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Enhancing Brain Tumour Identification through Convolutional Neural Network

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Abstract - A tumor is carried on by rapid and uncontrolled cell proliferation in the brain. If it is not treated in the early stages, it could prove fatal. Despite multiple significant efforts and encouraging outcomes, accurate segmentation and classification still pose a difficulty. Detection of brain tumors is extremely complicated by the distinctions in tumor position, structure, and proportions. Using computational intelligence and statistical image processing techniques, proposed in our project provide multiple approaches to detect brain cancer and tumors. Also shows an evaluation matrix for a specific system using particular systems and type of dataset. Also explains the morphology of brain tumors, accessible data sets, augmentation techniques, component extraction, and classification of Deep Learning (DL), Transfer Learning (TL), and Machine Learning (ML) models.

***Key Words*:** brain tumour, image classification, image sementation, convolutional neural networks.

1.INTRODUCTION

Uncontrolled growth of brain tissue is referred to as a brain tumour,causing pressure within the skull and disrupting normal brain functions. It falls into two categories: benign (non-cancerous) and malignant (cancerous). Particularly malignant tumors can spread to other areas of the body, grow quickly, and damage the surrounding tissues.

Brain tumors are further classified into four grades:

Grade I: These tumors develop slowly and have a low likelihood of spreading. They can often be completely removed through surgery and carry a relatively good prognosis. An example is pilocytic astrocytoma.

Grade II: These tumors develop slowly over time and may infiltrate nearby tissues, potentially progressing to higher grades. Despite treatment efforts, these tumors can persist. Oligodendroglioma represents a grade II tumor.

Grade III: The growth rate of these tumours is greater than grade II tumors and have a tendency to spread to adjacent tissues. They typically require additional treatment such as chemotherapy or radiation therapy after surgery, as surgery alone may not be sufficient. Anaplastic astrocytoma represents a grade III tumor.

Grade IV: These are the most aggressive tumors, growing rapidly and often spreading to other parts of the brain or body. They require aggressive treatment, including surgery, radiation therapy, and chemotherapy. Glioblastoma multiforme is the most common type of grade IV tumor.

Brain tumors, particularly glioblastoma multiforme, require timely identification and accurate classification for appropriate treatment and patient survival. However, due to the varied characteristics of tumors such as size, shape, location, and appearance, detecting brain tumors poses significant challenges. Both traditional and advanced techniques are utilized for this purpose.

Traditional methods such as Leksell Gamma Knife, Gamma Knife (GK), and radioactive beam therapies are valuable for lesion diagnosis but typically require human intervention and can be time-intensive. Conversely, modern medical imaging modalities are pivotal in detecting brain tumors. Techniques like Computer Tomography (CT), Magnetic Resonance Imaging (MRI), and Positron Emission Tomography (PET) scans are widely used for this purpose.

A distinctive MRI technique, known as chemical exchange saturation transfer (CEST), facilitates the visualization of substances at concentrations too minimal to impact conventional MR imaging contrast or to be directly discerned in Magnetic Resonance Spectroscopy (MRS) at standard water imaging resolutions.

Within these modalities, MRI scans offer a non-invasive means to obtain intricate images of internal body structures through the manipulation of magnetization and microwave pulses. In brain tumor diagnosis, three primary categories of magnetic resonance image patterns are employed: Fluid Attenuated Inversion Recovery (FLAIR), T1 weighted, and T2 weighted images. These patterns play a pivotal role in discerning various characteristics of brain tumors, facilitating precise diagnosis and treatment strategizing.

1.1 Overview of an Algorithm

CNN

A Convolutional Neural Network (CNN) consists of convolutional and pooling layers, fundamental elements within its architecture. Constructing a CNN model entails comprehensive research and dataset integration, requiring the incorporation of numerous neurons to shape its structure. Analyzing successful applications, notably those showcased in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) between 2012 and 2016, provides valuable insights into effective CNN architectures.
The swift progress of computer vision applications, propelled by extensive research and the deployment of CNNs in challenges such as ILSVRC, has spurred breakthroughs in CNN model design. To tackle overfitting and decrease operational time, a Cascade Deep Learning model is suggested. Within this framework, a Cascade Convolutional Neural Network is proposed. (C-ConvNet/C-CNN)

is recommended, especially well-suited for processing smaller segments of brain slices.
The C-CNN model embraces two distinct methodologies to capture both local and global features, bolstering its capacity for brain tumor detection. Furthermore, it introduces a novel Distance-Wise Attention (DWA) mechanism aimed at enhancing tumor detection accuracy compared to existing models. This mechanism accounts for the brain's central location within the model and the impact of tumors. Figure 1.1 illustrates the architecture of a CNN tailored for image processing, showcasing the diverse layers responsible for segmenting and filtering image frames.

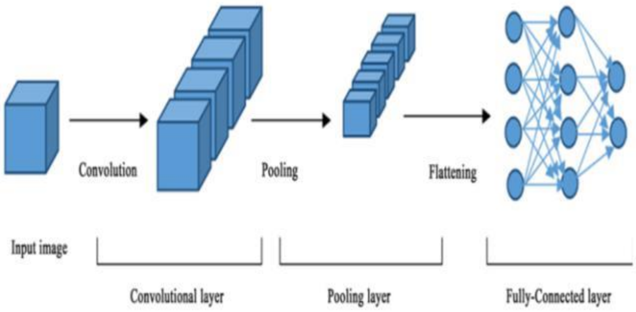

Figure 1.1 CNN architecture for image processing

RNN
An RNN (Recurrent Neural Network) finds application when network layers handle sequential or time series data. Examples such as Siri, voice search, and Google Translate showcase the versatility of RNNs across diverse domains, including medicine, where they play a crucial role in enhancing human life through deep learning concepts.

In medical applications, researchers construct models with necessary features and train them with desired network designs. RNNs employ a feed-forward concept to incorporate memory, enabling them to consider previous inputs and outcomes. The sequence of hidden layers refines results by incorporating information from preceding layers, treating latent and correlated values as coefficient values. These values undergo refinement across multiple hidden layers.

RNN outputs heavily depend on preceding layers in the network, leading to accurate predictions, especially in image values where multiple-layer correlations are prevalent.

2. LITERATURE REVIEW

In software development, conducting a literature survey is essential for gathering insights and information to enhance existing approaches. In our current project focusing on object tracking and detection, several research papers have been reviewed to gather pertinent information. The following section outlines key papers that have influenced our work in this field.

Segmenting brain tumors accurately remains a challenge due to variations in intensity contrasts, shapes, locations, and boundaries of brain tissue across individuals. Over time, numerous advanced segmentation techniques have been introduced to address this challenge. However, there is no perfect segmentation technique.

Deep learning has surfaced as a promising strategy for tackling challenges in image segmentation and classification.

In this context, deep learning methods for automatically segmenting brain tumors in MRI scans, employing datasets like BraTS (Brain Tumor Segmentation Challenge), have attracted significant interest. These approaches commonly employ deep neural network architectures, leveraging small convolution filters like 3 × 3 to sustain depth and efficiently learn features from input data in each layer of the network. This capability allows the network to capture subtle patterns and variations in the data, resulting in enhanced segmentation accuracy.

Machiraju Jaya Lakshmi et al. [1] presented a technique titled "SoftMax Classifier for Brain Tumor Classification," employing the Inception-V3 algorithm. Their model demonstrated an impressive accuracy of 89.00%. The research made use of a dataset comprising 3064 MRI images. This underscores the effectiveness of deep learning methods, particularly when utilizing sophisticated neural network architectures like Inception-V3, for precise brain tumor classification from MRI scans.

Ali Ari and Davut Hanbay et al. [5] proposed a "Convolutional Neural Network" incorporating the ELM-LRF algorithm. Their model achieved a notable accuracy of 97.20%. The dataset employed in their research was in the Digital Imaging and Communications in Medicine (DICOM) format. Cranial magnetic resonance (MR) images were categorized as either benign or malignant utilizing the ELM-LRF algorithm. This investigation underscores the effectiveness of convolutional neural networks, particularly when paired with sophisticated algorithms like ELM-LRF, for precise classification of brain tumors from DICOM images.

Rudresh D. Shirwaikar et al. [3] introduced a technique titled "Brain Tumor Segmentation, Detection, and Classification using 3D Convolutional Neural Networks." Their method incorporated diverse machine learning and deep learning classifiers. The dataset utilized in their investigation consisted of both real-time and synthetic datasets. This holistic approach emphasizes the importance of utilizing 3D convolutional neural networks for complex tasks like brain tumor segmentation, detection, and classification. It highlights the flexibility and efficacy of integrating various machine learning and deep learning methodologies in medical image analysis.

Dong Nie and colleagues [7] introduced a method entitled "Utilizing 3D Deep Convolutional Neural Networks for Classification," employing a technique known as 3D multi-level representation and organization using CNNs. Their model achieved an impressive accuracy rate of 99.60%. The dataset employed in their research consisted of brain images, encompassing T1 MRI, fMRI, and DTI scans sourced from patients with high-grade gliomas. This approach underscores the effectiveness of employing 3D deep convolutional neural networks for precise classification of brain images, particularly in the crucial task of diagnosing high-grade gliomas, marking a significant stride forward in medical image analysis.

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Minz and colleagues [6] presented a method named "CNN-based Preprocessing, Feature Extraction, and Classification," employing an algorithm that integrated GLCM features alongside machine learning and deep learning approaches. Their model attained an accuracy of 89.90%. The dataset utilized in their investigation comprised brain MR images. This strategy underscores the significance of preprocessing methods and feature extraction in combination with convolutional neural networks for precise classification of brain images, showcasing encouraging outcomes in the field of medical image analysis.

Yakub Bhanothu, Ananda Narayanan Kamala Kannan, and Govindaraj Rajamanickam [4] proposed a technique for "identifying and classifying diseases in MRI scans" using a Convolutional Neural Network (CNN) incorporating diverse VGG modules such as VGG16 and VGG32. Their method centered on utilizing CNN structures with extensive layers to efficiently process MR image datasets. Nonetheless, they observed that employing deep architectures with 50 or 100 layers could result in prolonged computation durations.

Their study emphasizes the importance of optimizing CNN architectures for efficient computation while maintaining high accuracy in disease detection and categorization tasks in MRI scans. This research contributes to the ongoing efforts to enhance medical image analysis techniques using deep learning algorithms
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Isselmou Abd E1 Kader and team [2] presented a method that employed a Deep Convolutional Neural Network (CNN) with 400 hidden layers and several SoftMax functions. Their methodology integrated a Deep Wavelet Autoencoder model. Yet, their assessment revealed a limitation in the model, as it concentrated solely on extracting features from the Homogeneous Encoder, disregarding other potentially beneficial features.
The dataset employed in their research consisted of MR brain images collected from diverse repositories, including BRATS (Brain Tumor Segmentation) datasets spanning from 2012 to 2015, as well as images from the 2015 challenge, and ISLES (Ischemic Stroke Lesion Segmentation) MRI Brain Images. This varied dataset enabled a thorough evaluation and validation of their proposed method for analyzing brain images.
Their study makes a substantial contribution to the progress of medical image analysis by exploring deep learning architectures and leveraging extensive datasets to improve the precision and effectiveness of disease detection and segmentation in MRI scans.

3. SYSTEM DESIGN

System Architecture
The methodologies and algorithms of the proposed approach are thoroughly detailed, outlining their application in the categorization of MRI brain images. A controlled experiment is conducted to validate the suggested methodology, wherein accuracy, precision, recall, and F1-measure metrics are computed. Python is employed for conducting this experiment. The study investigates the impact of independent variables on the dependent variable, which in this case is the accuracy of the proposed model. Various independent factors are examined and adjusted to assess their effects on the model's accuracy.

In the initial stage of the proposed model, the first step involves selecting the dataset. Following this, the second phase encompasses data pre-processing, which entails procedures such as thresholding, bicubic fractional ordering, and computation of extreme points.

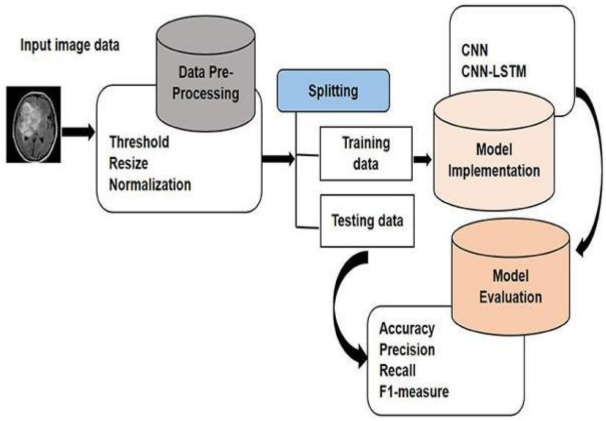


Figure 2: System Architecture

Sequence Diagram:

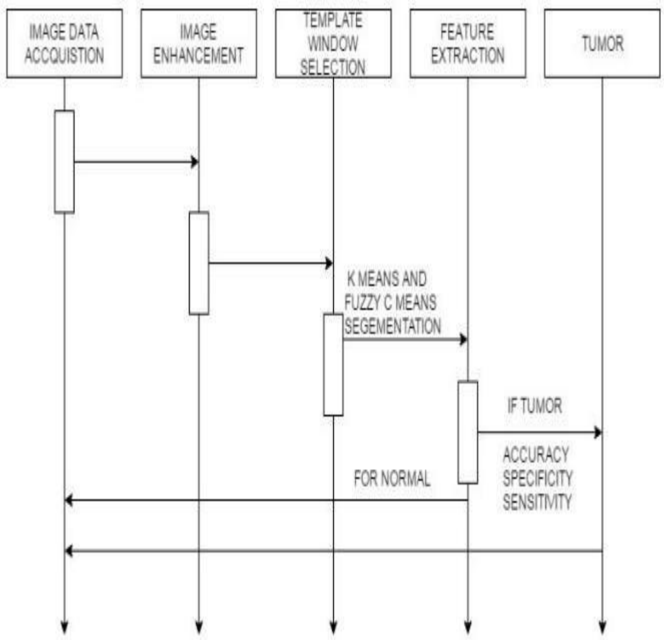


Figure 4: Sequence Diagram

UML Diagram

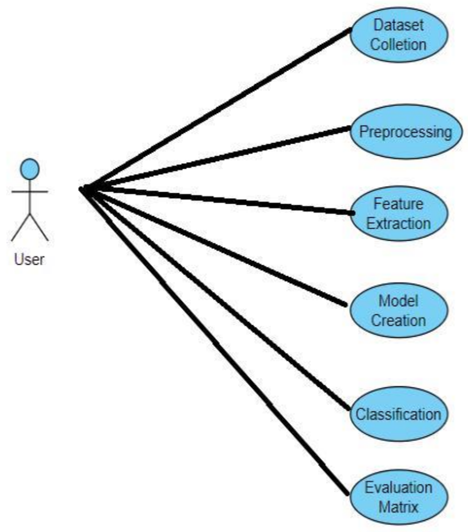


Figure 5: UML Diagram

Convolutional neural network

Convolutional Neural Networks (CNNs) utilize multiple convolutional layers to filter input data and extract relevant features. Convolutional filters applied through the CNN's convolutional layers enable the calculation of neuron outputs associated with specific regions in the input. This process facilitates the extraction of both temporal and spatial properties inherent in the image.
Three important layers make up the CNN model: In CNN architecture, three key layers are typically employed: the convolutional layer, the max-pooling layer, and the fully connected layer. Pitch, padding, and filter size are the three important characteristics of the convolutional layer. Each layer has a number of filters that are utilized for detailed feature extraction. Stride claims that the filters move inside the pictures. CNN performance declines if the value is more significant than two. The stride size is either one or two. When the filter does not completely screen all of the input images in the convolutional layer, Zero padding is essential to preserve structural integrity. Each convolutional layer serves a specific purpose; for example, the first layer emphasizes lesion edges, while the second layer enhances feature detection. The ReLU layer passes positive values, suppressing negative ones to zero. The max-pooling layer downsamples feature maps, commonly using max or average techniques. The fully connected layer, often with 512 units, classifies the image into multiple classes. Batch normalization normalizes feature maps, expediting network training. The dropout layer mitigates overfitting, as shown in Figure 6, depicting the CNN architecture.

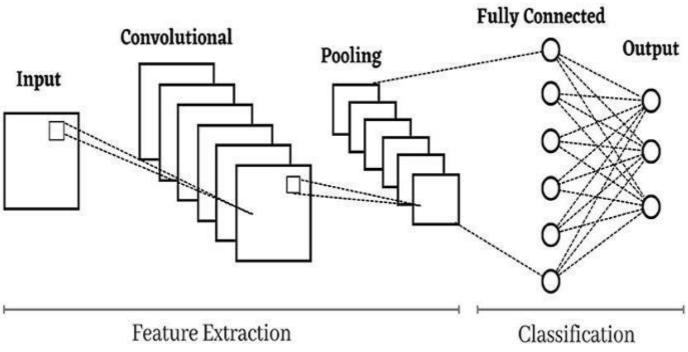
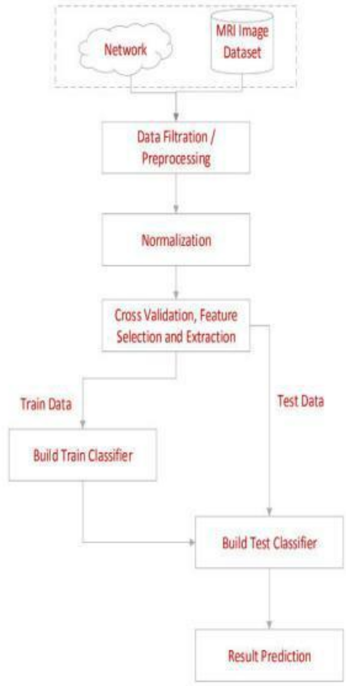


Figure 6: CNN Architecture

4. METHODOLOGY

Flowchart



A. DATASETS USED

The researchers conducted tests on a variety of publicly available datasets, focusing particularly on challenging ones. Among these, the BRATS datasets are considered the most demanding. These datasets, part of the BRAT'S Challenge released periodically over the years, feature a resolution of 1 mm3 voxel in the most recent challenges. Additionally, the researchers utilized one dataset sourced from The researchers utilized a variety of publicly available datasets to validate their proposed methodologies, focusing on challenging datasets of significant importance. The BRATS datasets are regarded as some of the most challenging MRI datasets, often issued as challenges at different times throughout the years. More recent challenges have featured a voxel resolution of 1 mm^3.

They employed two benchmark datasets and one dataset sourced from qualified radiologists. These datasets comprised 15 patient photographs, with each patient having 9 slices of imaging data. The core dataset used was the digital imaging and communication in medicine (DICOM) dataset, which included 22 photos, some depicting brain tissue infected with tumors. However, this dataset lacked ground truth images. In addition, they utilized the Brain Web dataset as a supplemental source of information.

B. TUMOR CLASSIFICATION APPROACHE

After sorting the input data using classification algorithms, various distinct classes, including both known and unknown examples, are utilized for training and validation purposes. One common use of machine learning is the classification of cancers into appropriate categories, including malignant and benign tumors, as well as tumors and non-tumors. KNN, support vector machines, closest subspace classification models, and representation classification models are all examples of supervised techniques.

C. DL MODELS

Deep learning (DL) models distinguish themselves from shallow Machine Learning (ML) techniques by emphasizing the learning of data representations and hierarchical features. They are descriptive data to capture the diverse forms of brain tumors. This approach shifts from manual feature engineering to data-driven classification, facilitated by deep learning techniques. In the realm of deep learning, Convolutional Neural Networks (CNNs) stand out as one of the most widely used architectures for brain tumor categorization, with significant advancements made. Various approaches are evident in the literature, differing in dataset composition, pre-processing and Ca augmentation methods, utilization of Region of Interest (ROI) segmentation, and choice between pre-trained or custom- designed. deep learning models. For instance, Bada and Barjaktarović utilized contrast-enhanced T1-weighted MRI images of brain tumors, including meningiomas, gliomas, and pituitary tumors. They conducted pre-processing techniques such as scaling, normalization, and data augmentation through flipping and rotation. A specially designed CNN classifier trained with the Adam optimizer and In the healthcare domain, deep learning techniques such as convolutional encoder networks, long short-term memories (LSTM), CRF, U-Net CNN, and WRN-PPNet have been utilized for training data, resulting in reported accuracies of 95.4%, 94.81%, 95.07%, and 94.94%, respectively. These methodologies play a pivotal role in enhancing medical image analysis and elevating diagnostic accuracy in healthcare applications.

D. FUTURE RESEARCH DIRECTIONS

Future research directions in brain tumor detection using deep learning techniques encompass addressing associated constraints and challenges. Researchers aim to achieve a comprehensive understanding to conduct new methodologies efficiently within reasonable timeframes.

While significant progress has been made with deep learning approaches, there's a necessity for a more generic approach that produces robust outcomes when trained and tested on comparable features like intensity range and resolution. Even slight variations between training and testing images can significantly impact the robustness of these methodologies.
Subsequent studies may focus on more precise brain cancer detection using real patient data, considering variations in image capture methods and scanners. Integrating handcrafted features with deep features holds promise for enhancing classification accuracy. Moreover, lightweight technologies such as quantum machine learning are crucial in improving accuracy and efficiency, thereby reducing radiologists' workload and increasing patient survival rates.

Attention-based mechanisms have emerged as valuable tools for brain tumor segmentation, addressing computational complexity. These mechanisms utilize image processing and attention mechanisms to extract desired image areas, followed by pre-trained encoder parts to extract essential features, thereby enhancing efficiency. Attention mechanisms are widely studied concepts in deep learning, applied in addressing various challenges like neural machine translation and image captioning. Supported by theories including Seq2Seq models, encoders, decoders, hidden states, and context vectors, attention mechanisms include useful methods such as channel attention, spatial attention, and block attention.

In summary, ongoing research efforts in deep learning for brain tumor detection hold promise for improving diagnostic accuracy and patient outcomes, with attention-based mechanisms and hybrid approaches showing particular potential for advancing the field.

5. CONCLUSION

CAD systems for brain tumor detection utilize brain MRI scans and digital image processing methods such as pre-processing, separation, and classification. This study discusses classic deep learning and machine learning techniques for identifying brain tumors, examining various research publications from reputable sources and providing a comprehensive analysis of each approach. A summary of commonly used MRI datasets is also provided. While multiple machine learning and deep learning methods are employed for classification, CNN has demonstrated high accuracy in brain tumor identification. CNN is commonly utilized to categorize brain tumors into two types: normal and pathological. The development of an autonomous brain tumor detection system must prioritize reliability, accuracy, and computational efficiency.This review not only explores current methodologies but also suggests their potential application in building effective diagnostic tools for other brain illnesses such as Alzheimer’s disease, Parkinson’s disease, dementia, and stroke using diverse MRI imaging modalities. Future research may involve implementing this system in conjunction with multiple deep learning algorithms, particularly deep hybrid learning, for enhanced brain tumor detection and classification capabilities.

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