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A Comprehensive Review of Deep Learning and Ensemble Approaches for Brain Tumor Prediction and Classification

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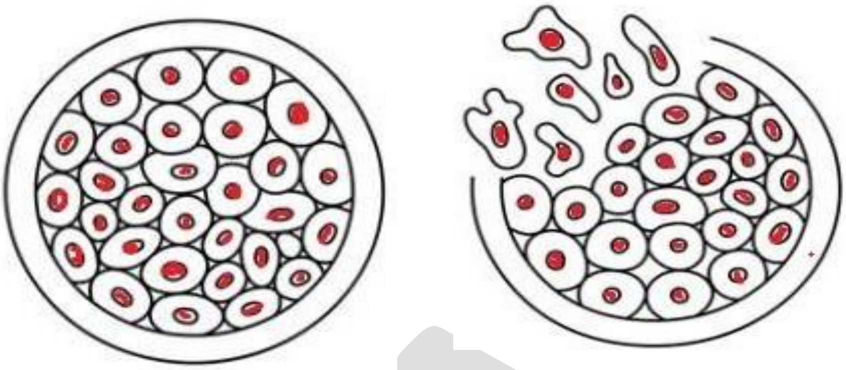
ABSTRACT
Brain tumor prediction is crucial for accurate diagnosis and early treatment of this fatal medical disease. Traditional methods relying on manual analysis of medical images are subjective and time-consuming. Machine learning, particularly deep learning, has shown promise in improving brain tumor prediction. Nevertheless, specialized approaches might have limitations. Modern health practices involve Artificial Intelligence (AI), Information Technology (IT), and E-healthcare processes to build a smart system that helps doctors provide quality health services to patients. Brain tumors are a major malfunction in the human brain caused by an aberrant growth of cells. It can adversely affect cognitive function and can be a fatal condition. This paper introduces the new area of hybrid machine learning for brain tumor prediction. Hybrid approaches attempt to enhance forecast precision, robustness, and explainability by incorporating numerous methodologies. The survey assesses new research papers published, reviews methodology utilized in hybrid models, and compares their performance against conventional methods.
Keywords — Brain tumor prediction, Deep Learning, Prediction.

1. INTRODUCTION

A brain tumor is an aggregation of abnormal cells within the brain. The skull may be rigid, enclosing the brain. Numerous complications arise from the proliferation of any tumor within this confined area. Brain tumors are primarily classified into two categories: malignant and benign. The skull experiences internal pressure to expand in the event of growth from any benign or malignant tumor [1] [2]. This tumor results in a cerebrum lesion, which may pose a threat to survival. Brain tumors are classified into two categories: primary and secondary. A tumor occurring in the cerebrum is referred to as primary brain cancer. Different shades of gray are soft. An optional cerebrum tumor is also a metastatic brain tumor. This tumor originates from the dissemination of malignant cells within the cerebral tissue, akin to an extension involving the lungs or breasts [3]. The encephalon may originate within the brain or disseminate from other anatomical organs. It can expand to the cerebrum. The growth rate and location of a brain tumor determine its effects on the functioning of the neurological system. The nature, size, and site of the brain tumor have guided the choice of treatment options.

1.1 Brain Tumor Stages

Approximately 130 unique types of tumors exist in the brain and central nervous system. Brain tumors are primarily categorized as either primary or metastatic. A primary brain tumor is an atypical growth that originates in the brain and generally does not metastasize to other regions of the body. Primary brain tumors can be classified as benign or malignant. A benign brain tumor with well-defined margins and infrequent metastasis will progress at a markedly slow rate. Although benign tumors are non-cancerous, they may exhibit aggressive behavior when located in a critical region. The malignant brain tumor will proliferate rapidly, exhibit uneven margins, and encroach upon adjacent cerebral areas [4]. Although commonly referred to as brain cancer, malignant brain tumors do not fit the conventional definition of cancer, as they do not metastasize to organs outside the brain and spinal cord [5]. Figure 1 presents graphic depictions of normal and malignant cells.



(a) Benign Tumor (b) Malignant Tumor

Figure 1: (a) Non –Cancerous (Benign) and (b) Cancerous (Malignant) Cells.

1.2 Types of Brain Tumors

Brain tumors can be categorized according to several criteria, including their cellular origin, anatomical location, and classification as primary or metastatic. Figure 2 exemplifies three prevalent forms of brain tumors.

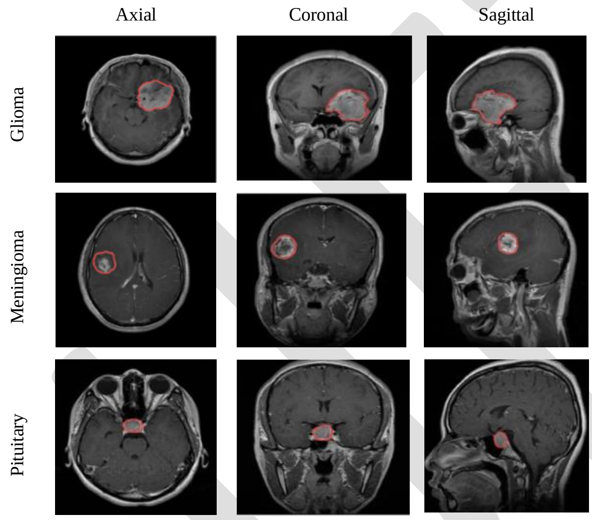


Figure 2: The Sample Three Types of Brain Tumors

Primary Cerebral Neoplasms

Glioma: The WHO grading system is commonly employed to classify gliomas, encompassing astrocytomas, oligodendrogliomas, and glioblastomas. In this approach, grade I represents the least aggressive classification, while grade IV denotes the most aggressive classification [6].

Meningiomas are often classified based on their size, location, and extent of invasion in surrounding tissues. The prevalent Simpson grading system ranges from grade I, indicating complete resection, to grade IV, denoting incomplete resection with persistent tumor [7].

The dimensions of the tumor, hormonal secretion, and encroachment upon adjacent tissues are commonly employed to stage pituitary adenomas. They are classified into two categories: macroadenomas (exceeding 1 cm) or microadenomas (measuring less than 1 cm).

Metastatic Brain Tumors

Metastatic brain tumors are grouped according to how far they are from the original cancer site [8]. Metastatic brain tumors can also be staged using the TNM (Tumor, Node, and Metastasis) system, commonly used for most cancer categories. This technique considers numerous characteristics, including the size and quantity of metastases, as well as the involvement of adjacent lymph nodes or other organs [9].

1.3 Brain Tumor Grades

A brain tumor may be classified as benign or malignant depending on its morphology, rate of development, and origin [10]. Malignant brain tumors, for instance, arise from inside the brain. The World Health Organization (WHO) categorizes brain tumors into four groups: Grade I to Grade IV. Each grade represents an increasing degree of cancer and a poorer prognosis. Figure 3 outlines the classification of brain tumor grades.

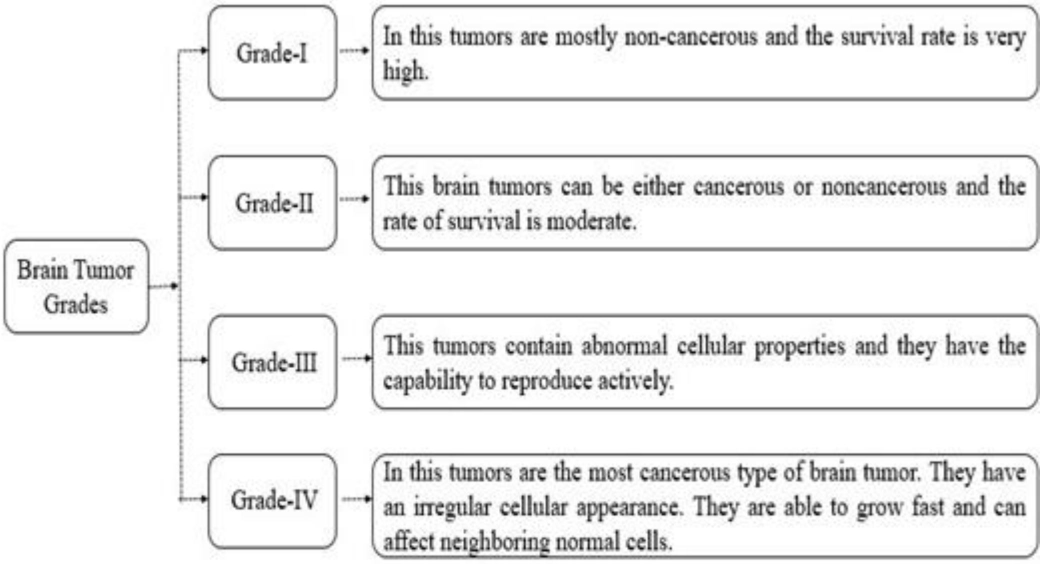


Figure 3: Classification of Brain Tumor Grades

2. LITERATURE REVIEW

Recently, the domain of brain tumor prediction has shown substantial progress due to the incorporation of machine learning methodologies. Mircea Gurbină et al. (2019) [11] described that Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), and Support Vector Machines were used to execute a brain tumor detection and prevention system. The suggested method was applied to distinguish between malignant and benign conditions. MRI of the brain was done to analyze different types of brain tumors, i.e., metastatic bronchogenic carcinoma, invasive glioma, and nonepithelial tissue. Different wavelet transforms and SVM were performed in order to identify and classify the brain tumors in magnetic resonance images. Correct and unbiased automatic categorization of MRI brain images is highly important for medical interpretation and analysis.

Shrutika Santosh Hunnur et al. (2017) [12] studied that MRI processing is a major area of image processing in the healthcare sector in recent years. The first step was the detection of tumor. The thresholding method was suggested for the detection of gray matter tumors. The suggested technique was successfully utilized to detect and extract cerebral cancer from magnetic resonance images acquired from the patient database. It proved to be a useful tool for clinicians working in this field.

Mahesh Swami et al. (2020) [13] presented a hybrid method using image processing and segmentation methods for analyzing radiographic CT and MRI images for the identification of brain tumors. Open-source brain scans by Google were used to obtain the database, and MATLAB v2019 was used to implement the system on Windows. This research first summarized medical imaging with image processing. The engineering evaluation showed that this technique accomplished 100% sensitivity, 89.66% similarity, and 87.50% accuracy. This study suggested the implementation of a low-cost system available to medical practitioners on regular computers.

Parveen et al. (2015) [14] suggested a novel hybrid method based on Support Vector Machines (SVM) and Fuzzy C-Means (FCM) to classify tumors. The FCM was applied with the SVM in a hybrid method in the suggested algorithm to classifiy brain tumors. Contrast enhancement and mid-range stretching were methods employed to sharpen the image in this algorithm. Double thresholding and morphological methods were used to perform the skull stripping. FCM clustering was used to segment the image and detect the suspicious region in the brain MRI. The GLRLM was utilized to extract features from the brain image. Then, Support Vector Machine was used for classification of brain MRI images with good accuracy and improved robustness. The result required the order of MRI pictures of the cerebrum.

Mahesh Kurnar et al. (2018) [15] studied that one of the major research areas was partitioning of cerebral cancer in MRI in the context of clinical imaging methods. Detection of gray matter was essential to ascertain the precise dimensions and location of the tumor. This work suggested a K-means clustering method for the detection of cancer on the basis of segmentation and morphological operations. The MRI-scanned image was preprocessed initially. Then, the image was processed with K-means clustering. The morphologic process was performed for separating the cancer from the initial MRI checkup image. The pull-out cancer element region has been calculated.

Zhenyu Tang et al. [16] provide a novel framework for the multi-Atlas Segmentation (MAS) of MRI brain tumor images. MAS operates by registering and integrating label information from multiple standard brain atlases into a novel brain picture for segmentation purposes. Primarily, it is designed for standard brain imaging; nevertheless, tumor brain images present a significant challenge. To address this issue, a novel low-rank method is being used in the first stage of the MAS framework to extract the recovered picture of a normal brain from the MR image of a tumor-affected brain, utilizing information from the normal brain atlas. In the subsequent phase, standard brain atlases are being aligned to restore the image without tumor interference.

Navpreet Kaur et al. [17] conducted self-adaptive K-means clustering to segment brain tumors. The subsequent steps constituted the preprocessing phase: A median filter was initially applied to eliminate noise, followed by skull stripping utilizing the brain surface extraction technique. Skull stripping is the procedure of eliminating any non-cerebral tissue from the fMRI or MRI image. This is essential, as ocular structures or osseous tissues may exhibit elevated intensity values and potentially resemble tumor morphology, complicating tumor diagnosis. The salt & pepper noise was subsequently eliminated. Subsequently, self-adaptive K-means clustering is employed to segment the image, followed by the application of a Sobel edge detector to further delineate boundaries.

3. CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network (CNN) is the deep learning model [18] to classify brain tumors. CNNs are efficient in medical imaging because of their capability to determine hierarchical features of pictures.

3.1 Convolutional Neural Network Layers

- **Input Layer** The input layer takes the inputs in the form of the pre-processed MRI images, which undergo a standardization process to a fixed size (224 224 pixels) and pixel intensity range. This layer is used to make sure that all information that is introduced into the network is always formatted and meets the criteria of the next convolutional operations needed to extract features well.
- **Convolutional Layers** These are the central extractors of features of the network, which uses various filters (learnable kernels) on the spatial dimensions of the input image. Each filter detects a local pattern of the image, edges, textures, or shapes, by calculating the weighted average of pixel values in small areas, producing feature maps that point to various features of the image that are useful in characterizing tumors.
- **Pooling Layers-** Pooling layers are used to reduce the spatial dimension of the feature maps produced by the convolutional layers, and the most common is max pooling or average pooling. The process reduces the data at all levels, making the model computationally attractive, and gives the model some sort of translational invariance, which guarantees that the learned features are resistant to small shifts or distortions in the MRI scans.

- **Dropout Layers -** Dropout layers can be used to reduce overfitting in training a model by randomly selecting some of the neurons in a layer and (dropping out) them on any single training step. Older dropout regularises the network by compelling it to use more than one pathway to extract features, enhancing its generalisation performance on images of unseen MRI scans.
- **Fully Connected Layers** Fully connected layers (or dense layers) use the flattened output of the previous layers and combine the extracted features to come up with classification decisions [19]. Each neuron of a fully connected layer is provided with all the activations of the previous layer in which the network is able to weigh and integrate learned features to the right categories of brain tumor which have high accuracy in brain tumor classification.
- **SoftMax Output Layer** SoftMax output layer is the last layer in CNN architecture and it transforms the networks output into class probabilities. In the case of multi-class brain tumor detection, this layer employs SoftMax activation function to produce a probability distribution of all possible tumor classes and non-tumor class that allow confident and explainable prediction outputs with each MRI input.

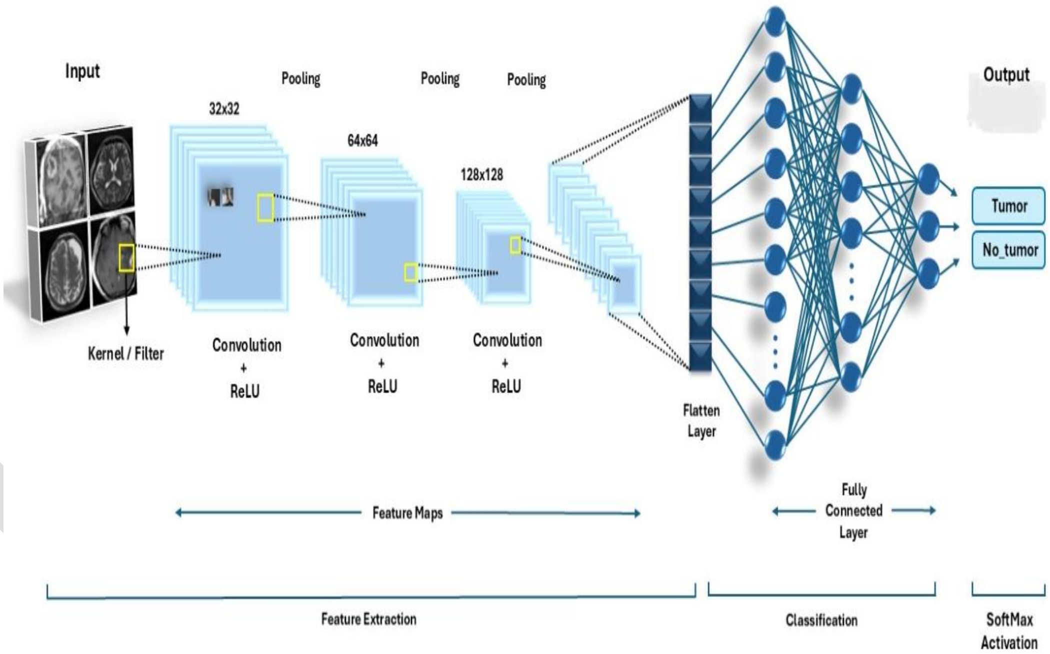


Figure 4: CNN Architecture used for Brain Tumor Detection

The Convolutional Neural Network (CNN) described in Figure 4 is designed to detect brain tumors. The model has several layers that sequentially remove and smooth features in the input MRI images. The input layer is fed with uniformly pre-processed images that are resized to 224x 224 pixels after which a series of convolutional layers are used to apply learnable filters to extract important spatial features like edges and textures that are important in tumor detection. The layers are then pooled to decrease the spatial dimensions, increasing computational efficiency and giving the layer translational invariance. In order to avoid overfitting, dropout layers randomly disable parts of the network during training, thus encouraging generalization. The flattened feature maps are then run through fully connected layers, which combine the extracted features to come up with an actual representation that can be used to classify. The last step is the SoftMax output layer which transforms these representations into probability distributions on the target classes which allows the brain tumors and non-tumor cases to be categorized accurately. The hierarchical design will utilize the advantage of CNNs in medical image analysis to support high-quality and strong brain tumor classification.

4. CONCLUSION

This paper comprehensively delineated the approach employed in this work to develop an effective system for detecting brain tumors using advanced deep learning algorithms and an intuitive graphical user interface (GUI). The novel algorithmic method can be further enhanced for the detection of brain tumors when it fails. The implementation of a novel neural network classifier enables more efficient classification of tumor regions. A comparative comparison of the performance of new and ancient algorithms for brain tumor identification is feasible.

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