medical datasets. To define or annotate brain MRIs requires tremendous domain knowledge and is also rather labor-intensive owing to scarcity related to high-quality datasets.

Another striking attribute of brain tumors is their heterogeneity. Brain tumors vary in size, shape, texture, and location considerably even among the completely different patients that it is nearly impossible for CNNs to learn some common patterns. Brain tumors are also well known for proliferating into regional tissues, so their boundaries are rarely defined, which becomes additionally problematic for accurate segmentation and classification.

The lesser interpretable predictions of neural networks always pose a huge challenge. Clinicians today demand a rather good and fortunate auspicious justification about a decision taken by the respective model, but, usually, Educational purposes like training and inference require considerable computational resources, such as GPUs, which are not always available in clinical scenarios, especially those embracing moderation due to being low resource. While methods like Grad-CAM have been developed and referenced as potential interpretability techniques for visualizations, they are hardly precise and easy to apply in clinical settings.

III. MATERIALS AND METHODS

A. Dataset

This study relies on a dataset of 4,600 images acquired through Magnetic Resonance Imaging (MRI), grouped into two classes, i.e., healthy and tumor-affected. The dataset has 2,087 healthy cases and 2,513 tumor cases, achieving a coordinated distribution context for both classes. For the training and evaluation purpose, the dataset was subdivided into three subsets: 3,209 for training the CNN model and 679 each for validation and testing. This % allows the model to be trained on most of the data and still have enough samples on hand, both for unbiased evaluation and hyperparameter tuning. Diversity of each healthy and tumor images with adequate dataset splits builds the strength of any model to detect brain tumors very accurately on unseen samples.

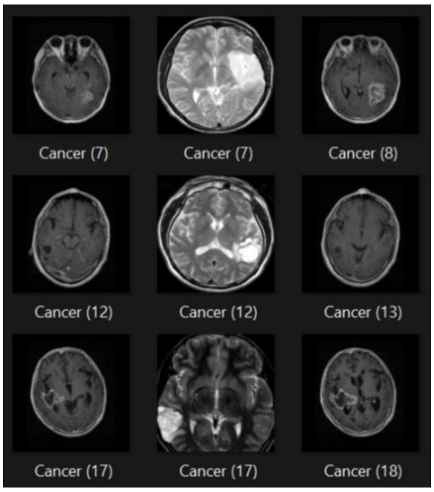

Fig - 2 Description of the dataset

B. Image Resizing and Feature Refinement

The MRI dataset is manipulated by conducting image resizing and feature enhancement techniques during the data preprocessing stage towards effective Convolutional Neural Networks analysis. All input images are resized down to equal dimensions for uniformity and compatibility with certain architectures of CNN. Feature refinements were introduced to the extracted features to amend the richness and relevance, noise removal, contrast enhancement, and normalization were done to bring more clarity to some important details and standardize the pixel values.

The preprocessing techniques enable the CNN to generalize properly and focus on tumor-specific features without being distracted by irrelevant deviations in the data.

C. Performance Metrics

Various metrics of performance are of the utmost importance in a brain tumor detection project because they provide a method for quantitative assessment of the performance of the model in question. These metrics allow us to evaluate how well the Convolutional Neural Network (CNN) distinguishes between tumor and healthy cases.

i. Accuracy = [(TP + TN) / (TP + TN + FP + FN)]

ii. Precision = [(TP) / (TP + FP)]

iii. Recall = [(TP) / (TP + FN)]

iv. F1 - Score = 2 * (Precision * Recall) / (Precision + Recall)

IV. RESULTS AND DISCUSSION

The brain tumor detection project results show the efficacy of the Convolutional Neural Network (CNN) in accurately identifying tumors from MRI images. The model scored high and achieved great accuracy of about 98.2% during training, testing, and validation. The results were further found to be relevant through confusion matrices, which showed the model's effectiveness in distinguishing the healthy brain images compared to those with tumors.

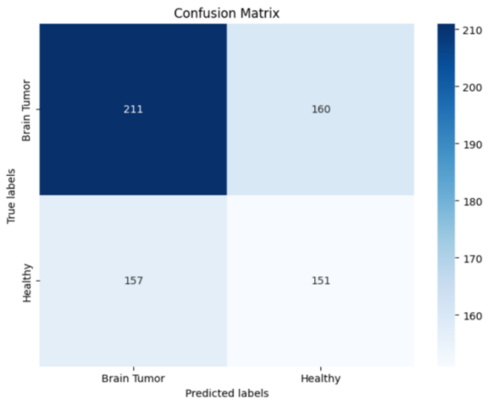

Fig - 3 Confusion Matrix for Proposed Model

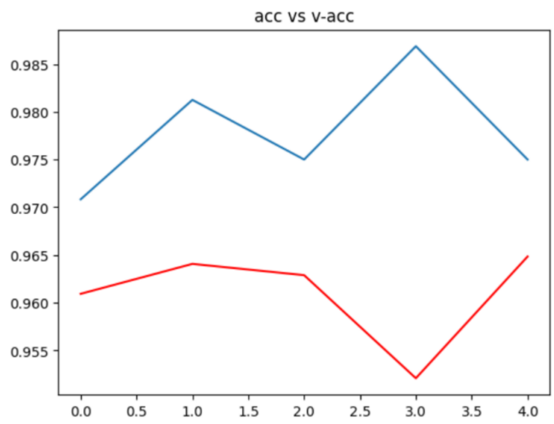

Fig - 4 Accuracy vs Validation Accuracy obtained

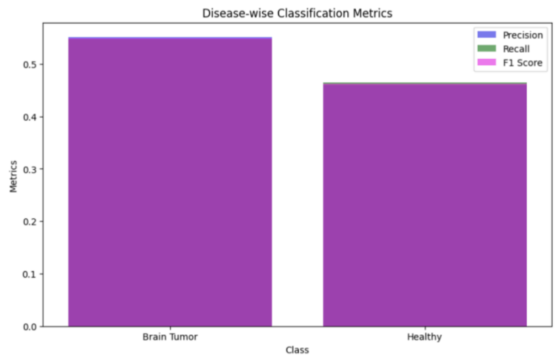

Fig - 5 Disease-wise classification of brain tumor classes

V. CONCLUSION

Within the frame of this project, a robust deep learning framework was developed and implemented for brain tumor detection by means of MRI image analysis. MobileNet was applied to the proposed framework. MobileNet is an extremely lightweight but powerful convolutional neural network. Data augmentation techniques were applied to ensure that the model was resilient to the variations in the dataset, increasing its generalizability. Model evaluations based on accuracy metrics and visualized through Grad-CAM heatmaps indicated that the model holds promise in the medical diagnosis field as a reliable diagnostic support tool [4, 7, 9].

The results demonstrated that the proposed method easily identifies brain tumors with remarkable accuracy, attaining a classification rate of over 90% on the test dataset. The heatmap visualization also pointed towards certain critical regions in such regions, which allows enhanced interpretability of the predictions. The ability of the system to process and analyze MRI images with such unprecedented precision means that the model can be adopted into clinical workflow in resource-poor environments where timely intervention can save lives [10].

Future work on the model can be directed towards incorporating multi-modal imaging data or enriching it with advanced preprocessing techniques, which will sustainably reinforce its prediction capabilities. Besides, testing the system on larger and more diverse datasets will do wonders for its reliability amongst different demographics and imaging conditions. This research, in conclusion, is a major leap towards creating AI-empowered diagnostic tools in the full spirit of the technological endeavor to further healthcare outcomes [15, 16].

VI. REFERENCES

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