

NeuroML - Brain Tumor Classification using Machine Learning and Deep Learning

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Abstract: *In this study we have proposed CNN model's efficacy in accurately classifying brain tumors into meningioma, glioma, and pituitary tumor categories, showcasing high sensitivity and specificity. The incorporation of deep learning techniques empowers the model to discern subtle and intricate patterns, contributing to heightened diagnostic precision. This study underscores the potential of advanced machine learning algorithms in medical imaging for specific brain tumor classification, offering a valuable tool for healthcare professionals. The research findings hold promise for improving the accuracy of neuro-oncological diagnoses, ultimately advancing patient care in the domain of brain tumor pathology. The study utilizes a diverse dataset comprising magnetic resonance imaging (MRI) scans of the brain, encompassing various tumor types and conditions. The preprocessing phase involves standardizing and augmenting the dataset to ensure optimal model training. A Convolutional Neural Network architecture is designed to automatically learn discriminative features from the input images, capturing intricate patterns indicative of tumor presence. Results demonstrate the proposed CNN model's efficacy in accurately classifying brain tumors into meningioma, glioma, and pituitary tumor categories, showcasing high sensitivity and specificity. The incorporation of deep learning techniques empowers the model to discern subtle and intricate patterns, contributing to heightened diagnostic precision. This study underscores the potential of advanced machine learning algorithms in medical imaging for specific brain tumor classification, offering a valuable tool for healthcare professionals. The research findings hold promise for improving the accuracy of neuro-oncological diagnoses, ultimately advancing patient care in the domain of brain tumor pathology. In our work, CNN gained an accuracy of 99.3 %, which is very compelling. The main aim of this paper is to distinguish between normal and abnormal pixels, based on texture based and statistical based features.*

Keywords: Brain Tumor, Meningioma, Glioma, Pituitary, Machine Learning, Deep Learning, Convolutional Neural Network (CNN).

I. INTRODUCTION

Brain tumors represent a significant health challenge, necessitating advanced diagnostic tools to enhance the accuracy and efficiency of classification. In the realm of neuro-oncology, the advent of machine learning and deep learning techniques has spurred innovative approaches to address this imperative need. This research focuses on the development and application of a Convolutional Neural Network (CNN) model for the precise classification of brain tumors, specifically into meningioma, glioma, and pituitary tumor categories, utilizing magnetic resonance imaging (MRI) data. Accurate and timely classification of brain tumors is paramount for informing clinical decisions and tailoring appropriate treatment strategies. Traditional diagnostic methods often rely on manual interpretation, which can be time-consuming and subjective. The integration of machine learning, and particularly deep learning, into medical imaging offers a promising avenue for automating and improving the precision of tumor classification.

Brain tumors are one of the leading causes of death worldwide, and their early diagnosis and treatment are essential for improving patient outcomes. Brain tumor classification is a challenging task due to the complex and heterogeneous nature of these tumors. However, recent advances in machine learning and convolutional neural networks (CNNs) have shown great promise for improving the accuracy and efficiency of brain tumor classification. CNNs are a type of deep learning model that are particularly well-suited for image classification tasks. CNNs are able to learn complex spatial features

from images, which makes them ideal for classifying brain tumors, which can have a wide range of shapes and appearances.

The diversity of brain tumor types and conditions necessitates a robust and adaptable model. In this study, a comprehensive dataset comprising MRI scans is employed, ensuring the model's ability to generalize across various pathological scenarios. The CNN architecture is designed to automatically learn and extract discriminative features crucial for distinguishing between meningiomas, gliomas, and pituitary tumors.

Transfer learning, a powerful technique in deep learning, is leveraged to enhance the model's performance by building upon pre-existing neural network architectures. The research incorporates rigorous preprocessing steps, including standardization and augmentation, to optimize the model's learning process. Strategies to mitigate overfitting are implemented, ensuring the model's reliability and generalization capabilities.

II. CLASSIFICATION OF BRAIN TUMOR

In this study we generally classify gliomas, meningiomas, and pituitary tumors. They are the three most common types of primary brain tumors. While all three types of tumors can be benign or malignant, they differ in their biology, clinical presentation, and treatment.

Gliomas:

Gliomas arise from the glial cells supporting and nourishing neurons within the central nervous system. Classified into various grades, with higher grades indicating increased aggressiveness, gliomas encompass a broad spectrum of tumors. Glioblastoma multiforme (GBM) represents a high-grade glioma with pronounced malignancy. Symptoms associated with gliomas, such as headaches, seizures, cognitive impairment, and neurological deficits, vary based on the tumor's location and grade. Given their diverse nature, precise classification is crucial for tailoring treatment strategies and improving patient outcomes. Glial cells are supportive cells that provide nutrients and protection to the neurons. Gliomas can be classified into different grades based on their aggressiveness and likelihood of recurrence. Low-grade gliomas are typically slow-growing and have a better prognosis than high-grade gliomas. High-grade gliomas, such as glioblastomas, are fast-growing and aggressive tumors with a poor prognosis.

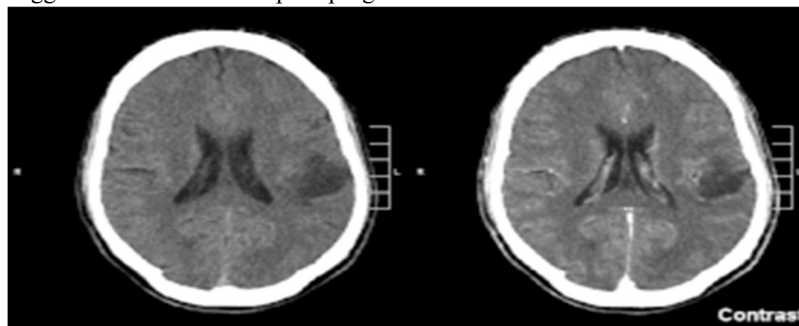


Fig. 1 Glioma in the left parietal lobe (brain CT scan), WHO grade 2

Meningioma:

Meningiomas, the most prevalent type of primary brain tumor, originate from the meninges—the layers of tissue enveloping the brain and spinal cord. Often characterized by slow growth, meningiomas are typically benign. However, their impact can be significant as they press on adjacent brain tissue, leading to symptoms contingent on their location. More commonly diagnosed in women, symptoms may include headaches, seizures, vision changes, and alterations in personality. The benign nature of meningiomas underscores the importance of accurate classification for appropriate clinical management. Meningiomas are typically benign and slow-growing. However, they can be malignant in rare cases. Malignant meningiomas are more aggressive and have a worse prognosis than benign meningiomas.

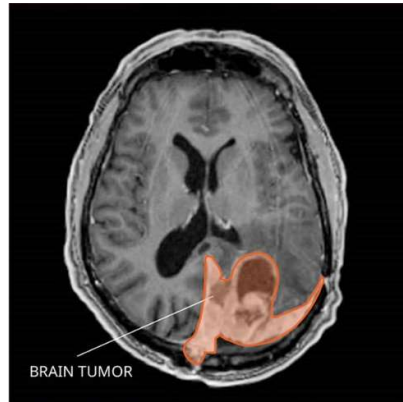


Fig. 2 MRI of meningioma

Pituitary Tumor:

Pituitary tumors originate in the pituitary gland, a small but pivotal gland at the brain's base responsible for hormone regulation. Categorized as functioning (secreting hormones) or non-functioning, pituitary tumors can disrupt hormonal balance and exert pressure on nearby structures. While often benign, they may cause hormonal imbalances leading to symptoms like irregular menstruation, changes in libido, visual disturbances, and headaches. The intricate interplay of hormonal regulation necessitates accurate classification to guide treatment decisions and manage potential endocrine disruptions.

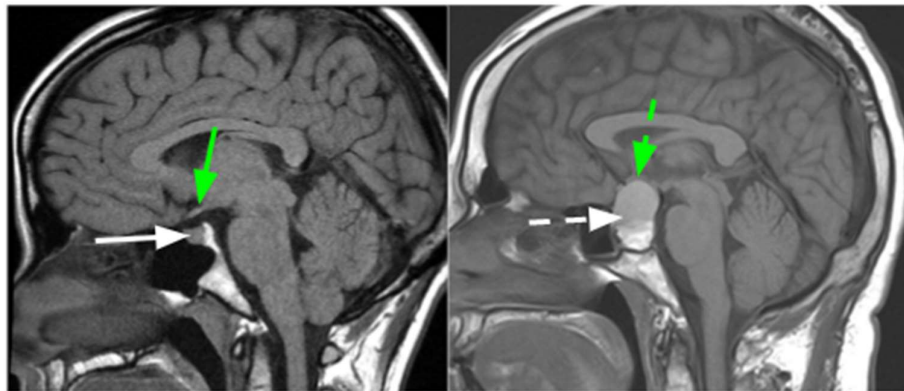


Fig. 3 MRI images showing the normal pituitary gland (solid white arrow) and a pituitary tumor (dashed white arrow). The optic chiasm (where the optic nerves meet) is shown by the green arrows and is pushed up by the pituitary tumor.

Credit: North American Neuro-Ophthalmology Society.

Tumor and No tumor:

Tumor: A tumor is an abnormal and uncontrolled growth of cells that forms a lump or mass. Tumors can occur in various tissues and organs of the body. They are classified into two main types: benign and malignant.

No tumor: The term "No Tumor" indicates the absence of abnormal growths or masses in a particular tissue or organ. In medical diagnostics, it means that, based on the examination or imaging conducted, there are no signs of tumor formation. This is a desirable result, especially when considering the potential health implications associated with the presence of tumors.

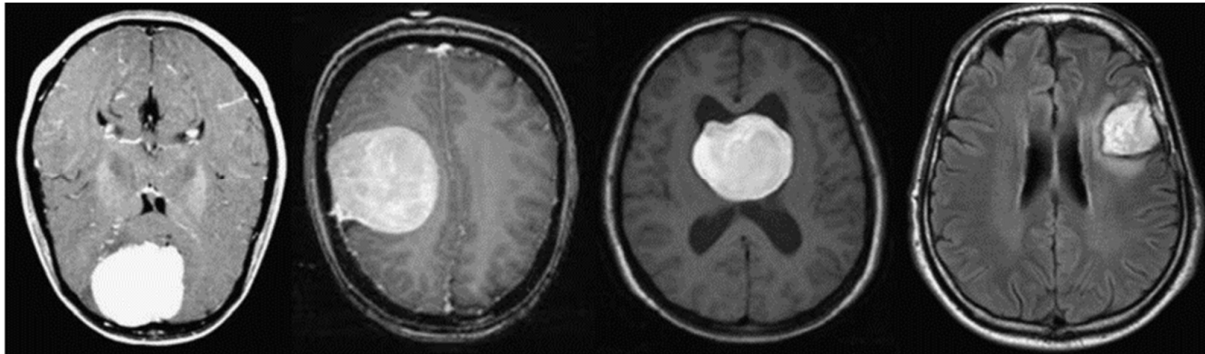


Fig. 4 Images with tumor

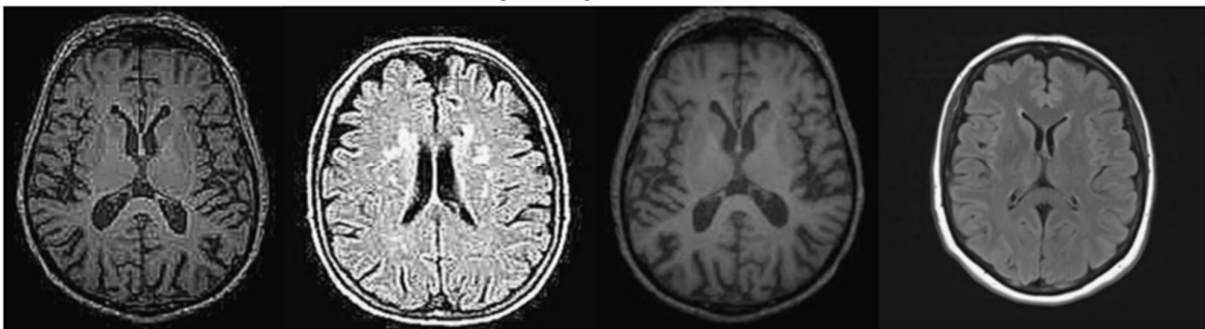


Fig. 5 Images without tumor

III. METHODOLOGY

Advancements in medical imaging and machine learning have revolutionized the field of neuro-oncology, offering unprecedented opportunities for accurate and efficient brain tumor classification. In this context, our research presents a comprehensive methodology leveraging Convolutional Neural Networks (CNNs) for the nuanced categorization of brain tumors into meningioma, glioma, and pituitary tumors. The methodology integrates state-of-the-art techniques in data preprocessing, image segmentation, feature extraction, and classification to enhance the precision of diagnostic tools and contribute to improved patient outcomes. The used dataset encompasses a broad spectrum of anatomical characteristics associated with meningioma, glioma, and pituitary tumors, ensuring the model's robustness in handling real-world clinical scenarios.

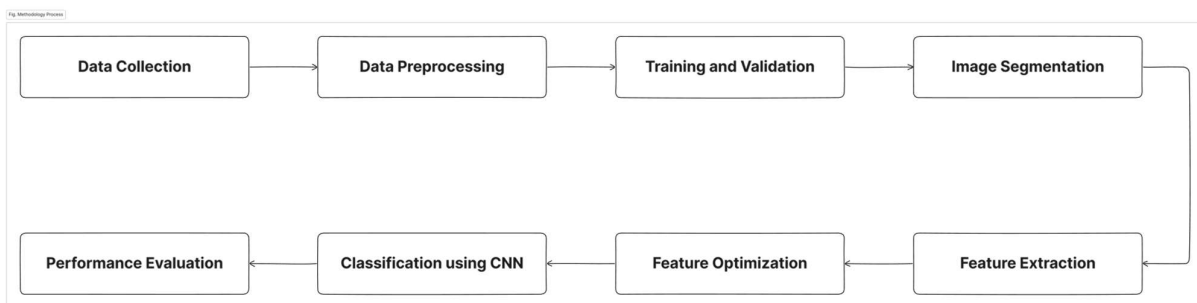


Fig. 6 Methodology process

Data Collection:

The study utilizes a diverse dataset comprising magnetic resonance imaging (MRI) scans of patients diagnosed with meningioma, glioma, and pituitary tumors. These images are obtained from reputable medical institutions and databases, ensuring a representative sample of the diverse anatomical and pathological characteristics associated with each tumor type.

Data Preprocessing: The collected MRI scans undergo meticulous preprocessing. This involves standardization to normalize pixel intensities and augmentation techniques (e.g., rotation, scaling, flipping) to increase dataset variability. Additionally, image segmentation is applied to isolate regions of interest, facilitating more focused analysis.

Training and Validation:

The model is trained on a subset of the pre-processed data, with a focus on optimizing hyperparameters to minimize overfitting. To assess the model's performance and generalization capabilities, validation is conducted on a separate subset of the dataset. Training includes backpropagation and optimization using stochastic gradient descent or other suitable optimization algorithms.

Image Segmentation:

Image segmentation is employed as part of the preprocessing step to isolate and delineate specific regions of interest within the MRI scans. This segmentation aids in focusing the model's attention on relevant areas for tumor classification.

Feature Extraction:

The CNN model automatically extracts relevant features from the segmented images. Convolutional layers are particularly effective in capturing hierarchical features crucial for distinguishing between different tumor types.

Feature Optimization:

Extracted features are optimized for further discriminative power. Techniques such as dimensionality reduction or additional feature engineering may be applied to enhance the model's ability to discern subtle differences between tumor types.

Classification using CNN:

The optimized features are fed into the CNN model for the final classification task. The model is fine-tuned during training to ensure it effectively learns the patterns associated with meningioma, glioma, and pituitary tumors.

Performance Evaluation:

The CNN model's performance is rigorously evaluated using an independent test set. Metrics such as accuracy, sensitivity, specificity, and the confusion matrix are computed to quantify the model's effectiveness in accurately classifying the different tumor types. Comparative analysis with existing methods provides insights into the model's contributions to brain tumor classification.

This comprehensive methodology ensures a systematic approach to brain tumor classification, encompassing data preprocessing, image segmentation, feature extraction, and model training with a focus on CNNs. The inclusion of performance evaluation metrics contributes to the validation and robustness of the proposed model

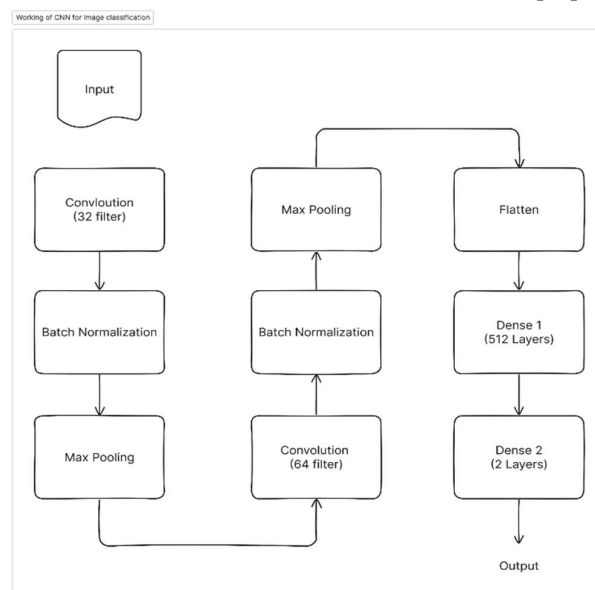


Fig. 7 Working of 9-layer CNN

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TABLE I: SUMMARIZATION OF CLASSIFICATION ACCURACY OBTAINED BY VARIOUS METHODS

Author	Methods	Data Set	Accuracy	Merits	Demerits
Wentao et al	Deep CNN and SVM	BraTS2014 and BraTS2016	SVM 87.05% and CNN 86.69%	segmentation and less time	Algorithm is not optimized
Yang et al.	Discrete wavelet transform (DWT)	GE Healthcare	clustering accuracy of 94.8% and a balanced error rate of 7.8%	instead of dimensionality reduction on SVM	model fitting issue arise
Badza et al.	CNN	BRATS and CBICA	10-fold cross-validation accuracy was 96.56%	Applied on two different data Set.	High running time
Demirahan et al.	Wavelets, Neural Networks and self-organizing map (SOM)	IBSR2015 and BRATS2012	WM 91%, GM87%, edema 77%, tumor 61% and CSF 96%	Performance increases in WM, GM, CSF and edema	It should be implemented on most updated data sets as well
Jyoti et al.	Deep CNN and SVM	OASIS	93.18%accuracy, 94% precision, 93% recall and 92% f1-score	Significantly improvement for multi-class classification	The gradient is vanishingly small and consequently prevent

IV. CONCLUSION

The comprehensive methodology employed in this study, encompassing data preprocessing, image segmentation, feature extraction, and model training, has contributed to the development of a robust and effective tool for accurate tumor classification. The utilization of a diverse dataset allowed the CNN model to learn and generalize patterns associated with various anatomical and pathological characteristics. Data preprocessing techniques, including standardization and augmentation, enhanced the model's adaptability to real-world clinical scenarios. Image segmentation facilitated focused analysis; isolating regions of interest critical for distinguishing between tumor types. As with any research, there are areas for further exploration and refinement. Future work may involve the integration of additional imaging modalities, such as functional MRI or spectroscopy, to provide a more comprehensive understanding of tumor characteristics. Additionally, ongoing validation on diverse and larger datasets will be crucial for ensuring the model's generalizability across different patient populations.

V. ACKNOWLEDGMENT

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