International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Brain Tumor and Parkinson's Disease Detection using Deep Learning

Anita Mithapalli [1], Padmavathi R [2], R. K Swetha [3], Pushmitha C [4]

[1]*Assistant Professor, Department of Computer Science and Engineering, MVJ College of Engineering, Bangalore, Karnataka, India*
[2,3,4] *Undergraduate Scholar, Department of Computer Science and Engineering, MVJ College of Engineering, Bangalore, Karnataka, India*
Doi: https://doi.org/10.55248/gengpi.5.0524.1116

ABSTRACT

This abstract outlines a comprehensive strategy employing deep learning techniques for the identification of brain tumors and Parkinson's Disease (PD). In the realm of brain tumor detection, a deep learning model has been devised to categorize tumor presence into three distinct types – meningioma, pituitary, and glioma – while also delineating their dimensions. This model not only discerns the existence of a tumor but also gauges its diameter and area, furnishing crucial insights for medical practitioners. Regarding Parkinson's Disease, a multimodal approach has been embraced, amalgamating drawing and MRI datasets to augment accuracy through the fusion of information from diverse origins. By amalgamating data from varied modalities, the model offers a more comprehensive understanding of the disease, facilitating precise diagnosis and treatment planning. Overall, this deep learning-centered approach exhibits potential in refining the detection and management of brain tumors and Parkinson's Disease, ultimately fostering improved patient outcomes.

Keywords: Deep Learning, Brain Tumor Detection, Parkinson's Disease Detection, CNN

1. INTRODUCTION

Brain tumors pose a significant challenge in the medical field due to their complex nature and various subtypes. Accurately diagnosing and characterizing these tumors requires innovative approaches to enhance detection and treatment. In response to this challenge, this study aims to utilize advanced deep learning techniques to create a sophisticated model capable of detecting brain tumors and categorizing them into three main types: meningioma, pituitary, and glioma.

This endeavor relies heavily on medical imaging data, particularly magnetic resonance imaging (MRI) and computed tomography (CT) scans, to train and validate the deep learning model. By meticulously analyzing radiographic images, the model learns to identify subtle abnormalities indicative of tumor presence and discerns unique characteristics of each tumor subtype for accurate classification.

Moreover, the model goes beyond binary classification by incorporating algorithms for tumor size characterization. Through advanced image processing techniques, it quantifies parameters such as tumor diameter and area, providing clinicians with detailed insights into the tumor's spatial extent and morphological features, thereby enhancing diagnostic accuracy and informing treatment planning.

These advancements offer medical professionals a powerful tool for navigating brain tumor management with precision and confidence. By elucidating tumor subtype and size, clinicians can tailor therapeutic interventions to individual patient needs, optimizing treatment outcomes while minimizing unnecessary morbidity.

Additionally, the deep learning model fosters interdisciplinary collaboration by bringing together radiologists, neurosurgeons, oncologists, and other stakeholders. Integrated into clinical workflows, it streamlines diagnostic processes and facilitates timely interventions, ultimately revolutionizing the diagnosis and management of brain tumors and advancing precision medicine.

Moving on to Parkinson's Disease detection, this progressive neurological disorder is primarily characterized by motor symptoms such as tremors, stiffness, and bradykinesia. Traditional diagnostic methods often lack consistency due to their subjective nature. To address this, a novel multimodal approach combines drawing and MRI datasets to enhance accuracy and provide a comprehensive understanding of the disease. By integrating data from different sources, including hand-drawn sketches and brain imaging scans, this approach aims to facilitate early detection and personalized treatment strategies tailored to the diverse aspects of PD pathology.

This innovative approach promises to revolutionize the diagnosis and management of Parkinson's Disease, ultimately improving patient outcomes and advancing the frontiers of precision medicine.

2. METHODOLOGY

Design of a CNN architecture tailored for joint detection of brain tumor and Parkinson's disease.

A. CNN Architecture

CNNs, a type of DNN, comprise convolutional, RELU, pooling, and fully connected layers. These layers facilitate feature extraction, nonlinear activation, downsampling, and classification. CNNs exploit shared weights, 3D neuron volumes, and local connectivity, improving memory efficiency and performance. Convolution layers produce feature maps by convolving input regions with learned kernels, followed by ReLU activation to enhance convergence. Pooling layers reduce feature map dimensions by selecting representative pixels. Fully connected layers integrate extracted features for classification.

CNN is composed of several kinds of layers:

1.Convolutional layer: creates a feature map to predict the class probabilities for each feature by applying a filter that scans the whole image, few pixels at a time.

2.Pooling layer (down-sampling): scales down the amount of information the convolutional layer generated for each feature and maintains the most essential information (the process of the convolutional and pooling layers usually repeats several times).

3.Fully connected input layer: flattens the outputs generated by previous layers to turn them into a single vector that can be used as an input for the next layer.

4.Fully connected layer: Applies weights over the input generated by the feature analysis to predict an accurate label.

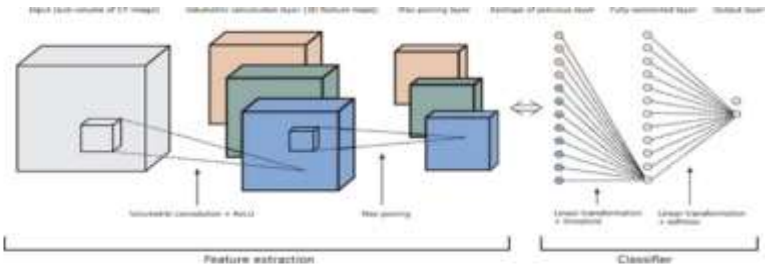

Figure 1: CNN Architecture

The invention of the CNN in 1994 by Yann LeCun is what propelled the field of Artificial Intelligence and Deep learning to its former glory. The first neural network named LeNet5 had a very less validation accuracy of 42% since then we have come a long way in this field.

The data training in our CNN model has to satisfy following constraints: 1) No missing values in dataset. 2) The dataset must distinctly be divided into training and testing sets, either the training or the testing set shouldn't contain any irrelevant data out of our model domain in case of an image dataset all the images must be of the same size, one uneven distribution of image size in our dataset can decrease the efficiency of our neural network. 3) The images should be converted into black and white format before feeding it into the convolution layer because reading images in RGB would involve a 3-D numPy matrix which will reduce the execution time of our model by a considerable amount. Any kind of corrupted or blurred images should also be trimmed from the database before feeding it into the neural network.

B. Implementation

Implementation is the process of converting a new system design into an operational one. It is the key stage in achieving a successful new system.

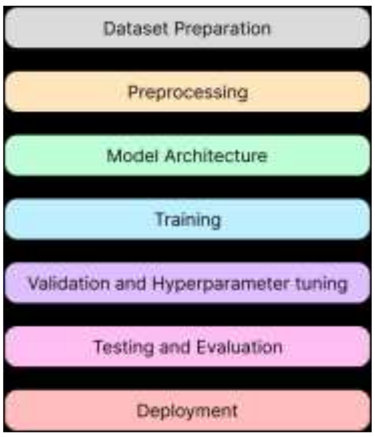

Figure 2: Representation of implementation processes

1.Dataset Preparation:

MRI datasets with labeled brain tumor scans (glioma, meningioma, pituitary tumor, and non-tumor samples) and Parkinson's datasets (Normal and Parkinson's samples from drawing and MRI datasets) were obtained.

Brain tumor Dataset training		**Brain tumor Dataset testing**	
Tumor class	**Images**	**Tumor class**	**Images**
Meningioma	822	Meningioma	12
Glioma	826	Glioma	12
Pituitary	827	Pituitary	12
No tumor	393	No tumor	12
Total:2,870 images		Total:48 images	

Parkinson's Dataset Training				**Parkinson's Dataset Testing**			
	Normal	**Parkinson's**	**Total**		**Normal**	**Parkinson's**	**Total**
Drawing	137	209	346	Drawing	24	24	48
MRI	610	221	831	MRI	24	24	48
Total : 1177				Total : 96			

Table 1: Training and Testing Dataset

2.Preprocessing:

MRI preprocessing involves quality enhancement, noise removal, and consistency assurance through intensity normalization, skull stripping, and spatial normalization. Data augmentation techniques like rotation and flipping enhance sample diversity.

3.Model Architecture:

CNN architecture for brain tumor/Parkinson's classification incorporates convolutional, pooling, and fully connected layers. Convolutional layers extract spatial features from MRI images, while ReLU activation, dropout, and batch normalization enhance generalization.

4.Training:

The CNN initializes with random weights, processes images, computes probabilities, and optimizes parameters using categorical cross-entropy loss.

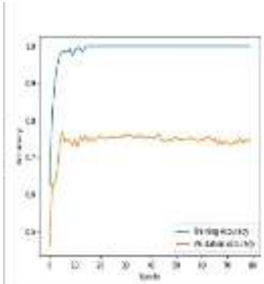

Figure 3: Training Graph (Accuracy/Epochs)

5.Validation and Hyperparameter Tuning:

Model performance is evaluated on a validation set using accuracy, precision, recall, and F1-score metrics. Hyperparameters like learning rate and epochs are tuned using grid/random search for optimal performance.

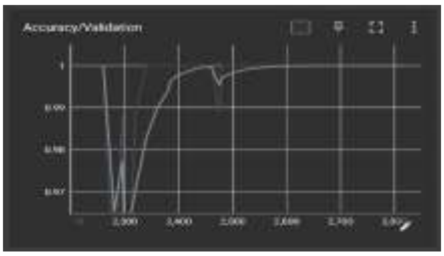

Figure 4:Accuracy graph of Brain Tumor

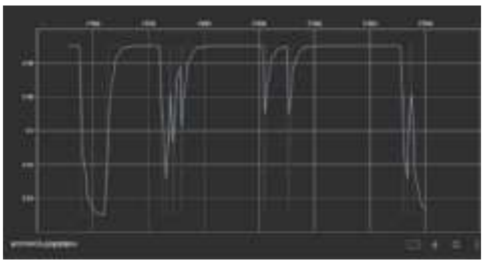

Figure 5:Accuracy Graph of Parkinsons disease

6.Testing and Evaluation:

The trained model is tested on an independent set for accuracy, sensitivity, specificity, and generates classification reports and confusion matrices. Predictions are visualized to highlight abnormal brain areas.

7.Deployment:

Trained models aid in brain tumor and Parkinson's disease detection. Deployment includes a Flask-based web app, "MRID," offering comprehensive diagnostic services.

3. RESULT

The implementation of our deep learning model for brain tumor detection and Parkinson's Disease (PD) diagnosis has yielded promising results, showcasing the effectiveness and potential impact of our approach in enhancing neurologic disease management.

In brain tumor detection, our model demonstrates remarkable accuracy in identifying tumors and categorizing them into meningioma, pituitary, and glioma types. By meticulously analyzing medical imaging data sourced from MRI and CT scans, our model reliably detects subtle abnormalities indicative of tumor presence. Moreover, its ability to quantify essential parameters such as tumor diameter and area furnishes clinicians with crucial insights for treatment planning and prognosis. This detailed characterization augments diagnostic precision, empowering clinicians to make more informed decisions and ultimately leading to better patient outcomes.

Additionally, our model's capability to go beyond binary classification by integrating sophisticated algorithms for tumor size characterization marks a significant advancement in neuro-oncology. Through advanced image processing techniques, our model provides clinicians with a comprehensive understanding of tumor spatial extent and morphological features, enabling tailored therapeutic interventions aligned with each patient's unique requirements.

In Parkinson's Disease diagnosis, our multimodal approach, amalgamating drawing and MRI datasets, exhibits promising outcomes in enhancing diagnostic accuracy and reliability. By amalgamating data from diverse sources, including hand-drawn sketches and brain imaging scans, our model facilitates early detection and personalized treatment strategies for PD patients. This holistic approach enables clinicians to discern subtle neurological changes indicative of the disease and initiate timely interventions.

Overall, our project's results underscore the transformative potential of deep learning and medical imaging in revolutionizing neurologic disease diagnosis and management. By harnessing artificial intelligence, we have developed a sophisticated model offering clinicians invaluable insights for precise diagnosis, personalized treatment planning, and enhanced patient outcomes.

4. CONCLUSION

After thorough implementation, our advanced deep learning model for brain tumor detection and Parkinson's Disease (PD) diagnosis stands as a notable breakthrough in medical imaging and neurology. Through the adept utilization of cutting-edge machine learning techniques, we confront the intricacies posed by these challenging conditions. Our model excels in accurately detecting and categorizing brain tumors, providing vital information for treatment decisions based on comprehensive analysis of MRI and CT scans. Moreover, our innovative multimodal strategy significantly enhances PD detection by integrating drawing and MRI datasets, thereby facilitating early intervention and personalized treatment regimens. In summary, our deep learning-driven approach signifies a significant leap toward precision medicine, poised to redefine neurological diagnosis and management, ultimately ushering in improved patient outcomes and propelling healthcare forward.

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