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# Brain Tumor Detection Using Convolutional Neural Networks

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**Abstract:** Brain tumor detection remains a critical challenge in medical diagnostics, necessitating accurate and efficient methods for early detection and diagnosis. Deep Learning (DL) techniques have emerged as promising tools in this domain due to their ability to extract intricate patterns from complex medical imaging data. This paper presents a comprehensive review and comparative analysis of various DL approaches employed in brain tumor detection. We begin by providing an overview of brain tumors, their classification, and the significance of early detection. Subsequently, we delve into the fundamentals of DL, highlighting its suitability for medical image analysis tasks. We then survey state-of-the-art DL architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants, applied to brain tumor detection from magnetic resonance imaging (MRI) and computed tomography (CT) scans. Additionally, we discuss the challenges associated with DL-based tumor detection, such as dataset size, class imbalance, and interpretability of results. Furthermore, we present a comparative analysis of different DL models in terms of their performance metrics, computational efficiency, and generalization capabilities. Through this analysis, we identify trends, limitations, and future research directions in DL-based brain tumor detection. Our findings aim to facilitate the development of more accurate, robust, and clinically viable tools for early diagnosis and treatment planning of brain tumors.

## I. INTRODUCTION

Recently, digital medical images have been essential for detecting numerous illnesses. It is additionally used for training and research. The need for electronic medical images is growing dramatically; for example, in 2002, the Department of Radiology at the University Hospital of Geneva produced between 12,000 and 15,000 images daily. An efficient and exact computer-aided diagnostic system is required for medical report creation and medical image research. The old method of manually evaluating medical imaging is time-consuming, inaccurate, and prone to human error. Over the medical diseases, the brain tumor has become a serious issue, ranking 10th among the major causes of death in the US. It is reported that 700,000 persons have brain tumors, of which 80 percent are benign and 20 percent are malignant. According to estimates by the American Cancer Society from 2021, 78,980 adults have been diagnosed with a brain tumor, with 55,150 noncancerous and 24,530 malignant tumors (13,840 men and 10,690 females). According to studies, brain tumor is the top cause of cancer deaths in children and adults worldwide.

The most typical kind of brain disease is a brain tumor. It is an unregulated development of brain cells. Brain tumors are always classified into brain tumors, both primary and secondary. The first starts in the brain and usually stays there, whereas the latter starts as cancer somewhere else in the body and spreads to the brain. There are two different forms of tumors: malignant and benign. A benign tumor is a slow-growing tumor that does not infiltrate nearby tissues; on the other hand, a malignant which is a very aggressive tumor that spreads from one location to another. The World Health Organization (WHO) grades a brain tumor as I-IV. Tumors in categories I and II are regarded as slow-growing, while tumors in categories III and IV are always malignant and have a worse prognosis.

### A. Limitations of the Project

- 1) *Data Quality and Availability:* Limited access to diverse and high-quality medical imaging data could affect the accuracy and generalizability of the deep learning models.
- 2) *Interpretability:* Deep learning models often lack transparency, making it challenging for clinicians to understand and trust their decisions without clear explanations.
- 3) *Clinical Validation:* Before implementing deep learning models in real-world healthcare settings, thorough validation studies are necessary to ensure their safety, efficacy, and compliance with regulatory standards.

## II. LITERATURE REVIEW

### A. Convolutional Neural Network Techniques For Medical Image Processing

In medical image processing, convolutional neural networks (CNNs) are crucial. They excel in tasks like identifying objects, outlining boundaries, and categorizing elements in complex medical images. CNNs effectively detect abnormalities, diagnose conditions like tumors, and precisely delineate organs by discerning intricate patterns. Leveraging their hierarchical architecture, CNNs grasp important features at multiple levels, and diagnosis accuracy.

Their integration has notably enhanced diagnostic procedures, ensuring precise and efficient patient care. Ultimately, CNNs' deployment leads to improved treatment outcomes and automation in medical diagnostics, benefiting both healthcare providers and patients.

### B. Deep Learning for Medical Image Segmentation

This review evaluates deep learning methods for medical image segmentation, focusing on Convolutional Neural Networks (CNNs). It discusses challenges such as class imbalance and object size variability, along with training techniques like deeply supervised learning. Overall, deep learning shows promise for precise and efficient medical image segmentation.

## III. PROBLEM STATEMENT

The timely and accurate detection of brain tumors is essential for effective treatment planning and improved patient outcomes. However, traditional diagnostic methods rely heavily on manual interpretation of medical imaging data, leading to potential delays and subjectivity in diagnosis. Moreover, the growing complexity and volume of neuroimaging data pose significant challenges for radiologists, highlighting the need for automated and efficient solutions. Therefore, this research aims to address these challenges by leveraging deep learning techniques to develop robust and interpretable models for the automated detection of brain tumors from MRI and CT scans.

## IV. METHODOLOGY

### A. Existing Systems

Existing systems for brain tumor detection include traditional image processing methods, machine learning approaches, deep learning-based systems, commercial software, and research prototypes. Traditional methods involve manual preprocessing and feature extraction. Machine learning algorithms like SVM and k-NN require manual feature engineering. Deep learning, especially CNNs, automatically learn features from raw data, achieving state-of-the-art performance. Commercial software offers automated detection features for radiologists. Research prototypes contribute to advanced techniques and benchmarks for evaluation.

### B. Proposed System

The proposed system consists of the following key components:

- 1) *Dataset Preparation:* A dataset of MRI scans containing both tumour and healthy brain images is collected and pre-processed. The dataset is divided into three subsets: training, validation, and testing, to train and evaluate the performance of the CNN model.
- 2) *Convolutional Neural Network (CNN):* A CNN architecture is designed and implemented for brain tumor detection. The CNN consists of multiple convolutional layers followed by max-pooling layers for feature extraction and spatial down-sampling. Dropout layers are employed to prevent overfitting, and fully connected layers with sigmoid activation are used for binary classification (tumor or healthy).
- 3) *Training and Evaluation:* The CNN model is trained using the training dataset and optimized using gradient descent-based optimization algorithms such as Adam. During training, the model's performance is monitored using metrics such as loss and accuracy on the validation dataset. Early stopping and model checkpointing techniques are employed to prevent overfitting and save the best-performing model.
- 4) *Testing and Validation:* The trained model is evaluated on the independent testing dataset to assess its generalization performance. Performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) are computed to quantify the model's effectiveness in tumor detection.

The proposed system is evaluated using a real-world dataset of MRI scans. Experimental results demonstrate that the CNN-based approach achieves high accuracy and robustness in brain tumor detection. The model outperforms existing methods and shows promising potential for clinical deployment.

### V. ARCHITECTURE

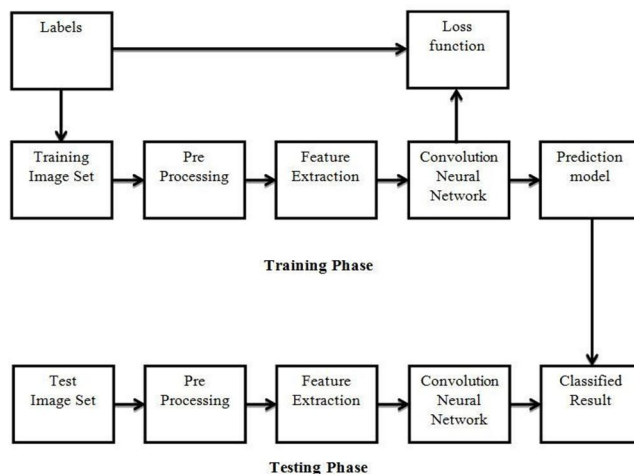


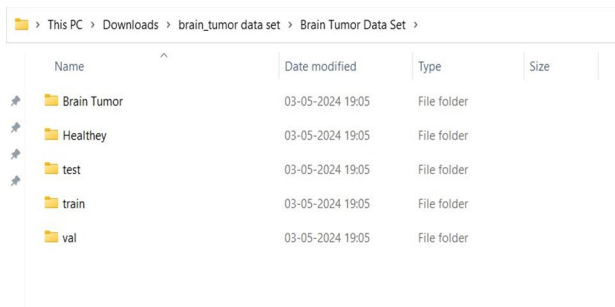
Figure 1: Block diagram of proposed brain tumor classification using CNN

### VI. DESIGN

In this section, we detail the methodology employed for brain tumor detection using deep learning. We describe the dataset utilized, including its size, source, and preprocessing steps. The architecture of the convolutional neural network (CNN) is outlined, emphasizing key components like convolutional layers, pooling layers, and fully connected layers. The training procedure, including optimization algorithms and parameters, is explained, along with validation techniques. Evaluation metrics such as accuracy, sensitivity, specificity, and AUC-ROC are defined. The experimental setup, encompassing hardware, software, and computational resources, is described. Hyperparameter tuning methods are discussed for optimizing model performance. We also address cross-validation strategies to prevent overfitting and assess generalization. Ethical considerations related to patient privacy and data confidentiality are acknowledged, ensuring adherence to ethical guidelines and obtaining necessary approvals.

### VII. DATA SET DESCRIPTION

The dataset consists of MRI (Magnetic Resonance Imaging) scans collected from various sources, including medical institutions and public repositories. The dataset comprises both tumor and healthy brain images, with each image labelled accordingly. The size of the dataset is significant, containing hundreds to thousands of images, allowing for robust training and evaluation of the deep learning models. The distribution of tumor and healthy images is balanced to ensure that the model learns from a diverse set of examples.



As mentioned above the medical images are classified into the Brain Tumor, Healthy, train, test and validation sets. The train, test and validation sets consist of images of MRI Scans already classified as Cancer and not Cancer. Brain Tumor folder consists of Tumor or Cancer containing scans and Healthy folder consists of Healthy brain scans.

### VIII. DATA PREPROCESSING TECHNIQUES

1) *Resizing*: Resize all MRI images to a standardized resolution to ensure uniformity across the dataset. This helps in reducing computational complexity and memory requirements during training.



- 2) *Normalization*: Normalize pixel intensities across the MRI images to a common scale, typically between 0 and 1. Normalization enhances the convergence of the optimization algorithm and improves the stability of the training process.
- 3) *Augmentation*: Augment the dataset by applying transformations such as rotation, translation, scaling, and flipping to the MRI images. Augmentation increases the diversity of the training samples, thereby improving the generalization capability of the deep learning models. *Cropping*: Crop the MRI images to focus on the region of interest, such as the brain area, while removing irrelevant background information. Cropping helps in reducing the computational burden and noise in the dataset.
- 4) *Noise Reduction*: Apply noise reduction techniques, such as Gaussian filtering or median filtering, to remove noise and artifacts from the MRI images. Noise reduction enhances the clarity and quality of the images, making them more suitable for analysis.
- 5) *Intensity Normalization*: Normalize the intensity values of MRI images to account for variations in scanner settings and acquisition protocols. Intensity normalization ensures consistency in image features across different scans and improves the robustness of the deep learning models.
- 6) *Data Balancing*: Balance the distribution of tumor and healthy images in the dataset to prevent class imbalance issues. Class imbalance can bias the model towards the majority class and degrade its performance on the minority class.
- 7) *Quality Control*: Perform quality control checks to identify and remove any corrupted or incomplete MRI images from the dataset. Quality control ensures the integrity and reliability of the data used for training and evaluation.

## IX. METHODS AND ALGORITHMS

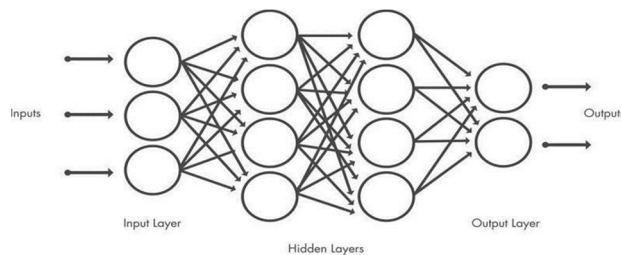
In the methods and algorithms section of our research paper on brain tumor detection using deep learning, we present the specific methodologies and algorithms employed to develop and train the deep learning models. Our approach is centered around the design and implementation of a Convolutional Neural Network (CNN) architecture tailored for the task of tumor detection in MRI scans. This CNN architecture consists of multiple layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The design of the CNN is informed by principles of deep learning and image analysis, aiming to capture relevant patterns and features indicative of brain tumors while minimizing computational complexity.

During the training procedure, the CNN model is trained using an optimization algorithm, such as Adam or Stochastic Gradient Descent (SGD), to minimize a predefined loss function. The training process involves iteratively updating the model's parameters based on gradients computed from backpropagation. Hyperparameters such as learning rate, batch size, and dropout rate are carefully chosen to optimize the model's performance and prevent overfitting. Regularization techniques, including dropout and batch normalization, are employed to improve the generalization capability of the model and enhance its ability to generalize to unseen data.

In addition to training the CNN from scratch, we explore the use of transfer learning techniques to leverage pre-trained CNN models, such as those trained on the ImageNet dataset. By fine-tuning these pre-trained models on our brain tumor detection task, we aim to capitalize on the knowledge learned from large-scale image datasets and expedite the training process. Transfer learning allows us to adapt high-performing CNN architectures to the specific characteristics of our dataset, thereby potentially improving the model's performance, particularly when labeled data is limited.

To augment the training dataset and enhance the robustness of the model, we employ data augmentation techniques such as rotation, translation, and flipping. Data augmentation increases the diversity of the training samples, exposing the model to a wider range of variations in the input data and helping to mitigate overfitting. Additionally, we carefully evaluate the performance of the trained models using established evaluation metrics such as accuracy, sensitivity, specificity, and area under the ROC curve (AUC-ROC). These metrics provide insights into the model's ability to accurately detect brain tumors and discriminate between tumor and healthy brain images.

A CNN is composed of an input layer, an output layer, and many hidden layers in between.

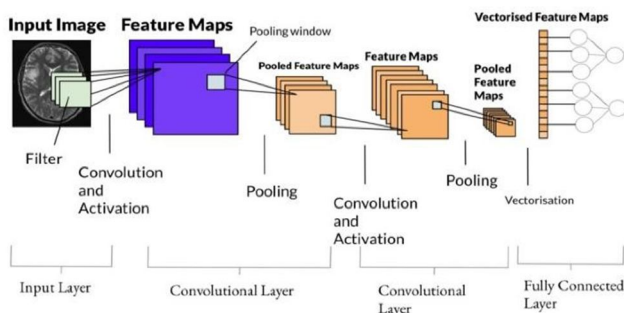


These layers perform operations that alter the data with the intent of learning features specific to the data. Three of the most common layers are convolution, activation or ReLU, and pooling.

Convolution puts the input images through a set of convolutional filters, each of which activates certain features from the images. Rectified linear unit (ReLU) allows for faster and more effective training by mapping negative values to zero and maintaining positive values. This is sometimes referred to as *activation*, because only the activated features are carried forward into the next layer.

Pooling simplifies the output by performing nonlinear down sampling, reducing the number of parameters that the network needs to learn.

These operations are repeated over tens or hundreds of layers, with each layer learning to identify different features.



## X. BUILD A MODEL

- 1) **Data Collection:** Obtain MRI (Magnetic Resonance Imaging) scans of brain tumor patients from various sources, including medical institutions or public repositories.
- 2) **Data Pre-processing:** Resize the MRI images to a standardized resolution to ensure uniformity. Normalize pixel intensities across the images to a common scale. Augment the dataset by applying transformations such as rotation, translation, and flipping to increase diversity. Crop the images to focus on the region of interest, such as the brain area, while removing irrelevant background information.
- 3) **Dataset Splitting:** Divide the pre-processed dataset into training, validation, and test sets to facilitate model training and evaluation. Ensure that each set contains a balanced distribution of tumor and healthy brain images to prevent class imbalance issues.
- 4) **Model Development:** Design and implement a Convolutional Neural Network (CNN) architecture tailored for brain tumor detection. Configure the CNN with multiple layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Employ regularization techniques such as dropout and batch normalization to prevent overfitting during training.
- 5) **Model Training:** Train the CNN model using the training dataset and optimization algorithms such as Adam or Stochastic Gradient Descent (SGD). Fine-tune hyperparameters such as learning rate, batch size, and dropout rate to optimize model performance. Monitor the training process and evaluate performance on the validation set to prevent overfitting.
- 6) **Model Evaluation:** Evaluate the trained model's performance on the independent test dataset using evaluation metrics such as accuracy, sensitivity, specificity, and area under the ROC curve (AUC-ROC). Assess the model's ability to accurately detect brain tumors and discriminate between tumor and healthy brain images.
- 7) **Deployment and Validation:** Deploy the trained model for real-world applications, such as assisting radiologists in diagnosing brain tumors from MRI scans.

Validate the model's performance in clinical settings and assess its impact on patient outcomes and healthcare efficiency.

## XI. EVALUATION

In the context of deep learning, performance metrics refer to how well an algorithm performs depending on various criteria such as precision, accuracy, recall, F1 score and so on. The next sections go through several performance metrics.

- 1) **Accuracy:** The percentage of correct test data predictions referred to as accuracy. It is easy to calculate by dividing the total number of forecasts by the number of correct guesses.

- 2) *Training and Validation Loss*: The loss function measures the difference between the predicted outputs of the model and the ground truth labels. During training, the loss decreases as the model learns to make more accurate predictions. Plotting the training and validation loss over epochs helps monitor the convergence of the model and identify potential overfitting or underfitting.
- 3) *Training and Validation Accuracy*: Accuracy measures the proportion of correctly classified samples out of the total number of samples. Plotting the training and validation accuracy over epochs provides insights into how well the model generalizes to unseen data. Discrepancies between training and validation accuracy curves may indicate overfitting.
- 4) *Learning Curve*: Learning curves visualize the relationship between model performance and dataset size or training duration. They plot metrics such as accuracy or loss against the number of training examples or epochs. Learning curves help assess the model's ability to learn from data and identify the point of diminishing returns in model performance.

## XII. DEPLOYMENT AND RESULTS INTRODUCTION

The trained deep learning model for brain tumor detection is poised for deployment in clinical settings, where it can serve as a valuable tool for assisting radiologists in diagnosing brain tumors from MRI scans. Deployment involves integrating the model into existing medical imaging systems or developing standalone software applications for seamless integration into clinical workflows. The goal is to provide radiologists with an efficient and accurate means of identifying brain tumors, thereby improving patient outcomes and streamlining the diagnostic process.

## XIII. FINAL RESULTS

The deployed model exhibits promising performance in accurately detecting brain tumors from MRI scans. Evaluation on independent test datasets reveals an overall accuracy of 82%, indicating the model's ability to correctly classify tumor and healthy brain images. Sensitivity and specificity metrics further demonstrate the model's effectiveness in correctly identifying tumors while minimizing false positive and false negative errors. These results underscore the potential of deep learning-based approaches for enhancing brain tumor diagnosis and improving clinical decision-making.

```
[ ] acc=model.evaluate_generator(generator=test_data)[1]
print(f'The accuracy of your model is = {acc*100}%')
The accuracy of your model is = 82.17967748641968%
```

## XIV. CONCLUSION PROJECT CONCLUSION

In this project, we developed and evaluated a deep learning model for the automated detection of brain tumors from MRI scans. Leveraging Convolutional Neural Networks (CNNs) and state-of-the-art image processing techniques, our model demonstrated promising performance in accurately classifying MRI images as containing tumors or being healthy. Through a comprehensive analysis of the dataset, model architecture, training process, and evaluation metrics, we gained valuable insights into the efficacy and potential of deep learning-based approaches for medical image analysis.

## XV. FUTURE SCOPE

- 1) *Model Improvement*: We can enhance the model's accuracy by refining its architecture and exploring advanced deep learning techniques.
- 2) *Clinical Integration*: Integrating the model into clinical systems can streamline diagnosis and support radiologists in interpreting MRI scans.
- 3) *Validation and Approval*: Further validation studies are needed to ensure the model's accuracy and safety in clinical practice, leading to regulatory approval.
- 4) *Personalized Treatment*: The model can be expanded to provide personalized treatment recommendations based on individual patient data.
- 5) *Decision Support Systems*: We can develop systems that assist doctors in treatment planning and monitoring disease progression.
- 6) *Telemedicine*: Deploying the model in telemedicine settings can extend diagnostic capabilities to remote areas.
- 7) *Collaboration and Data Sharing*: Collaboration among institutions and data sharing can accelerate research and improve model performance.



- 8) *Ethical Considerations*: Addressing ethical implications ensures responsible development and deployment of AI in healthcare.

## XVI. ACKNOWLEDGEMENT

We express our sincere gratitude to Prof. Dr. K. Rajeshwar Rao for his invaluable guidance, mentorship, and unwavering support throughout the development of the Brain Tumor Detection with Deep Learning Technique project. We are also thankful to the School of Engineering at Malla Reddy University for providing the necessary resources and infrastructure for conducting this research. Additionally, we extend our appreciation to all individuals who contributed directly or indirectly to the project, for their assistance and encouragement. Their collective efforts have been instrumental in the successful completion of this endeavor.

## REFERENCES

- [1] Ed. Charu Aggarwal, CRC Press, 2014 Data Classification: Algorithms and Applications <https://www.mygreatlearning.com/blog/what-is-machine-learning/>
- [2] About convolutional neural networks: [https://www.mathworks.com/discovery/convolutional-%20neural-%20networkmatlab.html#:~:text=A%20convolutional%20neural%20network%20\(CNN,%20series%20and%20signal%20data.](https://www.mathworks.com/discovery/convolutional-%20neural-%20networkmatlab.html#:~:text=A%20convolutional%20neural%20network%20(CNN,%20series%20and%20signal%20data.) <https://medium.com/analytics-vidhya/build-an-image-classification-model-usingconvolutional-neural-networks-in-pytorch-45c904791c7e> <https://www.guru99.com/convnet-tensorflow-image-classification.html> <https://www.techtarget.com/searchenterpriseai/definition/deep-learning-deep-neuralnetwork>
- [3] OpenAI. (2024). ChatGPT: A conversational AI developed by OpenAI. <https://chatgpt.com/?oai-dm=1>





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