**Medical Image analysis using Brain tumor detection**

**Introduction:**

Artificial intelligence (AI) technology has been a major factor in the recent rapid transformation of the healthcare industry brought about by technology advancements. Artificial Intelligence (AI) is a computer system that mimics human intelligence and has numerous medical applications. The fight against brain tumors is one such area. In the field of medicine, brain tumors represent a significant public health concern, and proper diagnosis, treatment, and follow-up procedures are essential. AI has emerged as a key instrument for enhancing these procedures and holds considerable promise for the early detection and management of brain tumors.

The location of brain tumors affects human health1. By combining technologies like big data analytics, machine learning, and deep learning, artificial intelligence (AI) is intended to assist in the diagnosis and treatment of complex diseases like brain tumors. Through the analysis of brain imaging methods like Magnetic Resonance Imaging (MRI), AI is able to identify and categorize tumors. The location, class, size, and aggressiveness of tumors can all be ascertained with the aid of AI algorithms. In addition to helping patients understand their health better, this assists doctors in providing a diagnosis and treatment plan that is more accurate [1].

There are 4 types of brain tumor images like: Gliomas, Meningiomas, Pituitary and No tumor images. Gliomas represent a diverse group of brain tumors with varying prognoses and treatment options. Early detection and a multidisciplinary approach to treatment are crucial for improving outcomes and quality of life for patients with gliomas. Ongoing research and advancements in medical technology continue to provide new insights and therapies for managing this challenging group of brain tumors. Meningiomas are a type of brain tumor that originates from the meninges, the protective membranes covering the brain and spinal cord. They are the most common type of primary brain tumor, accounting for about one-third of all brain tumors. Meningiomas are typically slow-growing and often benign, although some can be malignant. pituitary gland is a tiny organ at the base of the brain, often called the "master gland" because it controls many other glands and bodily functions by releasing hormones. Sometimes, tumors can grow in this gland, and these are called pituitary tumors. No Tumor image does not contain any type of tumor i.e. there is no brain tumor in the image.

In recent years, many methods have been presented for the automatic classification of brain tumors, which can be divided into Machine Learning (ML) and Deep Learning (DL) methods based on feature fusion, feature selection and the learning mechanism. In ML methods, feature extraction and feature selection are fundamental to classification [2] [3]. However, DL methods learn by extracting features directly from images. New DL methods, especially CNNs, offer excellent accuracy and are greatly employed in medical image analysis, including MRI analysis [4] [5] [6]. The disadvantages compared to traditional ML methods are also that it requires a large training dataset, high complexity of time. In addition, choosing the accurate deep learning model can be an intimidating task, requiring knowledge of numerous parameters, training methods, and topologies. Numerous Deep leaning-based models have been utilized for the brain tumor detection, i.e., VGG-16, VGG19, CNN, RESNET -100, AlexNet, EfcientNetB4, InceptionV3 and etc.

**Literature Review:**

MR imaging is actively used in contemporary medical procedures to diagnose brain cancer. This section thoroughly examines the reputation for excellence in the detection and classification of brain tumors. In recent years, many researchers performed work on the detection, segmentation, and classification of brain tumors. The importance of this topic is pertinacious in the medical community. This research work describes methods for the detection of brain tumors. Methods to diagnose brain tumors include generative and discriminatory methods to distinguish brain images. a lot of research has been directed toward the adaptation of deep learning models in diagnosing brain tumors. Academicians have put in their efforts and with the help of high-end computing devices, higher accuracy has been achieved.

Maqsood et al. [7] demonstrated a brain tumor detection method based on fuzzy logic and the U-NET CNN architecture. Contrast enhancement, the fuzzy logic-based edge detection method, and U-NET CNN classification were used in this method. A contrast enhancement method is applied to the source images for pre-processing, followed by an edge detection method based on fuzzy logic to discover the edges in the contrast enhanced images, and finally a dual tree-complex wavelet transform is applied at various scale levels. The characteristics are generated from decomposed sub-band images, which are then classed using the U-NET CNN classification method, which distinguishes between meningioma and non-meningioma in brain imaging. The presented method was compared against various recently developed algorithms, and achieved an accuracy rate of 98.59%.

Togacar et al. [8] developed a BrainMRNet network using the modulo and hypercolumn method. First, the source images were pre-processed and afterwards they proceeded to the attention modulo. The attention modulo regulates the main areas of the image and directs the image to the convolutional layer. One of the primary strategies utilized in the convolutional layers of the BrainMRNet model is the hypercolumn. With this method, the attributes extracted from each layer are retained in the array tree of the last layer and attained an accuracy rate of 96.05%.

Sajjad et al. [9] developed a CNN based brain tumor detection and classification method. The authors used a Cascade CNN algorithm for the brain tumor segmentation and a fine tuned VGG19 is used for the tumor classification and attained an accuracy of 94.58%. Prastawa et al. [10] demonstrate how to segregate tumor areas in brain MRIs by detecting borderline pixels. This method detects only the aberrant borders of the tumor region however, not the inner border of the tumor region and hence achieved an accuracy of 88.17%.

Swati et al. [11] used a fine-tuned pre-trained VGG19 model on contrast-enhanced MRI (CE-MRI) to improve the results and obtained an average accuracy rate of 94.82%. Kumar et al. [12] proposed a brain tumor method using ResNet50 CNN model and global average pooling to resolve the problem of overfitting and obtained an average accuracy rate of 97.48%. Anaraki et al. [13] proposed a strategy based on CNN and GA (genetic algorithm) to classify various types of Glioma images using MRI data. The proposed system used GA for an automatic selection of CNN structure. They obtained 90.9% accuracy predicting Glioma images of three types. Besides, the study brought an accuracy of 94.2 % in the classification of Glioma, Meningioma, and Pituitary.

Gumaei et al. [14] proposed a hybrid feature extraction method for brain tumor classification using a regularized extreme learning machine (RELM). The min–max normalization contrast enhancement method is used as a preprocessing step and the hybrid PCA-NGIST method is used for the feature extraction, and the RELM method is employed for the classification of the brain tumor. This work obtained an accuracy rate of 94.23%. Swati et al. [15] used a fine-tuned pre-trained VGG19 model on contrast-enhanced MRI (CE-MRI) to improve the results and obtained an average accuracy rate of 94.82%. Kumar et al. [16] proposed a brain tumor method using ResNet50 CNN model and global average pooling to resolve the problem of overfitting and obtained an average accuracy rate of 97.48%.

**Table.1 Detailed summaries of current research on the detection and classification of brain tumors**

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| **References** | **Methodology** | **Algorithms** | **Results** |
| Maqsood et al. [7] | Brain tumor detection method | Fuzzy logic, U-NET CNN | Accuracy - 98.59% |
| Togacar et al. [8] | BrainMRNet network | BrainMRNet model | Accuracy – 96.5% |
| Sajjad et al. [9] | Brain tumor detection and classification | Cascade CNN and VGG19 | Accuracy – 94.58% |
| Prastawa et al. [10] | BrainMRI | Geometric and Spatial Constraints | Accuracy – 88.17% |
| Swati et al. [11] | Fine-tunned VGG19 | Fine-tunned VGG19 | Accuracy – 94.82% |
| Kumar et al. [12] | Brain tumor method | ResNet50 CNN model | Accuracy – 97.48% |
| Anaraki et al. [13] | Brain tumor method | CNN, Genetic Algorithm | Accuracy - 90.9% |
| Gumaei et al. [14] | Brain tumor classification | PCA-NGIST and RELM | Accuracy – 94.23% |
| Swati et al. [15] | Brain tumor | fine-tuned VGG19 | Accuracy – 94.82% |
| Kumar et al. [16] | Brain tumor Method | ResNet50 and Global Average Pooling | Accuracy – 97.48% |

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