IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.102 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 4, April 2024

DOI: 10.17148/IJARCCE.2024.134205

# DeepBrain: Brain Tumor Detection and Stage Prediction using Deep Learning

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**Abstract:** Brain tumours are dangerous and serious disorders affected by uncontrolled cell growth in the brain. Brain tumours are one of the most challenging diseases to cure among the different ailments encountered in medical study. Early classification of brain tumours from magnetic resonance imaging (MRI) plays an important role in the diagnosis of such diseases. There are many diagnostic imaging methods used to identify tumours in the brain. MRI is commonly used for such tasks because of its unmatched image quality. The traditional method of identifying tumours relies on physicians, which is time-consuming and prone to errors, putting the patient's life in jeopardy. Identifying the classes of brain tumours is difficult due to the high anatomical and spatial diversity of the brain tumour's surrounding region. An automated and precise diagnosis approach is required to treat this severe disease effectively. The relevance of artificial intelligence (AI) in the form of deep learning (DL) has revolutionized new methods of automated medical image diagnosis. As a result, good planning can protect a person's life that has a brain tumour. Using the 2D Convolutional Neural Network (CNN) technique, this project proposes Computer-Aided Diagnosis (CAD) a deep learning-based intelligent brain tumour detection framework for brain tumour type (glioma, meningioma, and pituitary) and stages (benign or malignant). CNN is used to classify tumours into pituitary, glioma, and meningioma. Then its classify the three grades of classified disease type, i.e., Grade-two, Grade-three, and Grade-four. The performance of the CNN models is evaluated using performance metrics such as accuracy, sensitivity, precision, specificity and F1-score. From the experimental results, our proposed CNN model based on the Xception architecture using ADAM optimizer is better than the other three proposed models. The Xception model achieved accuracy, sensitivity, precision specificity, and F1-score values of 99.67%, 99.68%, 99.68%, 99.66%, and 99.68% on the MRI-large dataset. The proposed method is superior to the existing literature, indicating that it can be used to quickly and accurately classify brain tumours.

## I. INTRODUCTION

The brain is a complex organ that controls thought, memory, emotion, touch, motor skills, vision, breathing, temperature, hunger and every process that regulates our body. Together, the brain and spinal cord that extends from it make up the central nervous system, or CNS.

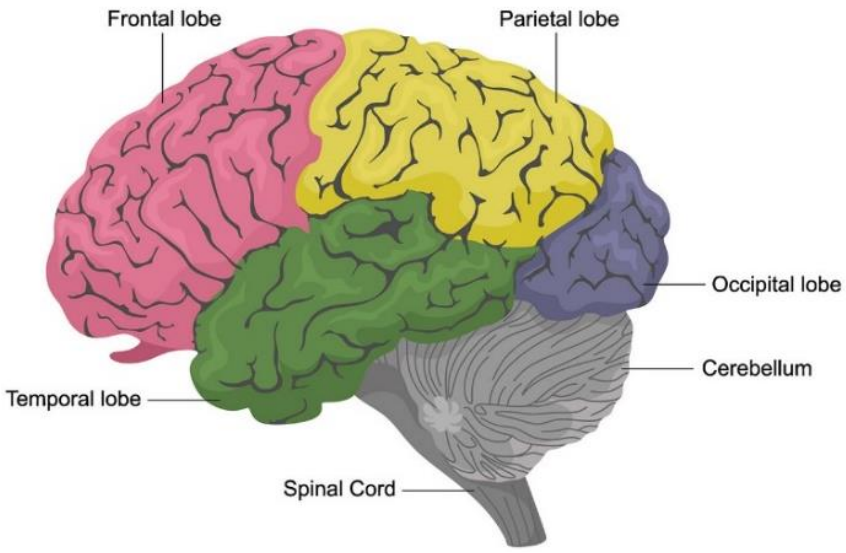


Figure 1.1. Brain

  

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Weighing about 3 pounds in the average adult, the brain is about 60% fat. The remaining 40% is a combination of water, protein, carbohydrates and salts. The brain itself is a not a muscle. It contains blood vessels and nerves, including neurons and glial cells.

### 1.1.1. Brain Tumour

A brain tumour is a growth of abnormal cells in the brain. The anatomy of the brain is very complex, with different parts responsible for different nervous system functions. Brain tumours can develop in any part of the brain or skull, including its protective lining, the underside of the brain (skull base), the brainstem, the sinuses and the nasal cavity, and many other areas. There are more than 120 different types of tumours that can develop in the brain, depending on what tissue they arise from.

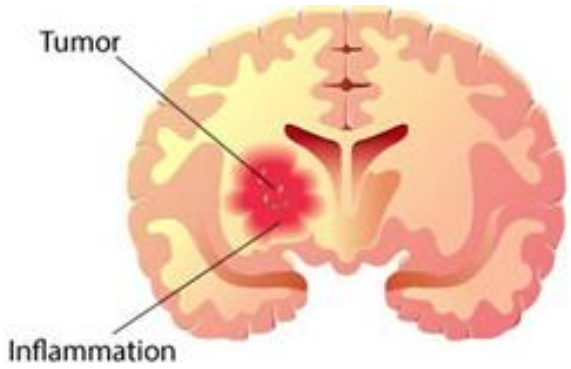


Figure 1.2. Brain Tumour

### 1.1.2. Types of Brain Tumour

There are many types of brain tumours. Each type can differ in growth rate, typical location, size at the time of diagnosis, and who they affect. Brain tumours are the most common type of tumour in children, and the second or third most common type in young adults (breast cancer is highest in females). Some brain tumour types affect males more often than females, or vice versa. The following are a few of the more common brain tumours and the percentage of the tumour count among all brain and other central nervous system (CNS) tumours.

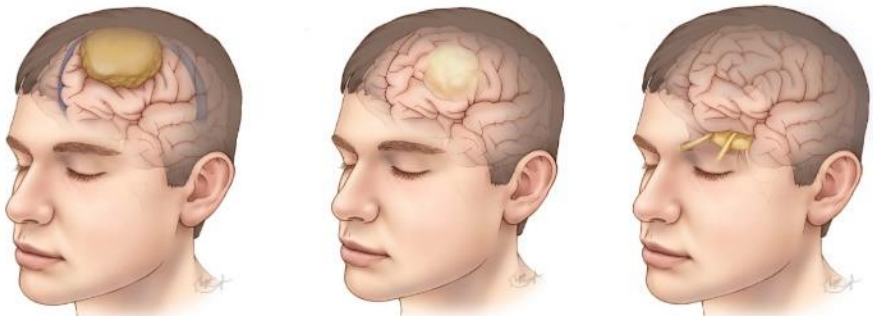

Figure 1.3. Different types of brain tumors. Meningioma (left), glioma (center), and pituitary tumor (right) are among the most common brain tumor types.

**Meningioma (38%)** arises from the membranous covering of the brain (meninges). Most are benign and grow slowly inward from the meninges to push on the brain and surrounding structures.

**Glioma (25%)** arises from glial cells that surround and support the neurons of the CNS. Tumours in this category are further classified according to the type of glial cell from which they originate (astrocytoma, glioblastoma multiforme, ependymoma, oligodendroglioma, mixed glioma). Although some types are relatively benign, gliomas comprise 80% of malignant brain or other CNS tumours.

**Pituitary tumour (17%)** arises from the pituitary gland at the base of the brain. The pituitary gland is important for normal hormone release. Most pituitary tumours are benign. However, large tumours can compress nearby nerves and tissues, causing vision defects and hormone abnormalities.

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Other brain tumour types include acoustic neuroma, craniopharyngioma, chordoma, chondrosarcoma, or brain metastases. Most brain metastases arise from cancers in the lung, breast, colon and rectum, skin (melanoma), and kidneys (renal cell carcinoma). In adults, brain metastases are more common than primary brain tumours. Brain tumours can arise from tissues within the brain (primary brain tumour) or from a cancer located elsewhere in the body (secondary or metastatic brain tumour). Benign brain tumours typically grow slowly and stay within the brain without invading surrounding tissues. In contrast, malignant brain tumours can grow quickly and spread to other body parts through a process called metastasis.

### 1.1.3. Grades of Tumour

Normally, the severity of cancer is assessed using a staging system that's broken into 4 or 5 stages depending on the size and development of the tumour. Brain cancers, however, are assessed using a system of grades, with the 'grade' of a tumour denoting how aggressively it grows. Higher grade tumours tend to grow faster, have an aggressive course, and are more likely to be malignant.

**Grade I** – The tumour is benign. The cells look nearly like normal brain cells. This grade is the least aggressive.
**Grade II** – The tumour is malignant. The cells look more abnormal, but they are generally slow-growing cells
**Grade III** – This is a malignant tumour with cells that look very abnormal and are actively growing (anaplastic).
**Grade IV** – The malignant tissue has cells that look most abnormal and tend to grow quickly.

### 1.1.4. Diagnosis of Brain Tumour

Sophisticated imaging techniques can pinpoint brain tumours. Diagnostic tools include computed tomography (CT or CAT scan) and magnetic resonance imaging (MRI). Other MRI sequences can help the surgeon plan the resection of the tumour based on the location of the normal nerve pathways of the brain. Intraoperative MRI also is used during surgery to guide tissue biopsies and tumour removal. Magnetic resonance spectroscopy (MRS) is used to examine the tumour's chemical profile and determine the nature of the lesions seen on the MRI. Positron emission tomography (PET scan) can help detect recurring brain tumours. Sometimes the only way to make a definitive diagnosis of a brain tumour is through a biopsy. The neurosurgeon performs the biopsy and the pathologist makes the final diagnosis, determining whether the tumour appears benign or malignant, and grading it accordingly.

## II. LITERATURE SURVEY

]The "DeepBrain" project is a groundbreaking endeavor poised to transform the landscape of brain tumor detection and stage prediction through the fusion of advanced deep learning techniques and medical imaging expertise.

**1. Convolutional Neural Networks (CNNs):**

At the heart of the "DeepBrain" project lies the utilization of Convolutional Neural Networks (CNNs), a class of artificial neural networks renowned for their efficacy in processing visual data. CNNs are adept at learning hierarchical representations of features within images, making them particularly well-suited for tasks such as medical image analysis. Within the context of "DeepBrain," CNNs are employed to meticulously analyze MRI images of the brain, enabling the automated detection of tumor presence and delineation of abnormal tissue regions.

**2. Hybrid Feature Extraction Techniques:**

Complementing the power of CNNs, "DeepBrain" incorporates hybrid feature extraction techniques aimed at capturing both high-level semantic features and low-level structural nuances from MRI scans. By combining traditional image processing methods with learned representations from deep neural networks, these hybrid techniques enhance the discriminative power of the model and facilitate the extraction of relevant features essential for accurate tumor classification.

**3.Regularized Extreme Learning Machines (ELMs):**

In addition to CNNs and hybrid feature extraction, "DeepBrain" leverages Regularized Extreme Learning Machines (ELMs) as part of its classification framework. ELMs provide a mechanism for refining the extracted features and optimizing the predictive performance of the model. Through regularization techniques, ELMs mitigate overfitting, ensuring robust generalization to unseen data and bolstering the reliability of stage predictions.

**4. Automated Detection and Staging:**

The overarching objective of "DeepBrain" is to automate the detection and staging process of brain tumors, thereby expediting diagnosis and enabling timely intervention. By leveraging the combined capabilities of CNNs, hybrid feature extraction techniques, and regularized ELMs, the project aims to provide clinicians with comprehensive insights into the nature and progression of brain tumors.

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**5. Impact on Patient Outcomes:**

Ultimately, "DeepBrain" holds immense promise for improving patient outcomes and advancing the frontier of precision medicine in neuro-oncology. Through its innovative approach to medical image analysis, the project empowers clinicians with unprecedented tools for early detection, accurate staging, and personalized treatment planning, thereby enhancing the quality of care for individuals affected by brain tumors.

In summary, the "DeepBrain" project represents a convergence of state-of-the-art technologies and medical expertise, with the overarching goal of revolutionizing the landscape of brain tumor diagnosis and management. By integrating advanced deep learning methodologies with insights from medical imaging, "DeepBrain" stands poised to redefine standards of care and usher in a new era of data-driven healthcare in the field of neuro-oncology.

## III. PROPOSED METHODOLOGY

The proposed methodology for the "DeepBrain: Brain Tumor Detection and Stage Prediction using Deep Learning" system involves several key steps aimed at leveraging deep learning techniques for accurate tumor detection and staging from MRI images. Here's an outline of the methodology:

**1.Data Collection and Preprocessing:**

Acquire a diverse dataset of MRI brain images containing both tumor and non-tumor cases.
Preprocess the images to standardize resolution, intensity normalization, and potentially address artifacts or noise.

**2. Training Data Preparation:**

Split the dataset into training, validation, and testing sets to facilitate model training and evaluation.
Annotate the MRI images with ground truth labels indicating the presence and stage of tumors.

**3. Model Architecture Selection:**

Design a deep neural network architecture tailored for brain tumor detection and stage prediction.
Consider variations of convolutional neural networks (CNNs) optimized for image classification tasks.

**4. Feature Extraction and Representation Learning:**

Employ the selected CNN architecture to extract features from the preprocessed MRI images.
Leverage transfer learning techniques, possibly utilizing pretrained models on large-scale datasets such as ImageNet, to accelerate convergence and improve generalization.

**5. Classification and Stage Prediction:**

Incorporate a classification head on top of the feature extraction backbone to predict tumor presence and stage.
Utilize softmax activation for multi-class classification, with each class representing a different tumor stage.

**6. Model Training and Optimization:**

Train the deep learning model using the prepared training dataset and validate its performance using the validation set.
Employ optimization techniques such as stochastic gradient descent (SGD) or adaptive learning rate methods to fine-tune model parameters.
Integrate regularization techniques like dropout or weight decay to prevent overfitting and enhance model generalization.

**7. Evaluation and Validation:**

Evaluate the trained model's performance on the held-out testing dataset to assess its ability to generalize to unseen data.
Employ standard evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) to quantify model performance.

**8. Deployment and Integration:**

Deploy the trained model into a production environment capable of processing new MRI scans in real-time.
Integrate the system with existing healthcare infrastructure, enabling seamless interaction with clinicians and radiologists for diagnosis and treatment planning.

**9. Continuous Improvement and Iteration:**

Monitor the performance of the deployed system in real-world settings and gather feedback from users.
Continuously update and refine the deep learning model based on new data, emerging research, and user experience to ensure ongoing efficacy and relevance.

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By following this methodology, the "DeepBrain" system endeavors to achieve state-of-the-art performance in brain tumor detection and stage prediction, ultimately enhancing patient care and contributing to advancements in medical imaging technology.

## IV. RESULT AND ANALYSIS

The results and analysis section of the "DeepBrain: Brain Tumor Detection and Stage Prediction using Deep Learning" project would typically encompass the evaluation of the trained model's performance, interpretation of findings, and comparison with existing methods.

Here's an outline of what this section might entail:

**1. Performance Metrics:**
Report the performance of the deep learning model on the testing dataset using various evaluation metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).
Provide a detailed breakdown of performance metrics for tumor detection **and** stage prediction, including results for different tumor stages if applicable.

2. **Comparison with Baselines:**
Compare the performance of the proposed "DeepBrain" system with baseline methods or existing state-of-the-art approaches for brain tumor detection and stage prediction.
Highlight any improvements or advantages achieved by the "DeepBrain" system over baseline methods in terms of accuracy, sensitivity, specificity, and computational efficiency.

**3. Visualization of Results:**
Present visualizations of model predictions overlaid on MRI images to illustrate the accuracy of tumor detection and stage prediction.
Provide examples of true positive, false positive, true negative, and false negative cases to demonstrate the model's strengths and limitations.

**4. Analysis of Errors:**
Analyze common sources of errors or misclassifications made by the model, such as misidentifying tumor boundaries or confusing tumor stages.
Identify potential factors contributing to model errors, including imaging artifacts, tumor heterogeneity, or ambiguous cases.

**5. Generalization and Robustness:**
Assess the generalization ability of the trained model by evaluating its performance on external datasets or unseen data collected from different sources or patient cohorts.
Investigate the robustness of the model to variations in imaging protocols, scanner types, or patient demographics to ensure consistent performance across diverse settings.

**6. Clinical Relevance and Interpretation:**
Discuss the clinical implications of the "DeepBrain" system's performance in terms of its potential utility for radiologists, neurosurgeons, and oncologists in clinical practice.
Highlight the system's ability to aid in early tumor detection, accurate staging, treatment planning, and monitoring of disease progression, thereby improving patient outcomes and healthcare efficiency.

**7. Limitations and Future Directions:**
Acknowledge the limitations and constraints of the "DeepBrain" system, including dataset biases, model interpretability, and scalability issues.

Suggest avenues for future research and development, such as exploring multimodal imaging integration, incorporating patient-specific clinical data, or enhancing interpretability through explainable AI techniques.

By presenting comprehensive results and analysis, the "DeepBrain" project aims to validate the efficacy and clinical relevance of its deep learning-based approach for brain tumor detection and stage prediction, paving the way for potential adoption in real-world healthcare settings.

  

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## V. CONCLUSION

The latest developments in medical imaging tools have facilitated health workers. Medical informatics research has the best options make good use of these exponentially growing volumes of data. Early detection options are essential for effective treatment of brain tumors. This project presented a CAD approach for detecting and categorizing BT's radiological images into three kinds (pituitary-tumor, glioma-tumor, and meningioma-tumor). We also classified glioma-tumor into various categories (Grade-two, Grade-three, and Grade-four) utilizing the DCNN approach (i.e., our proposed work). Firstly, pre-trained DensNet201 deep learning model was used, and the features were extracted from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Secondly, the features from different Inception modules were extracted from pre-trained Inceptionv3 model and concatenated and then, passed to the softmax for the classification of brain tumors. The proposed method produced 99.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor. The outcome of the presented architecture shows high training and validation accuracy with low training and validation loss. Moreover, the testing phase determines the overall portable EM imaging system's capability and potential of CNN architecture in detecting and localizing the brain tumor with high accuracy.

**Future Scope**

In the future, we are going to increase MRI images in the used dataset to improve the accuracy of the proposed model. Moreover, Applying the proposed approach to other types of medical images such as x-ray, computed tomography (CT), and ultrasound may constitute a principle of future studies.

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