IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

MACHINE LEARNING'S ROLE IN ADVANCING BRAIN TUMOR DIAGNOSIS

Darpan Gupta
Research Scholar
Teerthanker Mahaveer University
Moradabad, India

Prashant Kumar
Faculty Of Engineering
Teerthanker Mahaveer University
Moradabad, India

Dr. Pankaj Kumar Goswami
Faculty Of Engineering
Teerthanker Mahaveer University
Moradabad, India

Geeta Saini
GLB Institute of technology and Management
Knowledge Park Greater Noida, India

Dr. Alka Verma
Faculty Of Engineering
Teerthanker Mahaveer University
Moradabad, India

Abstract**—** In today's medical landscape, tumors are second ranked leading to cause of cancer and posing significant threat to patients' well-being. Detecting tumors, particularly brain tumors, swiftly and accurately is paramount in providing timely treatment and averting potential dangers. Traditional methods of manually analyzing MRI images for tumor detection are not only time-consuming but also prone to inaccuracies. To address these challenges, there's pressing need for automated, fast, and reliable techniques for medical field. Leveraging advanced image processing technologies, such as Convolutional Neural Networks and Transfer learning models like VGG 16, offers a promising solution. These sophisticated algorithms can analyze MRI images with precision, enhancing the efficiency of tumor detection processes. Brain tumors, characterized by uncontrolled cell growth, can jeopardize healthy tissues by depriving them of essential nutrients, leading to organ failure. Early detection of such tumors is critical for improving treatment outcomes and boosting patient survival rates. By implementing automated image segmentation techniques, we can streamline the identification and classification of brain tumors, significantly reducing the burden of manual analysis. These advancements enable healthcare professionals to promptly assess MRI scans, swiftly determining the presence or absence of tumors. This proactive approach not only accelerates diagnosis but also enhances treatment planning, ultimately saving lives. In summary, integrating cutting-edge technologies like CNNs and Transfer Learning into medical imaging processes revolutionizes tumor detection, facilitating quicker and more accurate diagnoses.

Keywords—Brain Tumor, Convolutional Neural Networks, Transfer Learning models, medical imaging processes

I. INTRODUCTION

The human brain serves as the central hub of the nervous system. The brain managed majority of bodily functions which include integrating, analyzing, organizing, giving rest body commands and helps in decision making. It is primarily the control station of the central nervous system and is responsible for performing the daily voluntary and involuntary activities in the human body. The brain is divided into three main parts; brain stem, cerebrum, and cerebellum. The weight of a normal human brain is approximately 1.2–1.4 Kg, with a volume of 1260 cm3 (male brain) and 1130 cm3 (female brain).

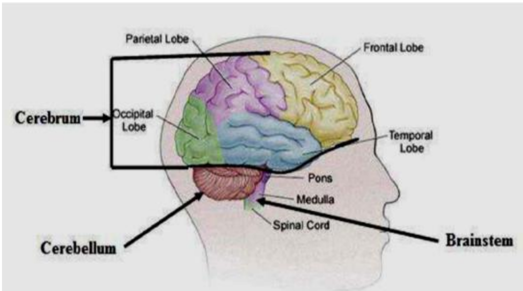

Fig1- Human Brain

With its intricate structure encased in protective layers of bone, fluid, and fat, the brain operates as a sophisticated control center, coordinating signals and commands that facilitate bodily movement, thought processes, and emotional responses. However, this vital organ is vulnerable to various neurological disorders such as stroke, infections, tumors, and migraines, posing significant challenges in terms of diagnosis, treatment, and management. Tumors encompass a broad spectrum of growths, classified as benign, typically noncancerous, or malignant, presenting a significant threat to overall health. Malignant tumors denote uncontrolled cell proliferation that jeopardizes bodily well-being. Globally, cancer stands as a leading cause of mortality, with an estimated 10 million fatalities projected for 2020, representing approximately one in every six deaths.

The confines within rigid skull housing the brain, the emergence of the abnormal cell clusters characterizes a brain tumor. Such growths, constrained within this limited space, pose inherent challenges. Any other type of the tumor which develop inside skull results into risk to brain function by which restricted space available for expansion. With diverse types of such tumors exhibiting variable survival rates contingent upon their characteristics such as location, texture, and morphology, brain tumors is ranked among top ten causes of mortality in both children and adults.

Brain tumors classified by the World Health Organization (WHO) into four grades: I-IV. Grades I and II denote slow-growing tumors, while grades III and IV signify malignancy with a worse prognosis.

Grade I: These tumors exhibit slow growth and do not spread rapidly often offering favorable long-term survival prospects. This can be removed almost completely by surgery. An example of such a tumor is grade 1 pilocytic astrocytoma.

Grade II: These tumors' growths are slow but those can spread to neighboring tissues and become higher grade tumors. These tumors can even come back after surgery so It may require recurrence post-surgery. Oligodendroglioma is a case of such a tumor.

Grade III: Grade III tumors, characterized by their accelerated growth compared to Grade II, demonstrate a propensity to infiltrate surrounding tissues. Addressing these tumors solely through surgery proves inadequate, necessitating the adjunctive use of radiotherapy or chemotherapy post-operation. Anaplastic astrocytoma stands as an illustrative example of this tumor category.

Grade IV: Grade IV tumors exhibit the highest level of aggression, with a notable propensity for extensive spreading, sometimes leveraging blood vessels for rapid dissemination. Glioblastoma multiforme exemplifies this highly aggressive tumor subtype.

However, manual tumor detection by radiologists can be time-consuming and subjective, leading to inaccuracies and increased costs. However, process of identifying the tumor will be expensive and imprecise. The brain tumor misdiagnosing can have grave consequences, significantly impacting a patient's chances of survival. Recent advancements in the machine learning, especially in the realm of deep learning which is having revolutionized classification & interpretation for the data in medical imaging. Such areas include successes in the possibility of extracting and retrieving knowledge from the data instead of learning from the experts or scientific texts. This technique of Machine learning are rapidly emerging as indispensable tools across various medical domains, enhancing performance in tasks such as disease prognosis and diagnosis, identification of molecular and cellular structures, tissue segmentation, and image classification. Currently, Convolutional Neural Networks (CNNs) stand out as the prevailing technique in image processing due to their multi-layered architecture and exceptional diagnostic accuracy, particularly in handling extensive input data volumes. Auto encoders, another notable method, operate on unsupervised learning principles, utilizing neural networks for representation learning. Notably, they demonstrate commendable diagnostic accuracy as well. Numerous studies have extensively explored different methods and models for brain tumor detection, reflecting the ongoing quest for improved diagnostic approaches.

From a scientific standpoint, the diagnosis of tumors through medical imaging is prone to errors and heavily reliant on the experience of radiologists. Given the wide spectrum of pathological variations and the potential for human specialists to experience fatigue, there is a growing recognition of the benefits of computer-assisted interventions for researchers and physicians in identifying and classifying brain tumors. Computational intelligence-oriented techniques offer promising avenues for assisting physicians in the identification and classification of brain tumors. Machine learning methodology, particularly those employing deep learning, are poised to play crucial role for segmentation, classification and analysis, of cancerous images, with a specific focus on brain tumors. These advanced techniques hold the potential to enhance accuracy and minimize errors in tumor identification, facilitating the distinction between tumors and other similar diseases with greater precision.

Cutting-edge imaging technologies such as MRI, CT, and PET are integral components of high-resolution medical systems. Among these, MRI stands out as a pivotal tool for exploring the intricate structures of the body. Its widespread adoption stems from its ability to deliver superior image quality, particularly in the assessment of brain function and detection of malignant tissues, surpassing traditional methods like X-rays or CT scans. MRI's non-invasive nature further enhances its utility in clinical practice.

At its core, MRI operates on the principle of utilizing a strong radio waves and magnetic field to capture images for body's internal structures, enabling monitoring of physiological irregularities. Image segmentation, a fundamental process in medical imaging, involves dividing an image into constituent elements or objects depends on criteria like color, intensity, or texture homogeneity. This segmentation technique plays a vital role in identifying and delineating boundaries within an image.

Over the past few decades, considerable efforts have been dedicated to refining the segmentation process, aiming to enhance its accuracy and efficiency in medical diagnosis and research.

Detection Techniques

A range of imaging methods are employed for the examination of brain tumors, including magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT), positron emission tomography (PET), and computed tomography (CT). Among these, CT and MRI are the most prevalent due to their widespread accessibility and capacity to generate high-resolution images depicting both normal anatomical structures and pathological conditions.

Computed Tomography (CT)

A CT scan provides more precise imaging of the body compared to traditional X-ray machines, offering enhanced clarity with or without differentiation. Utilizing an X-ray beam and computer technology, CT scans produce two-dimensional images of brain in the safe and non-invasive manner. Unlike MRI, CT imaging captures the brain's anatomy layer by layer, offering a detailed view of each slice. A dye is infused into circulation system. CT scans are particularly valuable for evaluating changes in hard tissues. They play a crucial role in describing both normal and abnormal structures within the body, facilitating precise instrument placement during procedures. Fast, painless, non-invasive, and highly accurate, CT scanning is an indispensable tool in medical diagnosis and intervention.

Magnetic Resonance Imaging

An MRI scan offers comprehensive analysis of various body parts and excels in detecting brain abnormalities at earlier stages compared to other imaging modalities. Unlike a CT scan, an MRI does not involve radiation exposure. Utilizing a magnetic field and radio frequency waves, MRI provides a detailed view of the brain's soft tissues in a non-invasive manner. It captures the brain's anatomy in three dimensions, allowing for cross-sectional views from multiple angles. Contrast agents may be injected intravenously to enhance visualization. MRI is valuable for the assessing brain injuries and their impact on surrounding tissues."

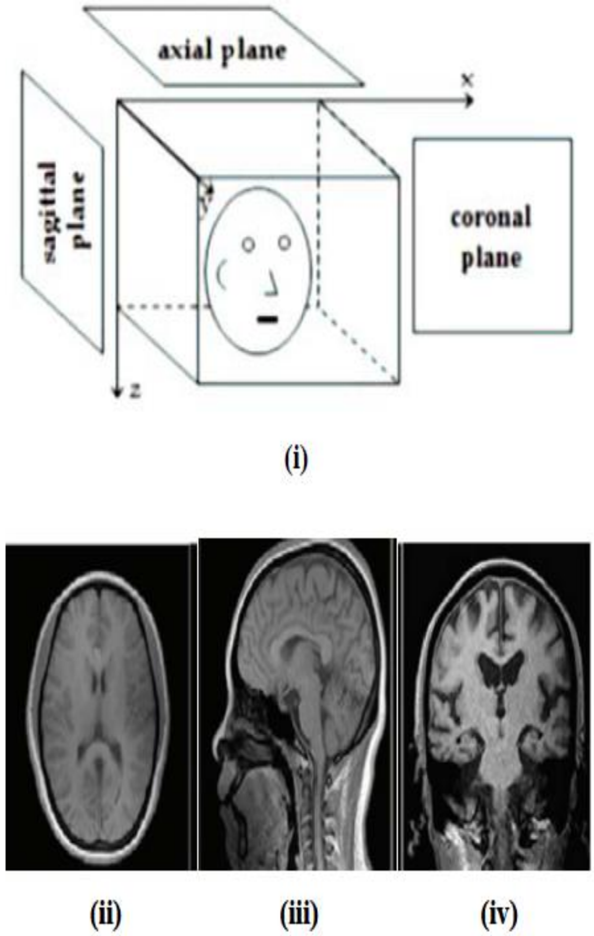

Fig 2- Brain MRI from (i) Cubical representation, (ii) Axial plane (iii) Sagittal plane and (iv) Coronal plane. MRI scanning is extensively employed in neurology due to its ability to conduct a comprehensive analysis for brain and skull. It offers coronal, axial, and sagittal imaging, enhancing the depth of evaluation. In addition to generating high-resolution images with excellent contrast, MRI stands out for its radiation-free nature. This quality makes it the preferred noninvasive imaging method for detecting various types of brain malignancies.

Angiography

The procedure involves injecting a dye into the artery, typically in the groin area. The dye then travels to the brain's arteries, enabling the physician to assess the tumor's blood supply. This information proves invaluable during surgical planning.

Brain Scan

A brain scan involves the use of a safe radioactive dye injected into a vein. An image is captured as the dye travels through the veins in the tumor.

Skull X-Rays

Brain tumors have the potential to cause fractures or fissures in the skull bones, which can be detected through specific X-ray imaging. These X-rays have the capability to detect calcium deposits, which are occasionally found within tumors. Calcium deposits may also be present in the bloodstream if the tumor has spread to the bones.

Biopsy

During a biopsy, a small portion of the tumor is extracted for examination. A specialist known as a neuropathologist analyzes sample in determining whether tumor cells are malignant or benign. Additionally, biopsy helps determine whether the malignancy originated in the brain or another part of the body.

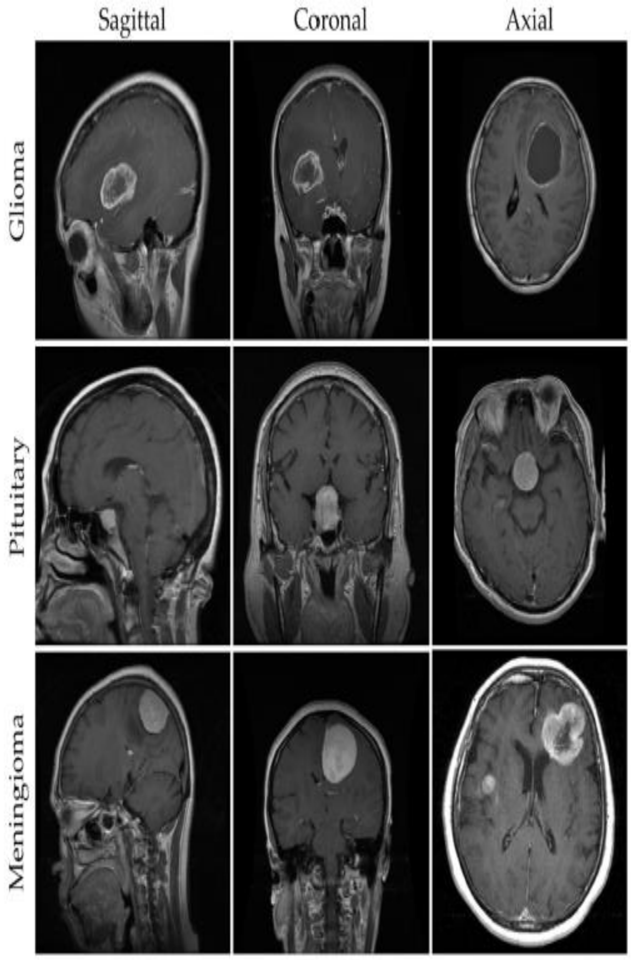

Fig 3- A Sample of MRI images from brain tumor dataset

Positron Emission Tomography (PET)

This imaging test, known as a PET scan, provides insights into the functionality of tissues and organs. PET scans utilize small amounts of radioactive materials called radiotracers, along with a specialized camera and computer, to assess organ and tissue functions. Fluorodeoxyglucose (FDG) is a commonly used PET tracer for brain imaging. However, FDG-PET images have limitations, such as the inability to distinguish between necrosis radiation and a recurrent high-grade tumor. Additionally, radioactive tracers used during PET scans can potentially cause adverse effects, including post-scan allergic reactions in some patients, particularly those allergic to substances like aspartame and iodine. Furthermore, PET tracers lack the precision in anatomical structure localization compared to MRI scans due to their relatively poor spatial resolution

Photo Acoustic (PA) Imaging

Also referred to as optoacoustic or thermoacoustic imaging, this technique has the capability to visualize organs in both animals and humans, such as the breast and the brain, with simultaneous high contrast and high spatial resolution. The Photo Acoustic (PA) effect serves as the fundamental principle for PA imaging, involving the generation of acoustic waves through the absorption of electromagnetic (EM) energy, including optical or radio-frequency waves. Artificial Neural Networks (ANNs) emulate the functioning of the human brain's nervous system. In this setup, a digital computer is interconnected with a large number of connections and networks, allowing the neural network to undergo training using simple processing units applied to the training set, thus storing experiential knowledge. ANNs consist of different layers of interconnected neurons. Through the learning process, the neural network acquires knowledge by utilizing datasets. Typically, there is one input and output layer, with any number of hidden layers in between. During training, weights and biases are adjusted for neurons in each layer based on input features and previous layers (for hidden and output layers). The model is trained using activation functions applied to input features and hidden layers, facilitating further learning to achieve the desired output
ANN operates with fully connected layers, which often require intensive processing. On the other hand, CNN (Convolutional Neural Network) derives its name from the convolutional operation, a key mathematical linear process. In CNN, the dimensions of the image are systematically reduced at each layer without compromising the essential information required for training. Various operations such as convolution, max-pooling, dropout, flattening, and dense layers are employed in building the model. This study concentrates on developing a custom architecture for both ANN and CNN models, followed by a comparison of their performance using brain tumor MRI datasets

Artificial intelligence (AI) has emerged as a valuable asset in the realm of brain tumor detection and diagnosis, offering crucial support to the complex domain of brain tumor surgery. Subfields within AI, such as deep learning (DL) and machine learning (ML) have brought about transformative changes in neuropath logical procedures. These methods encompass various stages including data preprocessing, feature extraction, feature selection, feature reduction, and classification. AI has significantly bolstered neuropathologists' confidence in brain tumor diagnoses, empowering them to make more informed decisions for their patients.

Numerous researchers have explored various algorithms aimed at classifying and detecting brain tumors with heightened accuracy & minimal errors. Technique of Deep Learning have emerged as prominent tools in such endeavor, facilitating the development of automated systems capable of swiftly and accurately classifying or segmenting brain tumors. DL leverages pre-trained Convolutional Neural Network (CNN) models, such as GoogLeNet, AlexNet, and ResNet-34, originally designed for diverse applications, including medical imagery for brain tumor classification. DL comprises a multi-layered deep neural network, and the backpropagation algorithm is utilized by neural networks (NN) to minimize the discrepancy between the target and actual values. However, as the complexity of artificial neural network models increases with additional layers, their development becomes more challenging. However, the scarcity of comprehensive medical datasets due to privacy concerns impedes research progress and collaboration. Moreover, existing methods often lack precision and recall, resulting in inefficiencies and prolonged image classification timelines, potentially delaying treatment initiation. These technologies hold promise for diagnosing neurological diseases and analyzing images of brain tumors.

Convolutional Neural Network

Advantages

1. Identification of brain tumors through analysis of MRI images.
2. Elimination of human intervention reduces the likelihood of errors.
3. Early tumor detection can potentially save lives.
4. Artificial intelligence systems offer heightened reliability.

Disadvantages

1. High system requirements are necessary for optimal model performance
2. Training the dataset requires a significant amount of time

While highly accurate, the model may not achieve absolute accuracy.

II. LITERATURE REVIEW

Magnetic resonance imaging (MRI) is used to detect brain tumor. Many techniques have been recommended for the detection of tumors in MRI images. Here is a summary and analysis of several recent studies. Banerjee's [1]approach involves passing MRI images through various layers including CONV2D, Pooling Layer, and Fully-Connected Layer, ConvNet. Sanjay Kumar[7] proposes the utilization of Fully Convolutional Neural Networks (FCN) for brain tumor prediction where FCN not only identifies tumor growth but also provides detailed descriptions of its core and peripheral regions. Derikvand [8] introduces a neural convolution-based method for Glioma Brain Tumor Segmentation in MRI, combining multiple CNN architectures to leverage both global and local brain tissue know-ledged for pixel-wise label prediction, thus improving segmentation outcomes

Deepa et al [15], provides a review for recent research on detection of segmentation and brain tumor, highlighting various techniques employed by researchers to identify tumors from images of MRI. Through this review, it becomes evident that the automated detection and segmentation of the brain tumors from the MRI images is a highly active research area. Bahadure et al [19] focuses on segmenting brain tissues from MR images, including normal tissues including gray matter, white matter, cerebrospinal fluid, and tumor-infected tissues. Pre-processing techniques were applied to enhance the SNR and remove unwanted noise effects. Additionally, an algorithm skull stripping based on cutoff techniques was utilized to enhance the performance of skull stripping processes. Kapoor et al [28] in the paper on the diverse techniques within Medical Image Processing, specifically focusing on their application in finding the brain tumors from MRI images an overview is presented. Drawing from extensive research, this paper compiles a comprehensive list of these techniques, accompanied by brief descriptions for clarity. Among all the steps involved in tumor detection, segmentation emerges as particularly significant due to its pivotal role in accurately delineating tumor boundaries and structures within the images. Praveen Gamage [29], presented a survey on brain tumors identification by MRI images, categorizing the process into the four main sections: feature extraction, image segmentation, pre-processing, and image classification. Somwanshi et al [30] developed various functions of entropy for segmentation of tumor and detection across a range of images of MRI. The specific definition of entropy influenced the cutoff values obtained, which, in turn, impacted the segmented results. Gore et al [31] presented a literature review focusing on brain disease detection utilizing deep learning techniques. The document examines and compares traditional methods, highlighting the challenges in translating prior data into probabilistic maps or selecting highly representative features for classifiers in conventional automatic glioma segmentation strategies. However, Convolutional Neural Networks (CNN) offer the advantage of automatically learning complex representative features from both normal and tumor tissues directly from multi-modality MRI scans. Biratu et al [32] explored the automation of brain tumor classification and segmentation, highlighting its significant benefits enhancing diagnosis, patient follow-up and treatment planning. By leveraging diverse techniques such as conventional image processing, shallow deep learning and machine learning, considerable advancements made in automating these critical tasks. Saeedi et al [33] developed the use of deep networks for disease detection through imaging analysis, specifically focusing on computational methods for brain tumor classification. The study proposes a novel approach utilizing a 2D CNN architecture, a convolutional auto-encoder network, and six standard machine learning techniques for brain tumor detection. The classification task was performed using a T1-weighted, contrast-enhanced MRI dataset comprising three tumor types and a healthy brain control group. Abdusalomov et al [34], investigated methods for improving the existing YOLOv7 model by employing transfer learning and fine-tuning techniques to detect gliomas, meningiomas, and pituitary brain tumors in MRI data. Our proposed CNN model highlights the considerable influence of deep learning models on tumor detection and demonstrates their transformative potential in this domain. Compared to traditional categorization methods, our technology not only detects the presence of brain tumors but also precisely pinpoints their locations within MRI images. Arabahmadi et al [35] found that despite the notable advancements facilitated by deep learning techniques, there remains a need for a universal approach. These methods demonstrate superior performance when both training and testing are carried out on datasets with consistent acquisition characteristics, such as intensity range and resolution. Nonetheless, even slight disparities between the training and testing images can significantly influence the robustness of these methods. Brindha et al [36] proposed CNN is considered as one of the most effective techniques for analyzing image datasets. It accomplishes predictions by efficiently reducing image size without compromising essential information. The ANN model presented in this study achieves a testing accuracy of 65.21%, which can be improved by augmenting the image dataset and applying image augmentation techniques. Further analysis of ANN and CNN performance is warranted. Hanaa et al [37] developed a model, the primary motive of the research is to enhance accuracy by developing an improved model. This paper introduces a CNN known as the Brain Tumor Classification Model (BCM-CNN). An adaptive dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) algorithm was used to fine tune the hyper parameter of CNN. In the experiments, the BCM-CNN served as the classifier, and after optimization, it exhibited superior performance, yielding the most favorable results among the evaluated models. Sharma et al [38] utilized the Convolutional Neural Network (CNN) machine learning algorithm to predict outcomes by efficiently reducing and resizing images while retaining crucial information for prediction. With an accuracy of 97.79% on the set of training data and 82.86% on the validation set, the model demonstrates strong performance. Additionally, the loss diminishes progressively with each epoch increase. Notably, the model exhibits minimal loss on the training set but comparatively higher loss on the validation set. Bathe et al [39] presented the application of deep learning techniques to MRI images aids in tumor detection. In their study, they utilized two techniques—CNN and depth-wise separable method—on the MRI image dataset. Experimental findings reveal that the depth-wise separable CNN outperforms traditional CNN, achieving an accuracy of 92% on the testing data.

Table-01

Sl. No.	Paper Name	Publication Year	Author:	Summary
1	"Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM"	2017	Bahadure et al	This paper focuses on segmenting brain tissues from MR images, including normal tissues including gray matter, white matter, cerebrospinal fluid , and tumor-infected tissues. Pre-processing techniques were applied to enhance the SNR and remove unwanted noise effects. Additionally, an algorithm skull stripping based on cutoff techniques was utilized to enhance the performance of skull stripping processes.
2	"Brain Tumor Detection Using Image Processing Techniques survey"	2017	Sanjeev et al	This paper performs an extensive survey of techniques within Medical Image Processing, particularly those utilized in the brain tumor detection from MRI images. Drawing from comprehensive research, the paper compiles a list of various techniques and provides concise descriptions for each. Additionally, the paper highlights segmentation as the most significant step in the process of tumor detection among all the various steps involved.
3	"Identification of Brain Tumor using Image Processing Techniques"	2017	Gamage et al	This paper presents a survey on brain tumors identification by MRI images, categorizing the process into the four main sections: pre-processing, feature extraction, image classification and image segmentation.
4	"The Review of Brain Tumor Detection from MRI Images"	2016	Deepa et. al	This paper provides a review of recent researches on detection of brain tumor and segmentation, highlighting various techniques employed by researchers to identify tumors from images of MRI. Through this review, it becomes evident that the automated detection and segmentation of the brain tumors from MRI images are highly active research area.
5	"An efficient Brain Tumor Detection from MRI Images using Entropy Measures"	2016	Somwanshi et al	In this paper, they explored various functions of entropy for segmentation of tumor and detection across a range of images of MRI. The specific definition of entropy influenced the cutoff values obtained, which, in turn, impacted the segmented results.
6	"Study of various techniques using Deep Learning for Brain Tumor Detection"	2020	Gore et al	This paper provides a literature review focusing on brain disease detection using deep learning techniques. It includes analysis and comparative study of traditional techniques. In conventional strategies of automatic glioma segmentation, interpreting previous information into probabilistic maps or selecting highly representative features for classifiers is challenging. CNN offers advantage of automatically learning complex features from both normal brain tissues and tumor tissues directly from multi-modality MRI snapshots.

7	“A Survey of Classification Algorithms and Brain Tumor Segmentation”	2021	Biratu et al	This paper explores the significant advantages of automating classification tasks and brain tumor segmentation, leading to improved diagnosis, treatment planning, and patient follow-up. By employing conventional image processing, shallow machine learning, and deep learning, considerable advancements have been made in automating these critical tasks.
8	“MRI-based brain tumor detection using chosen machine learning techniques and convolutional deep learning methods”	2023	Saeedi et al	In this paper, deep networks are introduced for disease detection through imaging, with a focus on proposing computational-oriented methods for classification of brain tumor. The study presents the development of a novel 2D CNN architecture, a convolutional auto-encoder network, and six common machine-learning techniques for brain tumor detection. Classification tasks were performed using a T1-weighted, contrast-enhanced MRI dataset comprising three tumor types and a healthy brain without tumors.
9	“Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging”	2023	Abdusalomov et al	In this investigation, we delved into improving the existing YOLOv7 model by employing transfer learning and fine-tuning techniques to detect gliomas, meningiomas, and pituitary brain tumors in MRI data. Our proposed CNN model highlights the considerable influence of deep learning models on tumor detection and demonstrates their transformative potential in this domain. Compared to traditional categorization methods, our technology not only detects the presence of brain tumors but also precisely pinpoints their locations within MRI images.
10	“New Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging.”	2021	Arabahmadi et al	Despite the notable advancements facilitated by deep learning techniques, there remains a need for a universal approach. These methods demonstrate superior performance when both training and testing are carried out on datasets with consistent acquisition characteristics, such as intensity range and resolution. Nonetheless, even slight disparities between the training and testing images can significantly influence the robustness of these methods.
11	“Brain tumor detection from MRI images using deep learning techniques”	2022	Brindha et al	CNN is considered as one of the most effective techniques for analyzing image datasets. It accomplishes predictions by efficiently reducing image size without compromising essential information. The ANN model presented in this study achieves a testing accuracy of 65.21%, which can be further improved by augmenting the image dataset and applying image augmentation techniques. Further analysis of ANN and CNN performance is warranted.

12	“Brain-Tumor Detection and Classification. Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization”	2022	Hanaa et al	The primary aim of this research is to enhance accuracy by developing an improved model. This paper introduces a CNN known as the Brain Tumor Classification Model (BCM-CNN). The hyperparameters of the CNN were fine-tuned using an adaptive dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) algorithm. In the experiments, the BCM-CNN served as the classifier, and after optimization, it exhibited superior performance, yielding the most favorable results among the evaluated models.
13	“Brain Tumour Detection Using Machine Learning”	2021	Sharma et al	The model is founded on the Convolutional Neural Network (CNN) machine learning algorithm. It predicts by effectively reducing and resizing images without compromising crucial information necessary for prediction. Upon application to the training set accuracy is 97.79%, and on the validation set, it accuracy is 82.86%. The loss diminishes gradually with an increase in the number of epochs. Notably, the model exhibits minimal loss on the training set but relatively higher loss on the validation set.
14	“Brain Tumor Detection Using Deep Learning Techniques”	2021	Bathe et al	Utilizing deep learning methodologies on MRI images significantly contributes to tumor detection. We employed two techniques, CNN and depth-wise separable method, on our MRI image dataset. Experimental findings reveal that the depthwise separable CNN outperforms traditional CNN, achieving an accuracy of 92% on the test set using Depthwise Separable CNN.
15	“A novel deep learning-based brain tumor detection using the Bagging ensemble with K-nearest neighbor”	2022	Archana et al	Segmenting brain tissues in MRI images serves various purposes in diagnosing, planning surgery, and treating brain disorders. For brain tumor segmentation, we utilize the U-Net architecture. Timely completion of assignments by medical specialists is crucial. However, achieving accurate segmentation is challenging due to intensity overlap across different tissues caused by intensity homogeneity and inherent errors in MRI.

III. PERFORMANCE METRICS

Performance metrics are essential for evaluating the effectiveness of a method. Various performance measures are available for this purpose.

Table 2 Performance Measures

Sl No.	Performance Measures
1	Accuracy
2	Specificity
3	Sensitivity

4	Dice Index
5	Peak Signal to Noise Ratio
6	Positive Predicted Value
7	Jaccard Index
8	Area Under Curve
9	Structured Similarity Index
10	MEAN Squared Error

IV. NEURAL NETWORK ARCHITECTURE

Each neuron employs mathematical functions on its input to generate an output, which is subsequently forwarded to the subsequent layer. The architecture of a neural network dictates the model's intricacy, capability, and operational characteristics.

The Neural Network Architecture functions by passing input data through a network of interconnected layers to derive meaningful representations. Beginning with the input layer, raw data undergoes processing in one or more hidden layers, executing mathematical computations. Ultimately, the output layer yields final results, such as predictions or classifications. The connections between neurons are characterized by weights, signifying the significance and impact of inputs on the neuron's output. Throughout the training phase, the neural network refines these weights based on provided data and desired outcomes, progressively enhancing its predictive or classificatory accuracy.

V. DATASET

Publicly accessible datasets serve as invaluable resources for researchers to assess the efficacy of their proposed methods. These datasets are widely utilized for evaluation purposes within the research community. Our model utilizes a carefully curated dataset sourced from the internet, comprising 253 MRI images. Initially, the dataset presented a challenge due to its limited size for training our neural network. To address this, we employed data augmentation techniques, crucial for mitigating data imbalances. Originally, the dataset comprised 155 positive cases and 98 negative cases, totaling 253 images.

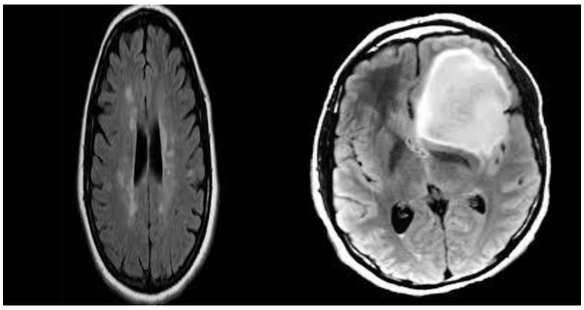

Fig 4-.MRI images of the brain without tumor and with tumor

Post-augmentation, the dataset expanded significantly, now containing 1085 positive cases and 980 negative cases, resulting in a total of 2065 images, inclusive of the original 253. The dataset is organized into distinct folders, each containing a specific image set, either depicting a healthy brain or a brain tumor. Our model underwent training on the entirety of this diverse dataset, with 15% of the images reserved for validation and another 15% for testing purposes. Notably, the MRI images in the dataset exhibit varying dimensions, presenting an additional challenge that our model effectively addresses.

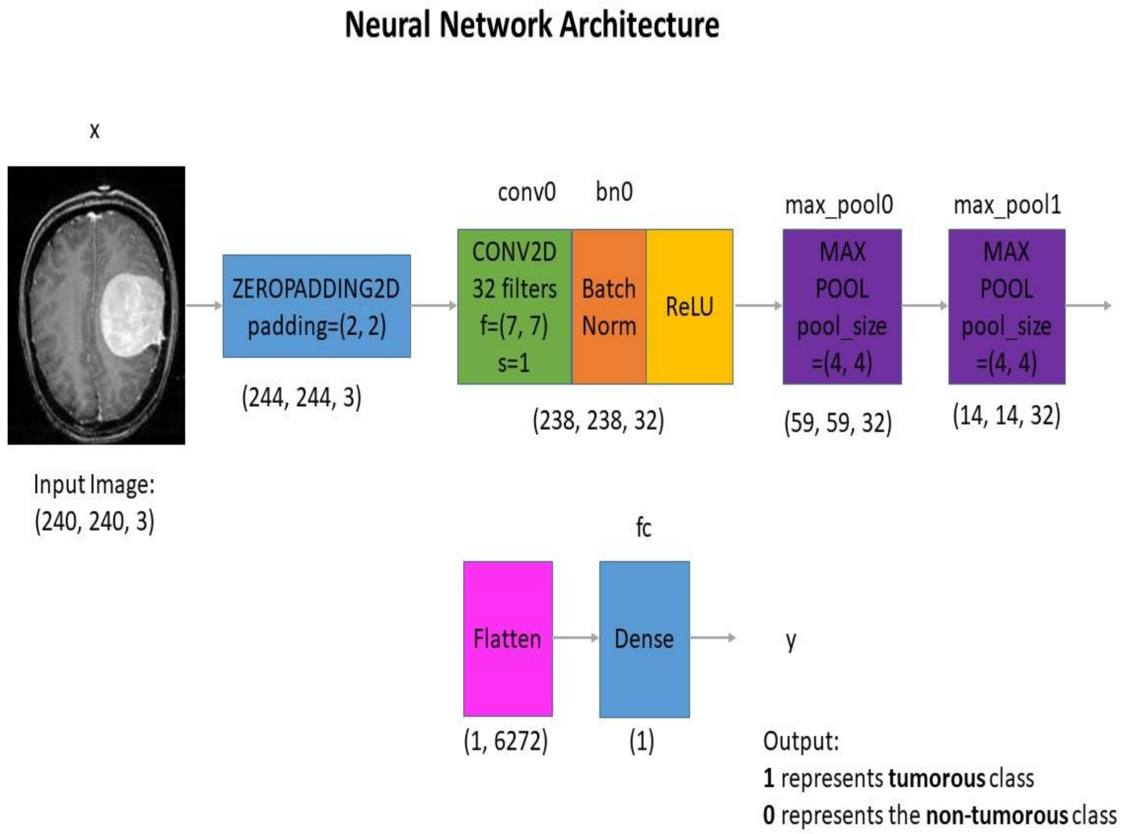

Fig 5- Neural Network Architecture

Data Split:

The dataset was partitioned into three subsets according to the following distribution:

1. 70% of the data was allocated for training purposes.

2. 15% of the data was reserved for validation to fine-tune model parameters.

3. The remaining 15% of the data was set aside for rigorous testing to evaluate model performance.

Table 3-Set of images

Numberof images	Folder directory
1445	Training
310	Testing
310	Validating

- Validation set–The validation set consists of images utilized during the training phase to fine-tune and adjust various parameters of the model

- Testing set–It is the set of images designated for evaluating the performance of the model during testing.

Methodologies

VI. DATA ACQUISITION

The collected data was categorized into two classes: healthy and non-healthy. Additionally, due to variations in image dimensions, all images were standardized to a uniform size of 240 x 240 pixels.

Data Preprocessing

At this phase, we aim to enhance the accuracy of the model by removing noise from the MRI images. MRI images frequently contain noise, which can introduce redundancy and consequently reduce model accuracy. Noise along the borders of an MRI image poses a particular risk, potentially leading to undetected tumors and impacting overall model accuracy. Pre-processing techniques such as scaling, reducing noise, and converting images to grayscale were employed to improve image quality, appearance, and characteristic features.

For each image, we implemented the following pre-processing procedures:

1. Cropping to isolate the brain, which is the Primary area of interest within the image.

2. Resizing the image to achieve a standardized shape of (240, 240, 3) — representing image width, height, and the number of channels — to ensure consistency across all images, as they initially varied in size.

3. Normalization was applied to rescale pixel values within the range of 0 to 1, enhancing uniformity across the dataset and facilitating optimal neural network input..

Image Smoothing

This involves the process of condensing images while retaining crucial information, with the objective of minimizing irrelevant noise or excessive detail without introducing significant distortion, thereby facilitating streamlined subsequent analyses.

Proposed Work

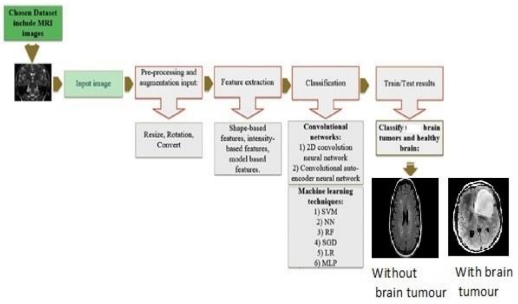

Figure 2. Flow chart of the proposed work

Fig 6- Praposed Model

The technique used for making this model work is CNN(Convolutional Neural Network).The various steps involved in the application of CNN on the dataset include:

The entire implementation is conducted utilizing Python 3.12 and executed on Google Colaboratory, with the resulting model stored in Google Drive.

VII. RESULTS

After applying the model to the testing dataset over 24 epochs, it achieved a validation accuracy of 91% and an F1 Score of 0.91. These outcomes demonstrate strong performance, particularly noteworthy given the balanced nature of the dataset.

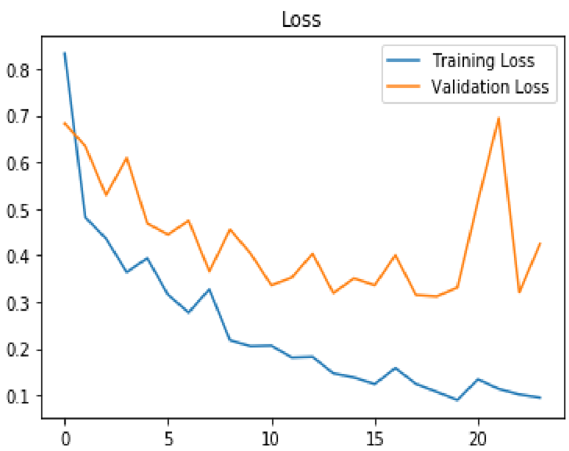

Fig 7-Model loss

As depicted in Figure 3, upon application to the validation set, the model initially exhibits a high loss. However, when applied to the testing set, the loss steadily diminishes as the number of epochs increases.

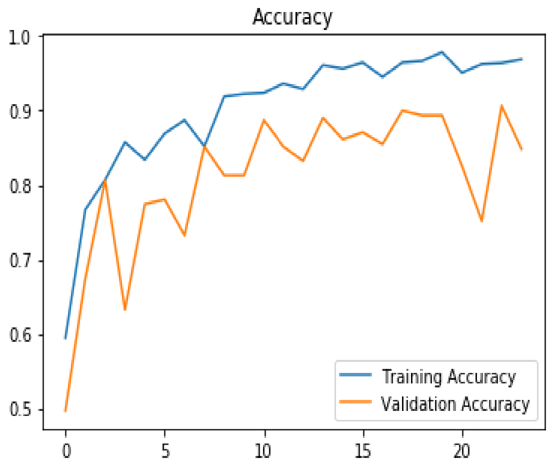

Fig 8-Model accuracy

Table 4

	Validation Set	Test Set
Accuracy	91%	93%
F1 Score	0.91	0.89

VIII. CONCLUSION

The objective of this study is to develop a highly accurate model for detecting brain tumors from MRI images. The dataset utilized comprises 253 brain MRI images, providing sufficient data to evaluate the model's performance. Based on the Convolutional Neural Network (CNN) machine learning algorithm, the model predicts by resizing and reducing the image without sacrificing crucial information required for accurate prediction. Upon evaluation, the model achieves an impressive accuracy of 97.79% on the training set and 82.86% on the validation set. Additionally, the loss gradually decreases with an increase in the number of epochs. Notably, while the model demonstrates lower loss on the training set, it exhibits higher loss on the validation set. Future work will involve applying different datasets to enhance the overall accuracy of the model.

IX. REFERENCES

[1] Subhashis Banerjee, Francesco Masulli, Sushmita Mitra, Brain Tumor Detection and Classification from Multi-Channel Magnetic resonance imagings using Deep Learning and Transfer Learning”(2017).

[2] Pareek, M.; Jha, C.K.; Mukherjee, S. Brain Tumor Classification from MRI Images and Calculation of Tumor Area. In Advances in Intelligent Systems and Computing; Springer: Singapore, 2020; pp. 73–83.

[3] Ayadi, W.; Charfi, I.; Elhamzi, W.; Atri, M. Brain tumor classification based on hybrid approach. Vis. Comput. 2020, 38, 107–117.

[4] Kokkalla, S.; Kakarla, J.; Venkateswarlu, I.B.; Singh, M. Three-class brain tumor classification using deep dense inception residual network. Soft Comput. 2021, 25, 8721–8729

[5] Öksüz, C.; Urhan, O.; Güllü, M.K. Brain tumor classification using the fused features extracted from expanded tumor region. Biomed. Signal Process. Control 2022, 72, 103356

[6] Kesav, N.; Jibukumar, M. Efficient and low complex architecture for detection and classification of Brain Tumor using RCNN with Two Channel CNN. J. King Saud Univ.-Comput. Inf. Sci. 2022, 34, 6229–6242.

[7] Sanjay Kumar, Dr. Ashish Negi, Dr. J.N Singh, Mr. Himanshu Verma, "A Deep Learning for Brain Tumor Magnetic resonance imaging Images Semantic Segmentation Using FCN ", 2018 4th International Conference on Computing Communication and Automation (ICCCA), ISBN: 978-1-5386-6947-1.

[8] Fatemeh Derikvand,Hassan Khotanlou,"Brain Tumor Segmentation in Magnetic resonance imaging Images Using a Hybrid Deep Network Based on Patch and Pixel", 2020 International Conference on Machine Vision and Image Processing (MVIP), ISBN: 978-1-7281-6832-6.

[9] L.Guo,L.Zhao,Y.Wu,Y.Li,G.Xu,andQ.Yan,"Tumordetection in MR images using one- class immune feature weighted SVMs," IEEE Transactions on Magnetics, vol. 47, no. 10, pp. 3849–3852,2011.

[10] R.Kumari,"SVMclassificationanapproachondetectingabnormalityinbrainMRIimages,"Inter nationalJournalofEngineeringResearchandApplications,vol.3,pp.1686–1690,2013.

[11] DICOM Samples Image Sets, http://www.osirix-viewer.com/.

[12] "Brainweb:SimulatedBrainDatabase" http://brainweb.bic.mni.mcgill.ca/cgi/brainweb1.

[13] Obtainable Online: www.cancer.ca/~/media/CCE 10/08/2015.

[14] J. C. Buckner, P. D. Brown, B. P. O'Neill, F. B. Meyer , C. J. Wetmore,J. H Uhm, "Central nervous system tumors." In Mayo Clinic Proceedings,Vol. 82, No. 10, pp. 1271- 1286, October 2007.

[15] Deepa , Singh Akansha. (2016). - Review of Brain Tumor Detection from tomography. International Conference on Computing for Sustainable Global Development (INDIACom)

[16] R. A. Novellines, M. D. - Squire's fundamentals of radiology; Six Edition; UPR, 2004.

[17] Preston, D. c. (2006). Magnetic Resonance Imaging (MRI) of the Brain and Spine from Basics. casemed.case.edu .

[18]Hendrik RE. (2005) Glossary of MR Terms from American College of Radiology .

[19]Demirhan, M. Toru, and I. Guler, "Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks," IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 4, pp. 1451–1458, 2015.

[20]Nilesh Bhaskarrao Bahadure , A.K. (2017, March 6). Retrieved from https://www.hindawi.com/journals/ijbi/2017/9749108/.

[21]S. Mohsin, S. Sajjad, Z. Malik, and A. H. Abdullah, "Efficient way of skull stripping in MRI to detect brain tumor by applying morphological operations, after detection of false background," International Journal of Information and Education Technology, vol. 2, no. 4, pp. 335–337, 2012.

[22] Gavale, P. M., Aher, P. V., & Wani, D. V. (2017, April 4). Retrieved from https://www.irjet.net/archives/V4/i4/IRJET-V4I462.pdf.

[23]N. Gordillo, E. Montseny, and P. Sobrevilla, "State of the art survey on MRI brain tumor segmentation,"Magnetic Resonance Imaging, vol. 31, no. 8, pp. 1426–1438, 2013.

[24]Samantaray, M.(2016, November 3). Retrieved from http://ieeexplore.ieee.org/document/7727089/ .

[25]Nandi, A (2016, April 11) Retrieved from http://ieeexplore.ieee.org/document/7449892/

[26]CC Benson and V. L. Lajish, "Morphology based enhancement and skull stripping of MRI brain images," in Proceedings of the international Conference on Intelligent Computing Applications (ICICA '14), pp. 254–257, Tamilnadu, India, March 2014.

[27]S. Z. Oo and A. S. Khaing, "Brain tumor detection and segmentation using watershed segmentation and morphological operation," International Journal of Research in Engineering and Technology, vol. 3, no. 3, pp. 367–374, 2014.

[28]R. Roslan, N. Jamil, and R. Mahmud, "Skull stripping magnetic resonance images brain images: region growing versus mathematical morphology," International Journal of Computer Information Systems and Industrial Management Applications, vol. 3, pp. 150– 158, 2011.

[29]Luxit Kapoor, Sanjeev Thakur,"A Survey on Brain Tumor Detection Using Image Processing Techniques", IEEE 7th International Conference on Cloud Computing, Data Science & Engineering, 2017.

[30]Praveen Gamage, "Identification of Brain Tumor using Image Processing Techniques", Research gate, 2017.

[31]Devendra Somwanshi , Ashutosh Kumar, Pratima Sharma, Deepika Joshi, "An efficient Brain Tumor Detection from MRI Images using Entropy Measures, IEEE International Conference on Recent Advances and Innovations in Engineering, 2016

[32]Deipali Vikram Gore , Vivek Deshpande, "Comparative Study of various techniques using Deep Learning for Brain Tumor Detection", International Conference for Emerging Technology (INCET), 2020

[33]Erena Siyoum Biratu , Friedhelm Schwenker , Yehualashet Megersa Ayano , Taye Girma Debelee, "A Survey of Brain Tumor Segmentation and Classification Algorithms", MDPI Journal of imaging, 2021.

[34]Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz and Sharareh R. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques", BMC Medical Informatics and Decision Making, 2023.

[35]Akmalbek Bobomirzaevich Abdusalomov , Mukhriddin Mukhiddinov and Taeg Keun Whangbo, "Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging", IEEE International Conference on Recent Advances and Innovations in Engineering, 2018.

[36]Mahsa Arabahmadi , Reza Farahbakhsh and Javad Rezazadeh, "New Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging", Complex and intelligent systems, 2021

[37]P Gokila Brindha, M Kavinraj, P Manivasakam and P Prasanth, "Brain tumor detection from MRI images using deep learning techniques", IOP Conference Ser, 2022.

[38]Hanaa et al, "Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization", MDPI Journal of imaging,2022.

[39]Manav Sharma , Pramanshu Sharma , Ritik Mittal , Kamakshi Gupta, "Brain Tumour Detection Using Machine Learning", Journal of Electronics and Informatics,2021.

[40]Bathe et al, "Brain Tumor Detection Using Deep Learning Techniques", ICAST 2021.

[41]A. Kassner and R. E. Thornhill, ''Texture analysis: A review of neurologic MR imaging applications,'' Amer. J. NeuroRadiol., vol. 31, pp. 809–816, May 2010.

[42]M. T. El-Melegy and H. M. Mokhtar, ''Tumor segmentation in brain MRI using a fuzzy approach with class center priors,'' EURASIP J. Image Video Process., vol. 21, no. 1, pp. 2–14, 2014.

[43]A. Demirhan, M. Törü, and I. Güler, ''Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks,'' IEEE J. Biomed. Health Inform., vol. 19, no. 4, pp. 1451–1458, Jul. 2015.

[44]A. Islam, S. M. S. Reza, and K. M. Iftekharuddin, ''Multifractal texture estimation for detection and segmentation of brain tumors,'' IEEE Trans. Biomed. Eng., vol. 60, no. 11, pp. 3204–3215, Nov. 2013.

[45]S. Lu, Z. Lu, J. Yang, M. Yang, and S. Wang, ''A pathological brain detection system based on kernel based ELM,'' Multimedia Tools Appl., vol. 77, no. 3, pp. 3715–3728, 2018.

[46]D. S. Nachimuthu and A. Baladhandapani, ''Multidimensional texture characterization: On analysis for brain tumor tissues using MRS and MRI,'' J. Digit. Imag., vol. 27, no. 4, pp. 496–506, 2014.

[47]G. P. Rathi and S. D. Palani, ''Brain tumor MRI image classification with feature selection and extraction using linear

discriminant analysis,'' Int. J. Inf. Sci. Techn., vol. 2, no. 4, p. 146, 2012.

[48] F. N. Karameh and M. A. Dahleh, ''Automated classification of EEG signals in brain tumor diagnostics,'' in Proc. IEEE Amer. Control Conf., Chiago, IL, USA, Jun. 2000, pp. 4169–4173.

[49] M. Ji et al., ''Detection of human brain Tumor infiltration with quantita- tive stimulated Raman scattering microscopy,'' Sci. Transl. Med., vol. 7, no. 309, p. 309ra163, 2015.

[50] B. H. Menze et al., ''The multimodal brain Tumor image segmenta- tion benchmark (BRATS),'' IEEE Trans. Med. Imag., vol. 34, no. 10, pp. 1993–2024, Oct. 2015.

[51] F. J. Martinez-Murcia et al., ''On the brain structure heterogeneity of autism: Parsing out acquisition site effects with significance-weighted principal component analysis,'' Hum. Brain Mapping, vol. 38, no. 3, pp. 1208–1223, 2017.