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An Intensive Review of Brain Tumor Detection from MR Images using Machine Learning and Deep Learning Networks

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***Abstract*— The use of Magnetic Resonance Imaging (MRI) scan techniques in the field of Brain tumor detection is the main topic of this review study, which explores the changing field of brain tumor detection. Brain tumors are a serious medical problem that require early and precise discovery in order to effectively treat. The introduction highlights the frequency of brain tumors and highlights the critical role that MRI scans serve in providing non-invasive, fine-grained soft tissue imaging. The paper critically addresses the challenges inherent in brain tumor detection, ranging from tumor size and location variability to limitations associated with conventional MRI methodologies. The study devotes a significant amount of space to the amalgamation of automated image processing and machine learning methodologies, specifically stressing the application of diverse machine learning models for automated identification of brain tumors in magnetic resonance imaging images. The investigation includes a review of datasets that are often used in research as well as approaches that have been adopted by more recent investigations. Comparative evaluation of several models and algorithms reveals the advantages, disadvantages, and performance indicators of each. The study concludes with an investigation of possible future paths, considering new technology and multimodal imaging strategies that may improve the precision and effectiveness of MRI scans in the identification of brain tumors. In conclusion, this comprehensive review not only synthesizes existing knowledge but also underscores the imperative for ongoing research to advance the field and improve outcomes for individuals grappling with brain tumors.**

***Index Terms*— Brain Tumor, Restoration, Enhancement, Machine-Learning, Pre-Trained Models, MRI data images.**

I. INTRODUCTION

Brain tumors are abnormal tissue growths within the brain cells, affecting individuals of all age groups and significantly impacting their bodily functions. Detecting brain tumors early is vital as it can prevent life-threatening risks. Brain tumors come in a variety of types, and each one is distinct in its origins, traits, and tissue involvement.

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Glioblastomas, astrocytomas, and oligodendrogliomas are the three most common types of gliomas. Glial cells are the source of gliomas. Benign tumors called meningiomas start in the meninges and often grow slowly. Pituitary tumors, which develop inside the pituitary gland, have an effect on hormone balance. Children frequently develop medulloblastomas, which are mostly found in the cerebellum. While Schwannomas develop from Schwann cells of the peripheral nerves, acoustic neuromas primarily damage the auditory nerve. Central neurocytomas often occur in fluid-filled parts of the brain, whereas ependymomas are derived from ependymal cells lining the ventricles. Understanding the many types of cancers is necessary for accurate diagnosis and specialized treatment regimens. Identifying brain tumors is one of the most challenging tasks in medicine as timely detection improves prognosis and treatment compliance. Crucial diagnostic parameters have included the patient's condition, the physical examination, and the laboratory results, including imaging. Numerous diagnostic imaging techniques, such as computed tomography (CT) scans and magnetic resonance imaging (MRI), are utilized to detect early alterations in body tissues. The brain, which is mostly composed of billions of neurons, is one of the most important organs in humans. A brain tumor is described as a growth of tissue in a part of the brain that shouldn't see much expansion. MRI scans were used to perform the categorization in the paper. Brain tumors are classified into two domains: malignant and benign, based on cell characteristics. Currently, MRI and CT scans are the most effective methods for detecting brain tumor lesions. Among these, MRI has shown notable advancements in identifying brain abnormalities, surpassing other scanning techniques. Recent studies have demonstrated the automatic identification of tumors along with non-tumors using MRI. In the field of medical imaging, Computer-Aided Diagnosis (CAD) systems play a vivacious role in aiding physicians with brain tumor detection, examination, and cataloguing.

These systems have proven to be valuable tools, empowering healthcare professionals in their efforts to better understand and manage brain tumors. Through a vast network of cells, the brain, an incredibly complex organ, carefully coordinates a number of processes within the human body. This fine equilibrium is upset, leading to the development of brain tumors. This is caused by unchecked cell division and abnormal growths that impair normal brain function and negatively impact nearby healthy cells. In the field of medical imaging, interpreting and comprehending the intricacies connected to these cancers depends heavily on the processing of MRI images. In the medical field, X-ray pictures are frequently used to evaluate and localize tumor growth within the body. Interestingly, brain tumors can affect people of any age, from toddlers to adults, raising intracranial pressure and impairing brain function in general. Tumors inside the skull can cause interference with the complex functions of the brain. In addition to the direct physiological effects, brain tumors can develop into cancer, which is a significant cause of death worldwide, making up around 14% of all fatalities that have been documented. Concerns are raised by the increasing global prevalence of cancer, which emphasizes the urgent need for cutting-edge medical treatments and extensive research to address this widespread health issue.

Fig. 1 Occurrence of Brain Tumor

The early phases of brain tumor growth, as shown in Figure 1, are a crucial moment when prompt detection is extremely important for patients as well as healthcare professionals. Because of the complexity of the human brain and the possible outcomes of unchecked cell development, aberrant growths must be identified quickly and accurately. When used to early detection, machine learning algorithms become indispensable instruments that can improve patient outcomes and augment the effectiveness of medical therapies. For patients, there are several benefits to early diagnosis. First and foremost, early diagnosis allows for the early initiation of treatment plans that may inhibit the tumor's development and minimize its harm to adjacent healthy brain tissue. As a consequence, the patient may have more practical therapy options, which would reduce their overall burden and perhaps enhance their quality of life. Furthermore, by raising the likelihood of good treatment results, early identification might enhance the overall prognosis for those dealing with a brain tumor diagnosis. Medical workers, including doctors, may reap significant advantages from early detection enabled by machine learning technologies. Timely identification allows for informed decisions on the best course of treatment, improving patient care and maybe even improving long-term outcomes for medical professionals. Furthermore, early detection assists in streamlining the healthcare system, making it easier to allocate resources and reducing the strain on hospitals. In summary, the application of machine learning techniques for early brain tumor detection not only enhances treatment outcomes and patient quality of life but also makes it possible for healthcare providers to deliver more targeted and efficient care, thus fostering a proactive and comprehensive approach to managing this challenging medical condition.

The US had over 22,000 new instances of brain cancer and other central nervous system cancers in 2009, according to the National Cancer Institute (NCI). Furthermore, within the same time frame, 62,930 additional instances of benign brain tumors have been documented by the American Brain Tumor Association (ABTA). Although the underlying cause of brain tumors is still unknown, radiation exposure from MRIs, CT scans, and X-rays has been linked to the condition. Because brain tumors are intricate, diagnosing them can be difficult. However, certain symptoms may indicate their presence, such as severe seizures, loss of body control, disturbances at neurological level, impassiveness, speech difficulties, hormonal abnormalities, and personality changes. Timely recognition of these symptoms is vital for early diagnosis and prompt medical intervention.

Radiologists utilize CT scans and MRIs to visually assess patients, examining structure of brain, size of the tumor, and location of it as depicted in MRI images. Imaging plays a crucial role in brain tumor diagnosis, where MRI images are often classified as hypo-tense or iso-tense. Edge detection techniques are employed to convert images into edge images, effectively capturing immediate shifts in grey tones.

By utilizing segmentation, the resulting images preserve the primary image's physical characteristics without any modifications. Radiologists can present detailed information, including tumor locations, facilitating a straightforward tumor diagnosis and preparation for surgical procedures. The integration of digital image processing techniques has enhanced brain tumor diagnosis, reduced the risk of misdiagnoses, and improved overall accuracy and reliability.

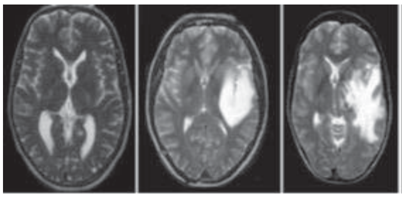

Fig. 2. Scan of healthy brain (Left) & with tumor (center and right)

Figure 2 depicts the brain section affected by a tumor, providing valuable information about the location of the infected area. Three-dimensional representations of the brain are generated using MRI, which utilizes a powerful magnetic field and radio waves without any ionizing radiation risk. The non-invasive nature of MRI scans is a significant advantage. Applying techniques for enhancing the image to boost the investigative capabilities of MRI data images, particularly in critical tasks like brain image analysis. Medical photographs created through image processing enable medical professionals to understand the internal workings of unseen organs within the human body, thereby easing the burden on patients along with the concerned physician. Identifying brain cancer with the aid of image processing has been a well-established method for several decades. Various semi-automatic and automatic image processing techniques have been proposed by researchers.

First major challenge is to manage the MRI images and make it appropriate for our desired data. To deal with this various image segmentation techniques can be used.

A. Need of Image processing

Image processing is a vital diagnostic tool that may be used to refine and interpret a wide range of medical pictures, including CT scans, MRIs, ultrasounds, and X-rays. Its primary function is to improve and interpret these pictures, giving medical practitioners an extra degree of accuracy that is vital. Medical professionals may extract fine details, identify abnormalities, and accurately diagnose illnesses and tumors by using sophisticated image processing techniques. This capacity eventually contributes to better patient outcomes and the progress of medical knowledge by improving the accuracy of medical diagnoses and facilitating informed decision-making during treatment planning.

B. Image segmentation

The technique of splitting a picture into separate areas according to features including colors, textures, brightness, contrast, and grayscale levels is known as image segmentation. Grayscale pictures are frequently segmented in medical imaging to detect abnormalities or structures, including cancers. There are several techniques for segmentation, such as the thresholding approach, which uses pixel intensity to figure out a threshold and then uses that threshold to classify voxels over it as tumor areas. [1] Beginning with a seed voxel, the area-expanding approach finds related voxels with comparable features to iteratively extend the tumor region. Tumor borders are found using density variations between voxels in the density-based region growth approach. Neural networks, decision trees, rule-based algorithms, and Bayesian networks are other segmentation strategies. The intended performance and the image qualities determine which approach is best. In medical imaging, accurate segmentation is essential for disease monitoring, therapy planning, and diagnosis.

C. Feature Extraction

By encapsulating an image's visual content, feature extraction facilitates decision-making processes such as pattern recognition. MRI images are segmented using the Discrete Wavelet Transform (DWT) after brain segmentation. The separation of low-frequency elements for the overall structure and high-frequency details for edges and textures is one of the key functions of the DWT's low-pass and high-pass filters. This distinction makes feature extraction more effective and improves classification performance.

D. Image classification

Sorting images into groups according to certain attributes is called classification. Genetic Algorithm (GA) is used in conjunction with other techniques to determine the greatest effectiveness for this purpose. A different strategy is also examined, in which followed distinct performance comparative classifiers—Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forests, Nearest-Neighbor and Classifiers Convolutional Neural Networks (CNN), and Machine Learning (ML) techniques—are integrated with GA. With this integration, the total classification performance and accuracy will be enhanced, allowing for more accurate and dependable picture categorization by utilizing the advantages of both GA and these classifiers.

E. Feature optimization

A critical stage in processing brain images is feature optimization, which includes feature extraction and selection. In order to facilitate effective detection, the feature selection procedure first lowers the dimensionality of the feature sets. Next, the best feature sets are extracted from the raw dataset using the Genetic Algorithm (GA). In brain image analysis tasks, GA aids in identifying the most pertinent and instructive characteristics, improving accuracy and cutting down on processing time. By combining feature selection and extraction using GA, the image processing system can efficiently handle brain image data and improve the overall performance of various brain-related analyses, such as tumor detection or disease classification.

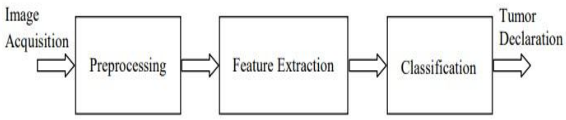

Fig 3 Generalized method of image processing in medical domain

F. Types of learning

In Figure 4 there are the all the major sorts of learning that we should be acquainted with as an AI specialist.

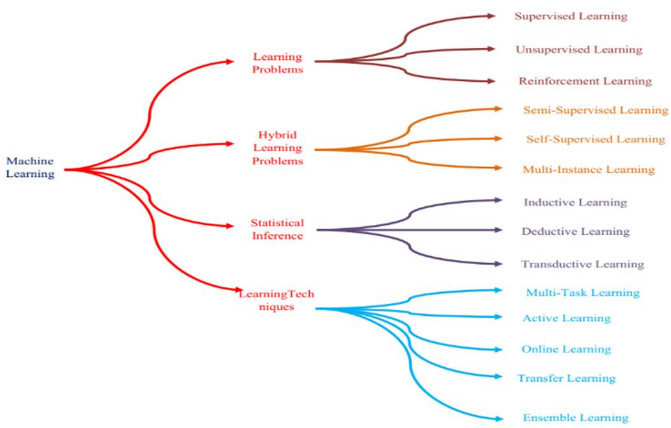

Fig. 4 Types of learning

II. DEEP LEARNING ARCHITECTURE

Over the past two decades, there has been a significant increase in the number of deep learning models available, which has allowed neural networks to handle a wider range of issues. Deep learning is a flexible class of algorithms that may be used to solve a wide range of problems rather than a single approach. Although connectionist architectures date back more than 70 years, modern designs and the computing power of GPUs (graphical processing units) are attributed for their rebirth in artificial intelligence. An illustration of the general architecture of neural networks is provided in Figure 5.
Although deep learning methods are not new, they are becoming more popular due to the combination of highly layered neural networks with GPU acceleration.

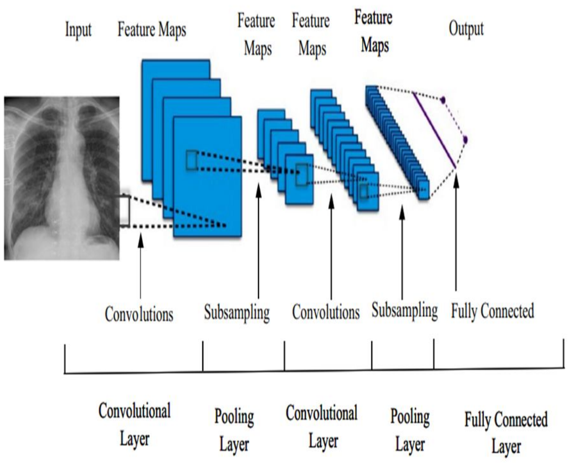

Fig.5 General architecture of neural network

The hidden layer (or layers) of the network is where its power resides, since nodes or neurons enable the modeling of complex data. Because only the input and output layers have access to the real values of these hidden layers' nodes, which are not given in the training dataset, these layers are essential. There is always at least one hidden layer in a neural network, yet the multiplication of inputs by N is not required by any rigid criterion. The idea that many layers are required may be called into question if the ideal number of hidden units is actually less than the inputs. With enough training data, using more hidden units can be advantageous, however in many cases, two hidden units are all that are needed to get good neural network performance.

A. Deep neural network (DNN)

This approach allows for the execution of both regression and classification tasks since nonlinear complications are introduced in at least two levels. The model's remarkable precision makes it popular. However, because mistakes spread backward through the layers and gradually lower the learning rate, training can be difficult. [2] [3] Furthermore, a delay in responding is a feature of the model's learning behavior that reduces its overall effectiveness.

B. Convolutional neural network (CNN)

It's possible that this model works better with 2D data. This network uses a convolutional filter, a fast-learning model with good performance, to convert 2D images into 3D. The classification procedure requires a large amount of labeled data. [4]Nevertheless, CNN encounters problems including human influence, sluggish convergence, and local minima. With AlexNet's enormous success in 2012, the usage of CNNs to improve human physicians' performance in medical image processing has increased.

C. Recurrent neural network (RNN)

One unique feature of RNNs is their capacity to recognize sequences by allocating neuron weights to each step of the sequence. Many variations have surfaced, including LSTM, BLSTM, MDLSTM, and HLSTM, which demonstrate cutting-edge accuracy in speech recognition, character identification, and other natural language processing applications. Their ability to learn consecutive events makes it possible to represent temporal situations.

But one drawback is that gradient vanishing makes problems more likely, and large datasets are needed for this design to work around constraints.

D. Support Vector

Within machine learning, Support Vector Machines (SVM) serve as crucial modal for picture categorization. Specifically designed for image classification applications, Support Vector Machines (SVM) are supervised learning algorithms that perform data analysis and categorization. SVM uses the optimum hyperplane to best divide several classes in the feature space in order to classify images. SVM is appropriate for handling picture data encoded as feature vectors since it can handle high-dimensional data.

III. Literature Review

Brain tumors are abnormal tissue growths that occur within the brain cells and can affect individuals of all age groups, significantly impacting the normal functioning of the human system. Early detection of brain tumors is vital to prevent potential lethal risks. These tumors are typically classified into two key types, one is malignant and other one is benign, based on the nature of the cells.

Currently, two methods which are preferred methods for detecting brain tumor lesions are MRI and CT scans, with MRI exhibiting superior performance compared to other scanning techniques. MRI has demonstrated significant improvements in identifying brain abnormalities, and recent studies have achieved automatic identification of tumor and non-tumor regions using MRI. Computer-Aided Diagnosis (CAD) systems have proven invaluable for physicians in various aspects, such as tumor detection, analysis, and classification.

Different image scanning methods play a crucial role in categorizing and making treatment decisions for brain tumors, particularly in their early stages. MRI stands out for its ability to enhance image quality and provide accurate detection. Recently, deep learning and machine learning approaches have been implemented to address challenges in brain tumor classification and segmentation. These approaches analyze limitations and significantly improve accuracy in classification and segmentation tasks. Utilizing deep learning methods, objects in the images can be categorized, and models can predict outcomes with increased accuracy through training.

Segmentation of brain tumors enhances image contrast, aiding in the accurate detection of abnormalities within brain cells. By employing these advanced techniques, medical professionals can make more precise diagnoses and improve treatment decisions for patients with brain tumors.

Sasikala, S et al. suggested a unique technique for glioblastoma expertise identification via deep neural networks (DNNs) for autonomous cancer detection. It makes advantage of the last layer that is applied to quick segmentation, which takes between 24 and 3 minutes for the whole lung region. [5]

Jyoti, et al. writing displays the most recent developments in biomedical image processing using magnetic resonance imaging. Brain cancers can be quickly diagnosed and localized thanks to imaging (MRI). Eight (8) categories will be produced from brain scans; seven of the categories will represent different tumor kinds, and one category will represent the normal brain. The proposed categorization technique is validated through the application of the Leave2-Out cross-validation process. [6]

Aneja, et al. suggested the segmentation algorithm and fuzzy clustering means approach, which use FCM clusters to process images with noise. Based on the cluster validity functions, runtime, and convergence error rate attained by 0.537 percent, the segmentation value is assessed. [7]

Alexander Zotin et al. introduces an efficient MRI brain tumor edge detection method for medical images. By denoising the input image with a median filter and enhancing it with BCET, followed by FCM clustering for segmentation and application of the Canny edge detector, the proposed approach demonstrates improved accuracy and stability in edge maps, enhancing image quality for medical analysis. Evaluation by experts indicates a 10-15% enhancement in segmentation accuracy over conventional methods. [8]

Kesav et al. (2021) recommended regions with a convolutional neural network (RCNN) model for brain tumor categorization and recognition. The execution time of the RCNN was reduced and used a low complexity scheme to analyze the brain tumor. Two channels were adopted to classify the healthy and unhealthy MRI images. This approach was used to extract the feature and to detect the tumors. This method has been applied to various kinds of tumors. This proposed model has attained less computation time than the remaining models. [9]

Khairandish et al. (2021) utilized MRI images to detect various types of tumors using a deep learning model. CNN model was employed for extracting the features by incorporating several methods. The classification accuracy was improved with this proposed model. Different classifiers were combined to perform the classification task and the detection was performed with threshold-based segmentation. [4]

Deepa et al. (2021) proposed a multi-level particle swarm optimization (MPSO) via ensemble-based categorization for brain tumor detection. At first, the noise-corrupted images were compressed with a wiener filter. The feature extraction phase was employed with Haralick features. The fuzzy segmentation with SVM was compared to the suggested model. Thus, the proposed model outperformed the existing works. [10]

Huang et al. (2022) have enhanced brain tumor detection by adopting a deep-learning approach. The proposed technique has adopted the normalized horizontal images from the T2-W images. The dense skip connection and the spatial mechanism were implemented to highlight the significance of T2-W images. The proposed technique has attained average accuracy with two different datasets. The suggested models have enhanced the detection task of brain tumors. [11]

Sultan et al. (2019) recommended a CNN approach to categorize the discrete forms of brain tumors with a benchmark dataset. The tumors were divided into many tumor kinds. The proposed model produced encouraging results and assisted in the classification of different types of cancers. [12]

Ramkumar et al. (2021) devised a technique for segmenting brain tumors using the Deep Convolution Neural Network Algorithm (DCNNA). For the segmentation job, the dataset was chosen from the BRATS dataset. The fuzzy technique was used for the preprocessing step, which improved the accuracy of the suggested model. The DCNNA model that was suggested served as an overview of the characteristics. As a consequence, the suggested model has shown good segmentation results for brain tumors. [13]

Huang et al. (2020) worked on a CNN-based Complex Networks (CNNBCN) model for the classification of brain tumors. Graph algorithms was used in this process. The classification of brain tumors outperformed the other classification approaches. The enhanced CNNBCN acquired high classification accuracy. This suggested model outperformed better when compared to the other existing deep learning and machine learning models. [14]

Rammurthy et al. (2020) proposed an optimization method named as “Whale Harris Hawks optimization” (WHHO) for detecting brain tumors via MRI brain images. The segmentation was performed with a rough set and cellular automata technique. From the segmented image, “the features were extracted”. The detection of brain tumors was employed with the deep learning method and the training process of the model was accomplished with WHHO. Thus, the model has obtained high accuracy. [15]

Nguyen et al. explores challenges in existing MRI tumor detection methods, presents a comparative analysis, and introduces a Matlab-based model utilizing randomly sourced SAR images for brain tumor classification, with potential enhancements for broader tumor types and increased accuracy through diverse datasets. [16]

Noreen et al. (2020) developed two deep learning pre-trained models like follow Inception-v3 and DensNet201 for concatenation and extracting the multi-features for the timely detection of brain tumors. The proposed model has consisted of two phases, classification and detection. In the first stage, the 25 - 25 features were extracted by the Inception-v3 model and it was further subjected to classification. Secondly, the classification of brain tumors was done with the SoftMax classifier. The suggested method has outperformed the other deep learning models. The dataset is gathered from three different publicly available databases. [17]

Wu et al. (2021) have introduced an efficient brain tumor segmentation technique called symmetric-driven generative adversarial network (SD-GAN). This suggested technique has detected the right side and the left side of the brain and it has identified the abnormal brain images. Initially, the brain images were reconstructed and then segmented to diagnose the brain tumors. The introduced method was more advanced than the remaining traditional techniques and the dataset images were taken from the MRI brain images. [18]

Harish et al. (2020) identified a deep learning technique for the robust approach to segment and classify data. The deep learning technique was used to assess and isolate the tumor-containing area of the brain from the neighboring normal area. The brain pictures were categorized using the transfer learning model. The recommended approach produced superior precision in a short amount of time. [19]

Debnath et al. (2021have created a method called contrast enhanced fuzzy c-means clustering (CEFCM) to divide the anomalous areas into two dimensions. Using a pixel-based voxel mapping approach, the obtained decision values from the segmented pictures were assigned to all pixels in 3D spaces (PBVMT). Comparing the suggested model to other conventional approaches, it has produced a higher degree of sensitivity and increased accuracy. [20]

In Vanherpa et al. (2021) have aimed to localize and detect the lesions in brain using Chemical Exchange Saturation Transfer (CEST) imaging. MRI imaging has localized the large and small lesions in brain. This proposed approach localized the lesions from the abnormal brain. Thus, the recommended model has enhanced the “detection of brain tumors” and it has attained high response in diagnosing the brain [21]

The table given below provide us a detailed overview on the comparison of different work done by various authors.

Author	Methods	Overall Accuracy	Dataset	Research Gap
Nguyen et al. [16]	KNN	86-88%	dataset available from doctors throughout the world	Not well optimized
Veer et al. [22]	MLP classifier	89%	MRI database	Accuracy is compromised
Balakumar et al. [23]	SOM neural network and GLC matrix	89.5%.	Brainix dataset	work is focusing the traditional parametric feature extraction technique
Khairandish et al. [4]	support vector machine (SVM)	The overall accuracy of the hybrid CNN-SVM obtained 98.4959%.	The overall accuracy of the hybrid CNN-SVM obtained 98.4959%.	Data Set is not diverse
Hemanth et al. [24]	CNN	91%	UCI datasets	Training is not done
Kesav et. al. [25]	Two Channel CNN and RCNN	RCNN-based object detection achieved an execution time of 277.174 seconds and maintained an impressive average confidence score of 98.83%.	From two prominent hospitals in China, specifically Nanfang Hospital and Tianjin Medical University.	Limited data set
Jyoti et al. [6]	SVM	Accuracy 93.18%, precision 94%, recall 93% and f1-score 92%	OASIS	The gradient is vanishingly small and consequently prevent
Deepak et al. [26]	GoogLeNet	SVM classifier 0.97% and DCNN 92.3%	Figshare	Poor performance of transfer model
Yang et al. [3]	Discrete wavelet transform (DWT)	Clustering accuracy of 94.8%	GE Healthcare	Model fitting issue arise
S Kumar et al. [27]	Fuzzy logic, K means and Neural Networks	FCM in WM, GM, CSF 29.60, 30.50 and 29.60	BRATS2010	Highly reduced misclassification error rate
Demirahan et al.. [28]	Wavelets, Neural Networks and self-organizing map (SOM)	WM 91%, GM87%, edema 77%, tumor 61% and CSF 96%	IBSR2015 and BRATS2012	It should be implemented on most updated data sets as well
Badza et al. [29]	CNN	10-fold cross-validation accuracy was 96.56%	BRATS and CBICA	Slow processing and high turnaround time
Aneja, et al. [7]	Fuzzy Clustering Means Algorithms	FCM 1.283, T2FCM 0.962 and IFCM 0.537	NSL-KDD	Least percentage of misclassification error

Different researchers have looked into different approaches for using CNNs on MRI scans to detect brain tumors. When Huang et al. used AMF-Net, it performed well overall on two databases but had inconsistent results. Kesav et al. used RCNN and Two Channel CNN, showing good execution times and confidence levels but running into issues with a limited dataset. Using Deep CNN and SVM, Jyoti et al. achieved good accuracy metrics on the OASIS dataset, although they had problems with gradient vanishing. Khairandish et al. integrated CNN and SVM, revealing the dataset's lack of diversity but claiming remarkable overall accuracy. Deepak et al. used Deep CNN and GoogLeNet, which exposed problems with the performance of the transfer model. Yang et al. utilized Discrete Wavelet Transform, achieving high clustering accuracy, yet facing challenges with model fitting. Various other approaches, such as Fuzzy Logic, K Means, Neural Networks, and combinations of Wavelets and Neural Networks, were explored by different researchers, each presenting specific advantages and limitations in brain tumor detection.

IV. TRENDS AND CHALLENGES

On average, there hasn't been a significant increase in the number of brain tumor cases each year. However, there is a notable 23% uptick in cases among individuals aged 75 and older, with various types of brain and intracranial tumors also on the rise in younger age groups. This increase is believed to be linked to periodic cell DNA damage. Conventional MRI scans face limitations in detecting flowing fluids, like blood in arteries, leading to the appearance of flow voids that manifest as black holes in the images. The detection of brain tumors is often delayed, and they are mostly identified in a malignant stage, as small tumors tend to go unnoticed in MRI, CT scan, and X-ray images [30]**.** Fig. 6 provides a visual representation of the number of brain cancer cases in India [31]

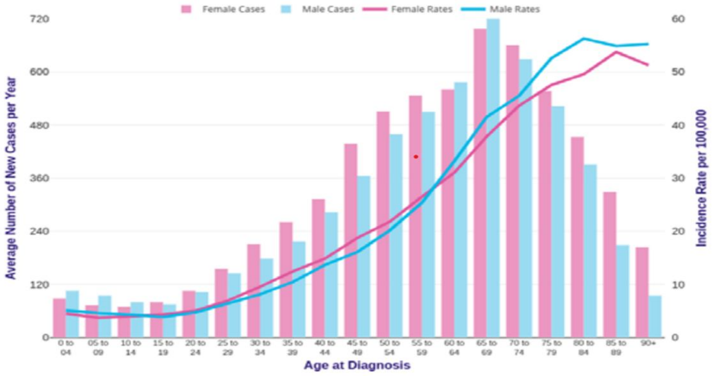

Fig. 6 The mean annual number of new cases and the age-specific incidence [30]

As we can observe, the number of cases of the brain tumor are rising around the globe and it is the need of the hour to diagnose it faster and in an efficient way. Machine learning can help us in diagnosing the tumor at an earlier stage so that we can do the needful as soon as possible. Deep learning model can be used very efficiently and in a very productive way to meet our needs. Several prominent trends have surfaced in the field of brain tumor identification deep learning model on MRI data. Deep learning model adoption is on the rise, indicating substantial progress in deep learning. Their extensive application has been facilitated by their ability to automatically extract complex characteristics from MRI scans without the requirement for explicit feature engineering. Furthermore, the use of transfer learning, which makes use of pre-trained models on sizable datasets, will play a vital role in improving generalization to new datasets on brain tumors. Using a multi-modal fusion strategy to integrate several modalities is a major trend. Interpretability and explain ability have emerged as key concerns. Radiologists are actively using visualization tools to highlight specific parts of interest and help them comprehend the reasoning behind the model. Furthermore, with the shift toward end-to-end systems, automatic segmentation has become more popular. This involves including deep learning-based models into the entire detection framework so that tumor zones may be automatically drawn.

Brain tumor detection using Deep learning models on MRI scans migth faces several challenges. Lack of labeled data inhibits deep learning (DL) model development and generalization, especially for uncommon tumor forms. Biased model performance is also caused by the unequal distribution of tumor and non-tumor samples. Variations in labeling criteria and inconsistent tumor annotations among radiologists pose difficulties related to inter- and intra-observer variability. Deep learning models require a significant number of resources because to their computational complexity, which restricts accessibility and makes the execution difficult for circumstances with limited resources. A major problem in clinical settings is adapting these models to address the real-world variability seen in various scanner types, patient groups, and acquisition circumstances. Addressing data privacy issues pertaining to patient information and making sure regulatory criteria are met in different locations are examples of ethical and legal considerations. Furthermore, it is crucial to take into thought the prevention of bias and the maintenance of balance across varied populations. Adoption and validation in the clinical setting entail stringent validation procedures and workflow integration, taking into account the influence on patient care and the requirement for regulatory approval. Gaining confidence from physicians and radiologists on the dependability and security of deep learning model based diagnostic instruments is another crucial step in triumphing in the identification of brain tumors.

V. Conclusion

To sum up, our thorough analysis has navigated the complex field of brain tumor identification by fusing the sophistication of MRI images with the power of machine learning. Through the analysis of several tumor forms using cutting edge imaging methods, we have shed light on the complex terrain that lies behind precise diagnosis. Our examination of neural network models, such as Support Vector Machines (SVMs), Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Deep Neural Networks (DNNs), demonstrates the wide diversity of methodologies employed in this subject. These models, with their distinctive topologies, show how well artificial intelligence and medical imaging may work together to increase diagnosis accuracy. The merging of technology with healthcare, in short, underscores the important impact that interdisciplinary collaboration can have on patient outcomes and the abilities of medical staff. The development of brain tumor detection and understanding from MRI scans to neural network models is a paradigm shift in our scientific approach and anticipates a day when new ideas will be readily applied to medicine to advance human health.

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