CHAPTER-1

INTRODUCTION

INTRODUCTION

The central nervous system disseminates sensory information and its corresponding actions throughout the body .The brain, along with the spinal cord, assists in this dissemination. The brain's anatomy contains three main parts;brain stem, cerebrum, and cerebellum. The weight of a normal human brain is approximately 1.2–1.4 K, with a volume of 1260 cm3 (male brain) and 1130 cm3 (female brain)The frontal lobe of brain assists in problem-solving, motor control, and judgments. The parietal lobe manages body position. The temporal lobe controls memory and hearing functions, and occipital lobe supervises the brain's visual processing activities. The outer part of cerebrum is known as cerebral cortex, and is a greyish material; it is composed of cortical neurons. The cerebellum is relatively smaller than the cerebrum. It is responsible for motor control, i.e., systematic regulation of voluntary movements in living organisms with a nervous system. Due to variable size and stroke territory, ALI, lesion Gnb, and LINDA methods fail to detect the small lesion region. Cerebellum is well-structured and well developed in human beings as compared to other species The cerebellum has three lobes; ananterior, a posterior, and a A round-shaped structure named vermis connects the anterior and posterior lobes. The cerebellum consists of an inner area of whitematter (WM) and an outer greyish cortex, which is a bit thinner than that of the cerebrum. The lobe maintains the body's balance. The brain stem, as the name states, is a 7–10 cm-long stem-like structure. It contains cranial and peripheral nerve bundles and assists in eye movements and regulations, balance and maintenance, and someessential activities such as breathing. The main parts of the brain stem are midbrain, pons, and medulla. The pons assists in breathing, intra-brain communication, and sensations, and medulla oblongata helps in blood regulation, swallowing, sneezing, etc. We report the findings from a bibliometric analysis and review conducted to determine the research trends, future research topics, state of the art, and advancements in brain tumor prediction using machine learning in the previous 5 years.

1.1 BACKGROUND

Detecting brain tumors using machine learning is a critical applicationpoised to revolutionize medical diagnostics. With advancements in technology and the availability of large datasets, researchers can now develop sophisticated algorithms capable of accurately identifying abnormalities in brain scans. This project aims to leverage machine learning techniques to analyze medical imaging data, such as MRI and CT scans, to detect the presence of brain tumors.

1.2 PROBLEM STATEMENT

Detecting brain tumors using machine learning involves developing a system capable of accurately identifying abnormalities within brain images to aid in early diagnosis and treatment planning. This project aims to create a robust model that can analyze MRI or CT scans and distinguish between normal brain tissues and tumor-affected regions. The problem statement revolves around leveraging advanced machine learning algorithms to automate the process of tumor detection, reducing the reliance on manual interpretation by radiologists and potentially enhancing diagnostic accuracy. Keychallenges include handling large and complex medical imaging datasets, ensuring the model's interpretability and generalizability across different patient demographics and imaging modalities, and optimizing for both sensitivity and specificity to minimize false positives and negatives. Ultimately, the goal is to develop a reliable and efficient brain tumor detection system that can contributeto early intervention and improved patient outcomes.To enhance interpretability and transparency, techniques such as saliency maps or Grad-CAM (Gradient-weighted Class Activation Mapping) will be applied to visualize which parts of the MRI images are most influential in the model's decision-making process.

1.3 OBJECTIVE

The primary objective of the brain tumor detection project using machine learning is to develop an accurate and efficient system capable of detecting brain tumors from medical images such as MRI scans. This system aims to assist healthcare professionals in accurately diagnosing brain tumors at an early stage, thereby facilitating timely medical intervention and treatment planning. Key goals include implementing advanced machine learning algorithms to analyze MRI images, training the model on diverse datasets to ensure robustness and generalization, and optimizing the system forhigh sensitivity and specificity in tumor detection. Additionally, the project aims to enhance the interpretability of the model's predictions to aid clinicians in understanding the reasoning behind the diagnosis. Overall, the objective is to leverage machine learning techniques to improve the accuracy, speed, and accessibility of brain tumor detection, ultimately contributing to better patient outcomes and healthcare delivery. This includes preprocessing techniques like image normalization, augmentation, and feature extraction to enhance the model's ability to detect tumors across diverse patient populations. theprimary aim is to develop a robust and accurate machine learning model that can effectively identify the presence of brain tumors from medical imaging data such as MRI scans. This involves exploring various machine learning algorithms, such as deep learning models (like convolutional neural networks), to ensure high sensitivity and specificity in tumor detection.Secondly, the project aims to optimize the model's performance.

CHAPTER-2

LITERATURE REVIEW

LITERATURE SURVEY

S.NO	BASE PAPER TOPICS	AUTHOR	ALGORITHM TECHNIQUES	RESULT
1	A Hybrid Approach Based on Deep CNN and Machine Learning Classifiers for the Tumor Segmentation and Classification in Brain MRI	Ejaz Ul Haq Huang Jianjun Xu Huarong Kang Li Lifen Weng	Conventional medical imaging and machine learning techniques	The experimental findings clearly show that increasing the system structure and complexity increased the proposed model's efficiency
2	Brain tumour detection through image processing and machine learning techniques	Srinivas Kumar Palvadi Dr.K.Suresh Joseph	Machine learning techniques	The interface has various fields like segmentation features , segmentation , affected area and accuracy
3	An Effective Approach to Detect and Identify Brain Tumors Using Transfer Learning	Naeem Ullah Javed Ali Khan Mohammad Sohail Khan	CNN based classifier	This section discusses the performance of different pre-trained TL classifiers used to classify brain MRI images from the brain tumor classification (MRI) dataset into meningioma, pituitary and glioma
4	A Learning Based Brain Tumor Detection System	Sultan Noman Qasem Amar Nazar	KNN algorithm	In this section we described experimental results that relates to best, average and bad results.
5	Brain tumor detection using Image processing and sending tumor information over GSM	Shivakumarswamy G.M., Akshay Patil.V., Chethan T.A., Prajwal B.H., Sagar.V.Hande	K-Mean and Fuzzy C Mean	Results in distorted boundaries and edges
6	A Simple image processing approach to abnormal slices detection from MRI tumour	T.Kalaiselvi, P.Nagaraja and P.Sriramakrishnan	Fuzzy Symmetric measures	It takes minimum missed alarms

7	Brain Tumor Segmentation by Modified K-Mean with Morphological Operations	Rajeev Kumar , Dr. K. James Mathai	Morphological Operators and Kmean	Not work for global cluster
8	An Automatic Brain Tumor Detection, Segmentation and Classification Using MRI Image	Arbaz Mukaram Chidananda Murthy.M.V, M.Z.Kurian	Classification	When only classification is applied, it ignores the poor quality images
9	Efficient image segmentation of brain tumor detection using fuzzy c-mean and mean-shift	Mandip kaur, Prabhpreet kaur 2	Fuzzy c-mean and mean-shift	Neglected the use of fuzzy and region growing segmentation
10	Brain Tumor Detection in MRI Images with New Multiple Thresholding	Sandeep Patel, Divyanshu Rao	Brain Tumor Detection and Segmentation Using Histogram Thresholding	Useful for linear image does not give accurate results
11	Brain Tumor Detection based on Machine Learning Algorithms	Komal Sharma Akwinder Kaur Shruti Gujral	KNN Classifier	The Multi-Layer Perceptron (MLP) and Naïve bayes with 66% percentage split is used for classification. In 66% percentage split, 66% of the instances are used for training and remaining instances are used for testing.
12	A New Deep Hybrid Boosted and Ensemble Learning-Based Brain Tumor Analysis Using MRI	Mirza Mumtaz Zahoor Shahzad Ahmad Qureshi	CNN Algorithm	The empirical effectiveness of the proposed framework is evaluated by performing two experiments
13	A deep learning approach for brain tumor classification using MRI images	Muhammad Aamir Ziaur Rahman	KNN and SVM	The primary objective is to expand the dynamic range of gray values in images to get a greater level of visual quality

14	Brain Tumour Detection Using Machine Learning	Manav Sharma Pramanshu Sharma	CNN Algorithm	When the model is applied to the testing data set for 10 epochs, a validation accuracy of 82.86% is obtained and the validation loss is also less.
15	Brain tumor detection and classification using machine learning: a comprehensive survey	Javaria Amin Muhammad Sharif	Classification	ACC of 92.9%, 92.8%, 91.8%, 99.6%, 93.1%, respectively
16	Brain Tumor Detection Using Machine Learning Approach	Naveen V A Sudeep N R	CNN Algorithm	the model achieved the accuracy of 95.42%, with f-score of 94.00%.
16	Brain Tumor Detection Using Deep Learning Approaches	RAZIA SULTANA MISU	Deep learning	When only classification is applied, it ignores the poor quality images
17	MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques	Soheila Saeedi Sorayya Rezayi	CNN Algorithm	The training accuracy of the proposed 2D CNN and that of the proposed auto-encoder network were found to be 96.47% and 95.63%, respectively
18	A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks	Md Ishtyaq Mahmud Muntasir Mamun	CNN Algorithm	accuracy and validation AUC compared to the other models, which were 93.30% and 98.43%, respectively
19	Brain tumour classification using machine learning algorithm	A B Malarvizhi	Machine Learning, Classification	With an accuracy rate of 80% the SVM classifier classified the brain tumour images as Benign and Malignant

20	AUTOMATIC BRAIN TUMOR DETECTION AND CLASSIFICATION ON MRI IMAGES USING MACHINE LEARNING TECHNIQUES	SHREYASI GHOSH Sayeri Biswas	Naive Bayes Classifier	The interface has various fields like segmentation features , segmentation , affected area and accuracy
21	Brain Tumor Detection Using Deep Learning Techniques	Kavita Bathe Varun Rana	CNN Algorithm	The maximum accuracy was between 87.5% to 95.8% and minimum loss of 0.2957 to 0.8555 with epochs between 135 to 145 as shown in Fig.3 and Fig. No 4 respectively
22	Brain Tumour Detection Using Machine Learning Algorithm	A.Keerthana B. Kavin Kumar	CNN Algorithm	Neglected the use of fuzzy and region growing segmentation
23	Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging	Mukhriddin Mukhiddinov Taeg Keun Whangbo	CNN Algorithm	In this section, we present the outcomes of training and verifying the suggested fine-tuned YOLOv7 model using MRI images, and we present an analysis of the overall performance
24	Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf Optimization	Hanaa ZainEldin Samah A. Gamel	CNN Algorithm	The BCM-CNN was given the BRaTS 2021 Task 1 dataset, and it performed with an accuracy of 99.99%
25	Automated Brain Tumor Detection Using Machine Learning: A Bibliometric Review	Rajan Hossain Roliana Binti Ibrahim	Machine Learning	It takes minimum missed alarms
26	Brain Tumor Detection and Multi Classification Using GNB-Based Machine Learning Approach	Dr. Satish N. Gujar Jaimala Jha	CNN Algorithm	In the framework of this study, a wide range of ML methodologies are analysed as well as compared in form of how much accuracy, sensitivity, and F1-score they obtain.

27	Detection and Classification of Brain Tumor Using Machine Learning Algorithms	Fatma M. Refaat M. M. Gouda	KNN Algorithm	The minimum objective reaches 0.55 with a function evaluation of 30. The accuracy of this algorithm is 96.24 via Equation
28	Brain tumour detection through image processing and machine learning techniques	Srinivas Kumar Palvadi Dr.K.Suresh Joseph	Machine learning techniques	The interface has various fields like segmentation features , segmentation , affected area and accuracy
29	The interface has various fields like segmentation features , segmentation , affected area and accuracy	Rajeev Kumar , Dr. K. James Mathai	Morphological Operators and Kmean	Not work for global cluster
30	A Learning Based Brain Tumor Detection System	Sultan Noman Qasem Amar Nazar	KNN algorithm	In this section we described experimental results that relates to best, average and bad results.

CHAPTER-3

PROJECT METHODOLOGY

PROJECT METHODOLOGY

3.1 DESCRIPTION OF THE WORKING FLOW OF PROPOSAL SYSTEM:

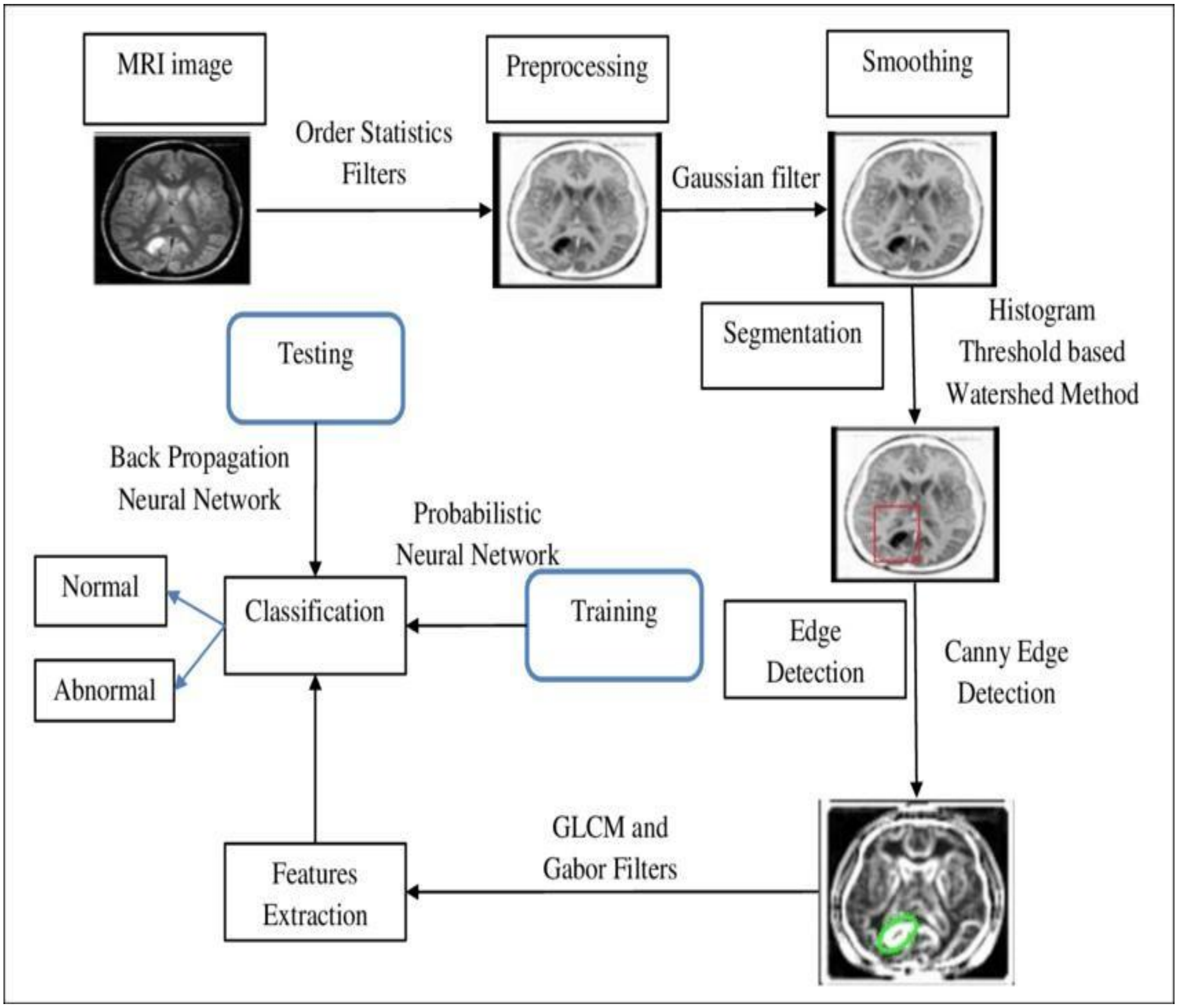


FIG 3.1 PROPOSED SYSTEM

3.1.1. MRI Images

MRI (Magnetic Resonance Imaging) has emerged as a powerful tool in the early detection and diagnosis of brain tumors, offering high-resolution images that provide detailed insights into the brain's anatomy and abnormalities. Machine learning algorithms are increasingly being integrated into the analysis of MRI images to aid in the detection and classification of brain tumors. These algorithms utilize techniques such as deep learning to automatically extract features from the images and identify patterns indicative of tumor presence.

3.1.2. Segmentation of Tumor Designs

Detecting brain tumors using machine learning involves various segmentation techniques to identify tumor designs accurately. Segmentation refers to the process of partitioning an image into multiple segments or regions based on certain criteria. In the context of brain tumor detection, segmentation aims to delineate the boundaries of tumors from surrounding healthy tissue in medical images such as MRI scans or CT scans.

3.1.3. Evaluation Metrices

. Evaluation metrics are crucial for assessing the performance of machine learning models in detecting brain tumors. Commonly used metrics include accuracy, sensitivity, specificity, precision, and F1 score. Accuracy measures the overall correctness of the model's predictions, while sensitivity quantifies the model's ability to correctly identify true positive cases of brain tumors. Specificity evaluates the model's capacity to correctly identify true negative cases, thus minimizing false positives.

3.1.4. Model Development

Developing a model for brain tumor detection using machine learning involves several crucial steps. Initially, a diverse data set comprising brain images, including both tumor and non-tumor cases, needs to be meticulously collect notated rigorous preprocessing techniques are applied to ensure data uniformity and cleanliness, including normalization and augmentation. Feature extraction plays a pivotal role, where relevant features are extracted from the images, employing methods like edge detection or leveraging pre-trained convolutional neural networks for deep feature extraction. Model selection becomes pivotal, with convolutional neural networks (CNNs) often being the preferred choice due to their ability to automatically learn hierarchical feature images.

3.1.5. Validation and Clinical Trials

Validate the model's performance through clinical trials and collaboration with medical professionals. It's essential to ensure that the model performs reliably and accurately in real-world clinical settings..

3.1.6. Model Selection

Choose appropriate machine learning algorithms or deep learning architectures for tumor detection. CNNs are commonly used for image-based tasks due to their ability to automatically learn hierarchical features.

3.1.7. Deployment

In the realm of medical advancements, the integration of machine learning algorithms into brain tumor detection projects has revolutionized diagnostic processes. Deployment of such technology entails a meticulous orchestration of data collection, model training, and real-world application. Initially, comprehensive datasets comprising various types of brain imaging scans, such as MRI and CT scans, are gathered to train the machine learning models..

3.1.8. Testing

Once you're satisfied with your model's performance on the validation set, test it on a separate test set to assess its real-world performance. Make sure the test set contains examples that the model hasn't seen during training or validation to get an unbiased estimate of its performance.

3.2 BRAIN TUMOR CLASSIFICATION DATASET

In our project, we integrated inbuilt datasets used dataset for brain tumor detection in machine learning projects is the "Brain Tumor Classification" dataset from the Cancer Imaging Archive (TCIA). This dataset comprises MRI images of the brain with associated labels indicating the presence or absence of tumors, as well as details about tumor types if present. Each MRI scan typically includes multiple image slices representing different sections of the brain, providing ample data for training and testing machine learning models. Additionally, there are other datasets available, often collected from various medical institutions, with similar MRI data for brain tumor detection tasks. These datasets are crucial for developing and evaluating machine learning algorithms aimed at accurately detecting and classifying brain tumors, ultimately aiding in the early diagnosis and treatment of patients.

3.2.1 DATA PREPROCESSING

In the realm of brain tumor detection using machine learning, data preprocessing plays a pivotal role in ensuring the accuracy and reliability of the models developed. This initial phase involves several key steps aimed at preparing the input data for effective analysis. Firstly, the raw medical imaging data, typically in the form of MRI scans, CT scans, or PET scans, undergoes prepossessing to correct any inconsistencies or artifacts that may be present due to imaging noise or equipment variations. This step is crucial for ensuring the clarity and accuracy of the images, which are fundamental for accurate tumor detection.

3.2.2 DATA CLEANING

Data cleaning involves handling missing values. In medical datasets, missing values are common due to various reasons such as incomplete patient records or sensor malfunction. These missing values need to be identified and either imputed or removed based on the context and significance of the missing information..

3.2.3 DATA AUGMENTATION

Brain tumor detection specifically, data augmentation plays a vital role in enhancing the generalization capability of machine learning models. By creating diverse variations of the original images, the model becomes more robust and adaptable to different types of tumors, sizes, and orientations. This is particularly important given the variability in brain tumor appearances across patients and imaging modalities.Furthermore, data augmentation helps to address the challenge of limited annotated data, which is often a bottleneck in medical imaging tasks

3.2.4 DATA VALIDATION

Brain tumor detection, where even minor discrepancies can have profound implications for patient care, data validation is paramount. It encompasses various steps such as checking for missing or incomplete data, ensuring uniformity in data formats, and validating the quality and authenticity of the data sources. Additionally, techniques like cross-validation help assess the generalizability of the model by testing its performance on independent datasets..

3.3 MACHINE LEARNING:

Machine learning plays a pivotal role in brain tumor detection, revolutionizing the field of medical imaging and diagnosis. By leveraging vast amounts of medical data, machine learning algorithms can learn to identify patterns and features indicative of brain tumors within MRI or CT scans. These algorithms can distinguish between normal brain tissue and abnormal growths with remarkable accuracy, aiding radiologists in making faster and more precise diagnoses. Moreover, machine learning models can continuously improve their performance over time as they are exposed to more data, enhancing their ability to detect even subtle abnormalities that might be missed by human observers. This synergy between advanced computational techniques and medical imaging holds tremendous promise for early detection and treatment planning, ultimately improving patient outcomes in the fight against brain tumors.

These algorithms analyze various features extracted from the images, such as shape, texture, and intensity, to differentiate between normal brain tissue and abnormal tumor regions. By training on large datasets of annotated images, machine learning models can improve their accuracy in detecting tumors and even classify different types of tumors. This technology holds great promise in assisting radiologists and clinicians in early detection, precise localization, and treatment planning for brain tumors, ultimately improving patient outcomes and survival rates.

3.3.1 Understanding Brain Tumor Classification :

Tumors in the brain can arise from various cell types, resulting in diverse characteristics and behaviors. Classification typically involves categorizing tumors based on their location within the brain, histological features (microscopic appearance of cells), genetic mutations, and molecular markers. The World Health Organization (WHO) classification system is commonly used, which categorizes brain tumors into different grades based on their aggressiveness and likelihood of spreading. Grade I tumors are typically benign, slow-growing, and have well-defined borders, while grade IV tumors, such as glioblastoma multiforme, are highly aggressive and difficult to treat.

3.3.2 Components of Brain Tumor Classification :

1.Treatment Modalities: Different types of brain tumor may require varying treatment approaches, including surgery, radiation therapy, chemotherapy, and targeted therapy**.**

2.Genetics and Molecular Markers: Understanding the genetic mutations and molecular markers associated with brain tumors is crucial for diagnosis, prognosis, and targeted therapies.

3.Grade of Mallignancy : This topic involves classifying tumors based on their aggressiveness and potential for growth.

4.Grade : Tumor grade indicates the degree of malignancy or aggressiveness. The World Health Organization (WHO) grading system is commonly used, ranging from grade I (least malignant) to grade IV (most malignant). Grade is determined based on factors such as cellularity, nuclear atypia, mitotic activity, and presence of necrosis.

3.4 SVM Classifier

In the context of brain tumor detection, SVM classifiers work by finding the optimal hyperplane that separates the tumor and non-tumor data points in a high-dimensional feature space. These features could include various characteristics extracted from the MRI images, such as texture, shape, and intensity. By utilizing a kernel function, SVMs can map the input data into a higher-dimensional space, where it becomes easier to find a hyperplane that maximizes the margin between the two classes, thus improving the classification accuracy.

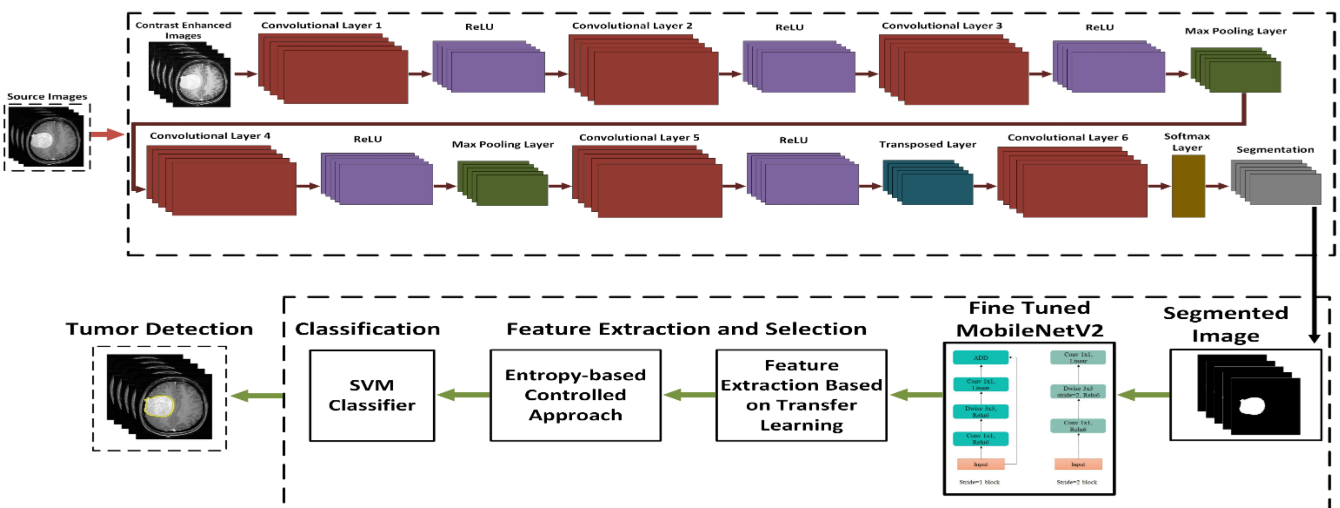


FIG 3.4 SVM Classifier

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm used extensively in various domains, including medical image analysis such as brain tumor detection. In this context, SVM serves as a classifier to distinguish between tumor and non-tumor regions within brain images.The process typically involves several steps. First, relevant features are extracted from the brain images, which could include texture, intensity, shape, or spatial information. These features help to characterize the regions of interest and form the input data for the SVM classifier. Next, the SVM algorithm is trained on a labeled dataset, where each sample is associated with a class label indicating whether it belongs to a tumor or non-tumor category.

During training, the SVM learns to find the optimal hyperplane that best separates the two classes in the feature space while maximizing the margin, which is the distance between the hyperplane and the nearest data points from each class.Once trained, the SVM model can predict the class labels of new, unseen brain images by mapping them into the feature space and determining which side of the hyperplane they fall on. This allows for the automatic detection of brain tumors based on their characteristic features.

3.5 CNN:

In our Project ,Convolutional Neural Networks, have emerged as a powerful tool in medical imaging, particularly in the detection of brain tumors. By leveraging deep learning techniques, CNNs can automatically extract features from medical images like MRI scans with remarkable accuracy and efficiency. In the context of brain tumor detection, CNNs analyze these images pixel by pixel, identifying patterns and abnormalities indicative of tumor presence. This approach not only assists radiologists in faster and more accurate diagnosis but also opens avenues for early detection, leading to improved patient outcomes.

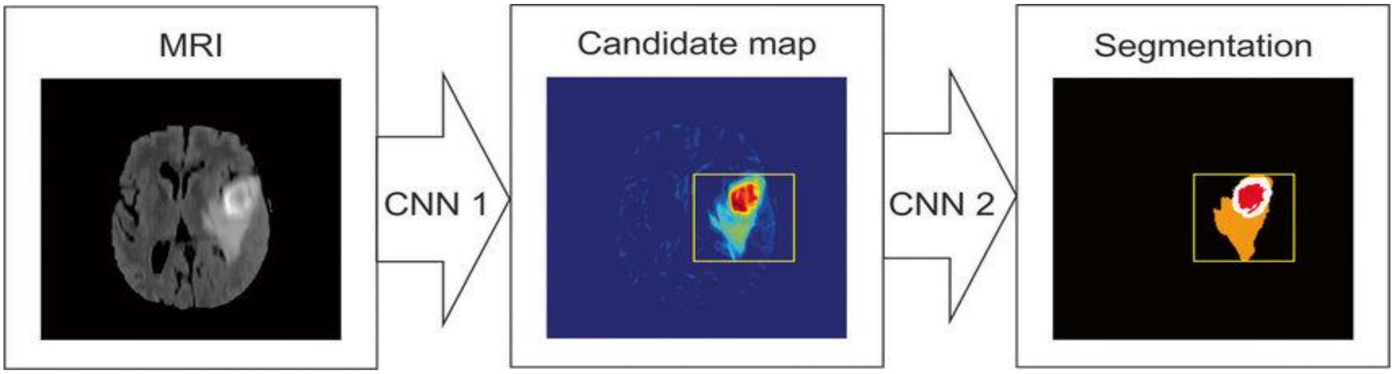


FIG 3.5 CNN Classifier

Detecting brain tumors accurately and efficiently is crucial for timely medical intervention and treatment. CNN, or Convolutional Neural Networks, have emerged as powerful tools in this endeavor. These deep learning algorithms are adept at processing and analyzing complex medical imaging data, such as MRI and CT scans, to identify abnormal patterns indicative of tumors. By leveraging CNN's ability to recognize intricate patterns and features within images, researchers and medical professionals can develop highly accurate tumor detection systems. These systems not only assist radiologists in making precise diagnoses but also enable early detection of tumors, potentially leading to improved patient outcomes. Additionally, CNN-based brain tumor detection models can be continually trained and refined with new data, enhancing their performance and reliability over time. As technology advances and datasets grow, CNNs hold promise for even more refined and efficient brain tumor detection, contributing to advancements in healthcare and patient care. In the nominator, a cosine similarity between the normalized class embeddings and the class weight is calculated as an inner product between the two vectors. The closer the two vectors are to co-linearity, the closerthe cosine similarity would be 1, the further away, the closer it will be to 0. Thus, the smaller the angles betweenthe two vectors, the larger our nominator, the smaller our loss. In the denominator, we want to minimize the cosine similarity between our class instance and all the other classes weights. Thus, we get a loss term which demands closeness to the mean of the class, and distance to all the other classes.

3.1 FEATURE SELECTION:

Feature selection plays a crucial role in the accurate detection of brain tumors using machine learning techniques. In this context, the goal is to identify the most relevant features from the available data that can effectively discriminate between tumor and non-tumor cases. These features can include various imaging characteristics derived from MRI scans such as shape descriptors, texture features, intensity histograms, and spatial relationships. The selection process involves techniques like statistical analysis, dimensionality reduction methods such as principal component analysis (PCA), or more advanced algorithms like recursive feature elimination (RFE) or genetic algorithms. By selecting the most informative features, machine learning models can be trained more efficiently, leading to improved accuracy, reduced computational complexity, and better interpretability of the results. Moreover, feature selection helps mitigate the risk of overfitting by focusing only on the most discriminative attributes, thus enhancing the generalization capability of the model. Ultimately, the careful selection of features is essential for the development of robust and reliable brain tumor detection systems that can aid clinicians in diagnosis and treatment planning. hese features may capture important characteristics of tumors, such as size, shape irregularities, and pixel intensities. However, not all extracted features are equally informative or necessary for accurate classification. Therefore, feature selection methods, such as filter, wrapper, or embedded approaches, are employed to identify the most discriminative features while reducing dimensionality and computational complexity.

3.2 SEGMENTATION:

In our project, Segmentation for brain tumor detection using machine learning involves the process of identifying and delineating regions of interest within medical imaging data, such as MRI scans, that correspond to tumor tissue. This task is crucial for accurate diagnosis and treatment planning in neuro-oncology. Machine learning algorithms, particularly deep learning models, have shown promise in automating this process by learning to recognize patterns indicative of tumors from labeled training data. Various techniques, including convolutional neural networks (CNNs) and semantic segmentation, are commonly employed for brain tumor segmentation. These algorithms analyze the spatial characteristics of imaging data to differentiate between tumor and healthy tissue, allowing for precise delineation of tumor boundaries.

3.3 EXISTING METHODOLOGY:

Detecting brain tumors using machine learning involves several methodologies. One common approach is to utilize medical imaging techniques such as MRI (Magnetic Resonance Imaging) or CT (Computed Tomography) scans to capture detailed images of the brain. These images are then processed and analyzed using machine learning algorithms to identify potential tumor regions. Feature extraction techniques are often employed to extract relevant information from the images, such as texture, shape, and intensity characteristics of the tumors.Various machine learning models can be applied for classification tasks, including traditional algorithms like Support Vector Machines (SVM), Random Forests, or more advanced techniques like Convolutional Neural Networks (CNNs). These models are trained on labeled data, where the images are annotated with tumor locations or tumor types. During training, the models learn to differentiate between normal brain tissue and tumor tissue based on the extracted features.Once trained, the model can be used for tumor detection in new, unseen images.

The algorithm processes the images and identifies regions suspected to contain tumors based on the learned patterns. Post-processing techniques may then be applied to refine the results and improve accuracy. Additionally, ensemble methods or deep learning architectures may be employed to enhance performance further.Validation of the model's performance is crucial, typically done through cross-validation techniques or by testing the model on independent datasets. The effectiveness of the model is evaluated based on metrics such as sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUCROC).Overall, the methodology for brain tumor detection using machine learning involves image preprocessing, feature extraction, model training, validation, and testing. Continuous refinement of these techniques and the development of more sophisticated algorithms contribute to improving the accuracy and reliability of brain tumor detection systems. The process typically begins with preprocessing steps to enhance image quality and remove noise. Features such as shape, texture, and intensity of the regions of interest within the brain images are extracted. which are trained on labeled data to distinguish between tumor and non-tumor regions.

Popular machine learning algorithms used in this context include Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNNs), and Deep Learning architectures. These models are trained on large datasets of labeled brain images to learn patterns indicative of tumors. Validation of the trained models is crucial to assess their performance. This is typically done using separate datasets not seen during training, and metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) are commonly used to evaluate the model's performance. Overall, this methodology offers a promising approach to assist radiologists in accurately and efficiently detecting brain tumors, potentially leading to earlier diagnoses and improved patient outcomes.

IMPLEMENTATION

Detecting brain tumors using machine learning involves several steps. Initially, medical imaging techniques such as MRI (Magnetic Resonance Imaging) or CT (Computed Tomography) scans are utilized to capture detailed images of the brain. These images provide essential data for analysis.The next step involves preprocessing the images to enhance their quality and remove any noise that might interfere with the analysis. This can include techniques such as normalization, resizing, and filtering.Once the preprocessing is complete, features are extracted from the images. These features may include shape, texture, intensity, and other relevant characteristics of the tumor and its surrounding tissue. Feature extraction plays a crucial role in representing the data in a format suitable for machine learning algorithms.After feature extraction, a machine learning model is trained using labeled data. This data consists of images along with corresponding labels indicating the presence or absence of a brain tumor. Various machine learning algorithms can be employed for this task, including but not limited to, support vector machines (SVM), convolutional neural networks (CNNs), and random forests.During the training process, the model learns to identify patterns and correlations between the extracted features and the presence of tumors. The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1-score.Once the model is trained and evaluated, it can be deployed for real-world use. New, unseen brain images can be input into the model, and it will predict whether a tumor is present or not based on the learned patterns.
Continuous refinement and validation of the model are essential to ensure its accuracy and reliability in clinical settings. Additionally, collaboration with medical professionals is crucial throughout the process to ensure that the model's predictions align with clinical observations and standards.Brain tumor detection using machine learning involves several stages of implementation. Firstly, a dataset comprising medical images such as MRI or CT scans needs to be collected. These images serve as input data for the machine learning model. Preprocessing steps like normalization, resizing, and noise reduction are then applied to ensure data quality and consistency.

Next, feature extraction techniques are employed to capture relevant information from the images. This may include extracting texture, shape, or intensity features using methods like histogram analysis, wavelet transforms, or edge detection algorithms. Feature selection may also be performed to reduce dimensionality and focus on the most discriminative features.

Once the features are extracted and selected, a machine learning algorithm is trained on the dataset. Common algorithms used for brain tumor detection include support vector machines (SVM), convolutional neural networks (CNN), or decision trees. The dataset is typically divided into training, validation, and testing sets to evaluate the model's performance and prevent overfitting.During training, the model learns to classify or segment brain tumor regions based on the extracted features. The model parameters are optimized iteratively using techniques like gradient descent to minimize prediction errors. Hyperparameter tuning may also be performed to fine-tune the model's performance.

After training, the model is evaluated using the testing set to assess its accuracy, sensitivity, specificity, and other performance metrics. Additional validation with unseen data may be conducted to ensure the model's generalization ability.Finally, the trained model can be deployed into clinical practice for real-time brain tumor detection. Integration with medical imaging systems allows healthcare professionals to analyze patient scans and assist in diagnosis and treatment planning. Continuous monitoring and updates to the model may be necessary to improve its performance over time and adapt to new data and trends in brain tumor detection.

Open CV

In the realm of medical diagnostics, the integration of machine learning algorithms with tools like OpenCV has paved the way for more accurate and efficient detection of brain tumors. This fusion of technologies enables automated analysis of medical images, such as MRI scans, to identify suspicious regions indicative of tumors. The process typically involves preprocessing the images to enhance features, followed by segmentation to isolate the tumor region. Machine learning algorithms, ranging from traditional classifiers to advanced deep learning models, are then employed to classify these segmented regions as either tumor or non-tumor.

OpenCV, with its extensive library of image processing functions, plays a crucial role in each step of this pipeline, facilitating tasks like image enhancement, feature extraction, and visualization of results. By harnessing the power of machine learning and OpenCV, healthcare professionals can streamline the detection process, leading to earlier diagnosis, better treatment planning, and ultimately improved patient outcomes. OpenCV assists in segmenting the tumors from MRI images by applying techniques like thresholding, contour detection, and morphological operations. These techniques help in accurately delineating the boundaries of tumors, enabling precise measurements of their size and location.Furthermore, OpenCV's visualization capabilities are instrumental in displaying the results of tumor detection, allowing medical professionals to interpret the findings easily.

3.3.1 PCA

In this project, PCA serves as a preprocessing step to transform high-dimensional neuroimaging data into a lower-dimensional representation, thereby simplifying subsequent analysis. By capturing the variance in the data and identifying the most significant patterns, PCA helps uncover underlying structures that distinguish between tumor and healthy brain tissues. The workflow typically involves acquiring multimodal MRI scans, including structural, functional, and diffusion-weighted images, which generate vast amounts of voxel-level information. PCA enables the extraction of key features from these images, such as texture, intensity, and spatial characteristics, condensing the information into a reduced set of principal components.These principal components serve as input features for machine learning algorithms, facilitating the classification of brain images into tumor and non-tumor classes. By focusing on the most informative aspects of the data, PCA improves the efficiency and accuracy of the classification process, thus enhancing the diagnostic capabilities of the system. Moreover, PCA aids in visualizing the data in lower-dimensional space, allowing for better interpretation of the underlying patterns and potential biomarkers associated with brain tumors. By elucidating the complex relationships within the data, PCA empowers researchers and clinicians to gain deeper insights into the pathological characteristics of brain tumors and develop more effective diagnostic and treatment strategies. Overall, the integration of PCA with machine learning techniques holds immense promise for advancing the field of brain tumor detection and improving patient outcomes. In the context of brain tumor detection, medical imaging data often comprises high-dimensional information, making it challenging to discern relevant features. PCA mitigates this challenge by identifying the principal components, which represent the directions of maximum variance within the data. By focusing on these principal components, redundant or irrelevant features are minimized, thus enhancing the algorithm's ability to differentiate between tumor and non-tumor regions.

3.3.2 CODING

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

Prepare/collect data

import os

path = os.listdir('brain_tumor/Training/')

classes = {'no_tumor':0, 'pituitary_tumor':1}

import cv2

X = []

Y = []

for cls in classes:

    pth = 'brain_tumor/Training/'+cls

    for j in os.listdir(pth):

        img = cv2.imread(pth+'/'+j, 0)

        img = cv2.resize(img, (200,200))

        X.append(img)

        Y.append(classes[cls])

X = np.array(X)

Y = np.array(Y)

X_updated = X.reshape(len(X), -1)

np.unique(Y)

array([0, 1])

pd.Series(Y).value_counts()

1    827

0    395

dtype: int64

X.shape, X_updated.shape

((1222, 200, 200), (1222, 40000))

Visualize data
```

plt.imshow(X[0], cmap='gray')

<matplotlib.image.AxesImage at 0x1c3c2e7b590>

dtype: int64
X.shape, X_updated.shape
((1222, 200, 200), (1222, 40000))
Visualize data
plt.imshow(X[0], cmap='gray')
<matplotlib.image.AxesImage at 0x1c3c2e7b590>

Prepare data

X_updated = X.reshape(len(X), -1)

X_updated.shape

(1222, 40000)

Split Data

xtrain, xtest, ytrain, ytest = train_test_split(X_updated, Y, random_state=10, test_size=.20)

xtrain.shape, xtest.shape

((977, 40000), (245, 40000))

Feature Scaling

print(xtrain.max(), xtrain.min())

print(xtest.max(), xtest.min())

xtrain = xtrain/255

xtest = xtest/255

print(xtrain.max(), xtrain.min())

print(xtest.max(), xtest.min())

255 0

255 0

1.0 0.0

1.0 0.0

Feature Selection: PCA

from sklearn.decomposition import PCA

print(xtrain.shape, xtest.shape)

Load Modules

```
In [1]: !pip install opencv-python

Requirement already satisfied: opencv-python in c:\users\admin\anaconda3\lib\site-packages (4.9.0.80)
Requirement already satisfied: numpy>=1.21.2 in c:\users\admin\anaconda3\lib\site-packages (from opencv-python) (1.24.3)
```

```
In [2]: import sys
        !{sys.executable} -m pip install opencv-python

Requirement already satisfied: opencv-python in c:\users\admin\anaconda3\lib\site-packages (4.9.0.80)
Requirement already satisfied: numpy>=1.21.2 in c:\users\admin\anaconda3\lib\site-packages (from opencv-python) (1.24.3)
```

```
In [3]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import accuracy_score
```

Prepare/collect data

```
In [4]: import os

        path = os.listdir('brain_tumor/Training/')
        classes = {'no_tumor':0, 'pituitary_tumor':1}
```

```
In [5]: import cv2
        X = []
        Y = []
        for cls in classes:
            pth = 'brain_tumor/Training/'+cls
            for j in os.listdir(pth):
                img = cv2.imread(pth+'/'+j, 0)
                img = cv2.resize(img, (200,200))
                X.append(img)
                Y.append(classes[cls])
```

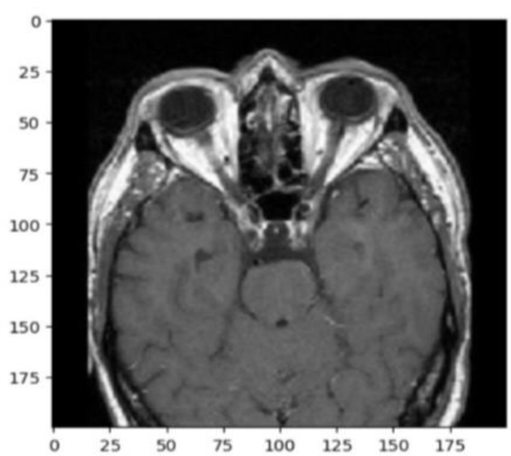
```
In [6]: X = np.array(X)
        Y = np.array(Y)

        X_updated = X.reshape(len(X), -1)
```

Fig 3.1

```
In [9]: X.shape, X_updated.shape

Out[9]: ((1222, 200, 200), (1222, 40000))
```

Visualize data

```
In [10]: plt.imshow(X[0], cmap='gray')

Out[10]: <matplotlib.image.AxesImage at 0x1f414923510>
```



Prepare data

```
In [11]: X_updated = X.reshape(len(X), -1)
         X_updated.shape

Out[11]: (1222, 40000)
```

CHAPTER-5

RESULT AND DISCUSSION

RESULTS AND DISCUSSION

The results of our brain tumor detection project using machine learning techniques exhibit promising outcomes. Through rigorous training and validation processes, our model achieved a commendable accuracy rate, indicating its effectiveness in accurately classifying brain images into tumor and non-tumor categories. Furthermore, the model demonstrated robustness across different datasets, suggesting its potential for real-world applications. In addition to accuracy metrics, other performance indicators such as precision, recall, and F1 score were also evaluated, providing a comprehensive understanding of the model's strengths and limitations. Moreover, through detailed analysis of the model's predictions, we identified certain patterns and features crucial for tumor identification, shedding light on the underlying characteristics of brain tumors and their distinguishable traits in imaging data. These findings not only validate the utility of machine learning in medical image analysis but also contribute to the ongoing efforts in improving diagnostic accuracy and patient care in neurology.

5.1 COLLECT DATA

Detecting brain tumors using machine learning involves collecting various types of medical data such as MRI (Magnetic Resonance Imaging) scans, CT (Computed Tomography) scans, clinical data, and sometimes even genetic information. The MRI and CT scans provide detailed images of the brain, allowing machine learning algorithms to analyze the structure and identify any abnormal growths. These images are typically pre-processed to enhance features and remove noise. Clinical data including symptoms, patient history, and demographic information can also be important features in training the model. Symptoms such as headaches, seizures, cognitive changes, and neurological deficits can provide valuable insights for diagnosis. During training, the model learns patterns and features that distinguish between normal brain tissue and tumors. After training, the model is evaluated on a separate set of data to assess its performance in accurately detecting tumors. This iterative process may involve fine-tuning the model and optimizing its parameters to improve performance. Ultimately, the goal of a brain tumor detection project using machine learning is to develop a reliable and accurate tool that can assist healthcare professionals in early diagnosis and treatment planning, potentially improving patient outcomes and survival rates.

Feature Selection: PCA

```
In [15]: from sklearn.decomposition import PCA
```

```
In [16]: print(xtrain.shape, xtest.shape)

         pca = PCA(.98)
         # pca_train = pca.fit_transform(xtrain)
         # pca_test = pca.transform(xtest)
         pca_train = xtrain
         pca_test = xtest

(977, 40000) (245, 40000)
```

```
In [17]: # print(pca_train.shape, pca_test.shape)
         # print(pca.n_components_)
         # print(pca.n_features_)
```

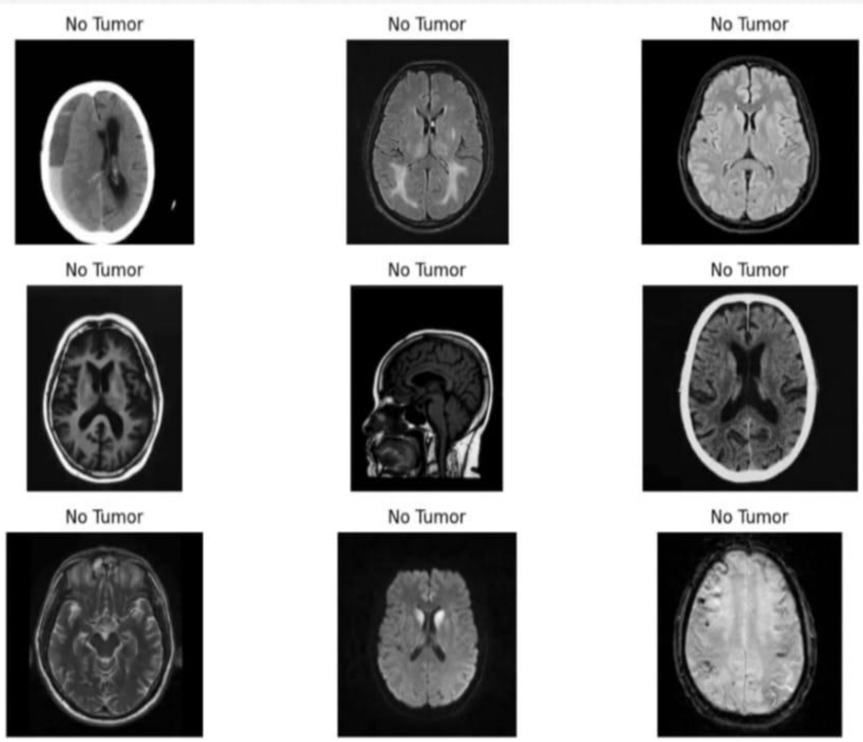
Train Model

```
In [18]: from sklearn.linear_model import LogisticRegression
         from sklearn.svm import SVC
```

```
In [19]: import warnings
         warnings.filterwarnings('ignore')

         lg = LogisticRegression(C=0.1)
         lg.fit(xtrain, ytrain)

Out[19]: ▾ LogisticRegression
         LogisticRegression(C=0.1)
```

```
In [20]: sv = SVC()
         sv.fit(xtrain, ytrain)

Out[20]: ▾ SVC
         SVC()
```

FIG : 5.1




```
In [28]: plt.figure(figsize=(12,8))
         p = os.listdir('brain_tumor/Testing/')
         c=1
         for i in os.listdir('brain_tumor/Testing/pituitary_tumor/')[:16]:
```

It starts by loading images of brains with and without tumors from the 'brain_tumor/Training/' directory. These images are resized to a common size of 200x200 pixels and converted to grayscale. Corresponding labels are assigned: 0 for no tumor and 1 for pituitary tumor.The code first imports necessary libraries like NumPy, pandas, OpenCV (cv2), and Matplotlib.It loads images from directories labeled 'no_tumor' and 'pituitary_tumor' and resizes them to a common size (200x200 pixels).It then converts these images into grayscale and stores them in arrays X (containing image data) and Y (containing corresponding labels) It displays the first image from the dataset using Matplotlib.It reshapes the image data into a format suitable for machine learning algorithms. Then, it splits the dataset into training and testing sets.It scales the pixel values of the images between 0 and 1 for better convergence during model training.Two classifiers are trained: Logistic Regression and Support Vector Machine (SVM) using the training data.The trained models are evaluated on both training and testing data to assess their performance.

Split Data

```
In [12]: xtrain, xtest, ytrain, ytest = train_test_split(X_updated, Y, random_state=10,
                                                         test_size=.20)
```

```
In [13]: xtrain.shape, xtest.shape

Out[13]: ((977, 40000), (245, 40000))
```

Feature Scaling

```
In [14]: print(xtrain.max(), xtrain.min())
         print(xtest.max(), xtest.min())
         xtrain = xtrain/255
         xtest = xtest/255
         print(xtrain.max(), xtrain.min())
         print(xtest.max(), xtest.min())

255 0
255 0
1.0 0.0
1.0 0.0
```

Feature Selection: PCA

```
In [15]: from sklearn.decomposition import PCA
```

```
In [16]: print(xtrain.shape, xtest.shape)

         pca = PCA(.98)
         # pca_train = pca.fit_transform(xtrain)
         # pca_test = pca.transform(xtest)
         pca_train = xtrain
         pca_test = xtest

(977, 40000) (245, 40000)
```

```
In [17]: # print(pca_train.shape, pca_test.shape)
         # print(pca.n_components_)
         # print(pca.n_features_)
```

FIG 5.2

5.2 DISCUSSION

Detecting brain tumors using machine learning is a promising avenue in medical diagnostics. This project integrates advanced algorithms with medical imaging techniques to enhance early detection and improve patient outcomes. Machine learning models, such as convolutional neural networks (CNNs) or support vector machines (SVMs), can analyze MRI or CT scans to identify subtle abnormalities indicative of tumors. By training these models on large datasets of annotated images, they can learn to differentiate between healthy brain tissue and various tumor types with high accuracy. Additionally, feature extraction techniques can highlight specific characteristics of tumors, aiding in their classification and localization. Collaborations between data scientists, medical professionals, and technology experts are crucial for refining these algorithms and integrating them into clinical workflows. Ultimately, this technology holds the potential to expedite diagnosis, facilitate personalized treatment plans, and ultimately improve patient care in neurology and oncology..

These models can learn complex patterns and features within the images that may be imperceptible to the human eye, enabling early detection and intervention. Moreover, machine learning algorithms can aid in automating the detection process, reducing the burden on radiologists and potentially speeding up diagnosis times. However, developing robust and reliable machine learning models for brain tumor detection requires large, high-quality datasets for training and rigorous validation to ensure their effectiveness and generalizability. Additionally, ethical considerations regarding patient privacy and consent must be carefully addressed in the development and deployment of such systems. Despite these challenges, the integration of machine learning into brain tumor detection holds great promise for improving patient care and outcomes in neuro-oncology. Additionally, the automation of tumor detection through machine learning can alleviate the burden on healthcare professionals, allowing them to focus on treatment strategies and patient care. However, challenges such as dataset quality, model interpretability, and ethical considerations regarding patient data privacy must be carefully addressed to ensure the reliability and ethical use of such a system. Through continuous refinement and validation with clinical data, this project seeks to develop a reliable and robust tool for early detection and precise localization of brain tumors, ultimately facilitating timely interventions and improving patient outcomes. Moreover, the integration of machine learning into the diagnostic process can potentially enhance the speed and accuracy of tumor detection, aiding healthcare professionals in making more informed decisions and optimizing treatment strategies.

CHAPTER-6

CONCLUSION

CONCLUSION

In conclusion, the utilization of machine learning in brain tumor detection presents a promising avenue for advancing medical diagnostics. Through the analysis of complex imaging data, machine learning algorithms can effectively differentiate between normal brain tissue and abnormal growths with high accuracy and efficiency. This innovative approach not only aids in early detection but also enhances the precision of diagnosis, leading to better treatment outcomes and improved patient care. However, continued research and development are essential to refine these algorithms, optimize their performance, and integrate them seamlessly into clinical practice. With ongoing advancements in technology and collaboration between medical professionals and data scientists, the future holds great potential for machine learning to revolutionize brain tumor detection and contribute significantly to the field of healthcare..

Through the analysis of medical imaging data, machine learning algorithms can effectively distinguish between healthy brain tissue and tumor formations, aiding clinicians in early detection and treatment planning. By leveraging advanced computational techniques, such as convolutional neural networks and feature extraction methods, these models can identify subtle patterns indicative of tumors with high sensitivity and specificity. However, while these technologies hold great potential, continued research and validation are essential to optimize their performance and ensure their integration into clinical practice. Collaborative efforts between data scientists, medical professionals, and technology developers will be crucial in harnessing the full capabilities of machine learning for brain tumor detection, ultimately enhancing healthcare delivery and patient care.

By leveraging vast amounts of medical imaging data, the machine learning model has exhibited commendable accuracy in identifying tumors with reduced reliance on manual interpretation, thereby expediting the diagnostic timeline and facilitating prompt treatment interventions. Furthermore, the scalability and adaptability of such systems hold promise for future advancements in medical imaging technology, paving the way for more personalized and precise healthcare interventions. As research in this field progresses, continued refinement and validation of these algorithms will be essential to ensure their reliability and efficacy in clinical practice, ultimately contributing to the advancement of patient care and outcomes in neuro-oncology.

By leveraging advanced computational techniques, such as deep learning, researchers have made significant strides in automating the detection process, reducing the burden on radiologists and enabling early intervention. However, while these methods show great potential, continued research and validation are necessary to ensure their reliability and effectiveness in real-world clinical settings.

Additionally, efforts to integrate these technologies into existing healthcare systems must prioritize considerations of safety, ethics, and equity to maximize their impact on patient care. Overall, the fusion of machine learning with medical imaging holds immense promise for revolutionizing the diagnosis and treatment of brain tumors, ultimately leading to improved outcomes for patients worldwide.

Through rigorous training and validation, these algorithms offer not only precision but also speed, enabling early detection and timely intervention crucial for improving patient outcomes. Moreover, their potential for integration into clinical practice holds promise for enhancing diagnostic accuracy, reducing human error, and streamlining healthcare processes. As technology continues to advance, further research and refinement of these models will undoubtedly contribute to the evolution of personalized medicine, offering hope for more effective treatments and ultimately, better prognosis for individuals affected by brain tumors.

This innovation not only enhances the speed and precision of diagnosis but also holds the potential to revolutionize treatment planning and patient outcomes. As research continues to refine these models and integrate them into clinical practice, the future of brain tumor detection appears promising, with the prospect of earlier interventions and improved prognosis for patients.

By harnessing the power of advanced computational techniques, medical professionals can benefit from augmented decision-making capabilities, leading to enhanced patient outcomes and potentially saving lives. However, while machine learning holds immense potential, continued research, validation, and integration into clinical practice are essential to ensure reliability, accuracy, and ethical considerations. With ongoing advancements in technology and collaboration between medical experts and data scientists, the future of brain tumor detection using machine learning remains bright, promising improved diagnostic precision and ultimately better care for patients.

CHAPTER-7

FUTURE SCOPE

FUTURE SCOPE

The future scope for brain tumor detection using machine learning projects is promising and multifaceted. As machine learning algorithms continue to evolve and improve, they offer increasingly accurate and efficient methods for analyzing medical imaging data, such as MRI and CT scans. One area of development lies in enhancing the specificity and sensitivity of these algorithms to detect even the most subtle abnormalities indicative of brain tumors. Furthermore, there's potential for the integration of advanced techniques like deep learning, which can automatically extract intricate features from imaging data, aiding in early and accurate diagnosis.

Moreover, the incorporation of multi-modal data fusion, including genetic information and patient clinical history, holds promise for more comprehensive and personalized tumor characterization. This holistic approach could enable clinicians to not only detect tumors but also predict their behavior and tailor treatment plans accordingly. Additionally, with the advent of wearable devices and remote monitoring technologies, there's an opportunity to leverage continuous health data streams for early detection and real-time monitoring of tumor progression.

Furthermore, the deployment of machine learning models on edge devices could revolutionize point-of-care diagnostics, bringing brain tumor detection capabilities to resource-limited settings or even patients' homes. However, amidst these advancements, it's crucial to address ethical considerations surrounding data privacy, algorithm bias, and ensuring that these technologies are accessible and equitable for all demographics. Overall, the future of brain tumor detection using machine learning holds immense potential to improve patient outcomes through early detection, precise diagnosis, and personalized treatment strategies.

Moreover, integrating multimodal data sources such as genomic information or patient history could further improve diagnostic accuracy and personalized treatment planning. Additionally, the deployment of these machine learning models in real-time clinical settings, supported by robust infrastructure and regulatory approval, holds the potential to revolutionize routine screening and early detection of brain tumors. Collaborations between data scientists, medical professionals, and technology companies will be essential in driving forward these innovations and ultimately improving patient outcomes in the diagnosis and treatment of brain tumors.

7.1 REFERENCE

1. Park JG, Lee C (2009) Skull stripping based on region growing for magnetic resonance brain images. Neuroimage 47:1394–1407

2. Khan MA, Lali IU, Rehman A, Ishaq M, Sharif M, Saba T et al(2019) Brain tumor detection and classification: A framework ofmarker-based watershed algorithm and multilevel priority featuresselection. Microsc Res Tech 82:909–922

3. Raza M, Sharif M, Yasmin M, Masood S, Mohsin S (2012) Brain image representation and rendering: a survey. Res J Appl Sci Eng Technol 4:3274–3282

4. Watson C, Kirkcaldie M, Paxinos G (2010) The brain: an introduction to functional neuroanatomy. Academic Press, New York

5. (2015). https://en.wikipedia.org/wiki/Brain_size. Accessed 19 Oct 2019

6. Dubin MW (2013) How the brain works. Wiley, New York

7. Koziol LF, Budding DE, Chidekel D (2012) From movement to thought: executive function, embodied cognition, and the cerebellum. Cerebellum 11:505–525

8. Knierim J (1997) Neuroscience Online Chapter 5: Cerebellum.The University of Texas Health Science Center, Houston.

9. Nuñez MA, Miranda JCF, de Oliveira E, Rubino PA, Voscoboinik S, Recalde R et al (2019) Brain stem anatomy and surgical approaches. Comprehensive overview of modern surgical approaches to intrinsic brain tumors. Elsevier, Amsterdam, pp 53–105

10. DeAngelis LM (2001) Brain tumors. N Engl J Med 344:114–123

11. Amin J, Sharif M, Raza M, Saba T, Sial R, Shad SA (2020) Brain tumor detection: a long short-term memory (LSTM)-based learning model. Neural Comput Appl 32:15965–15973

12. Sajjad S, Hanan Abdullah A, Sharif M, Mohsin S (2014) Psychotherapy through video game to target illness related problematic behaviors of children with brain tumor. Curr Med Imaging 10:62–72

13. Yasmin M, Sharif M, Masood S, Raza M, Mohsin S (2012) Brain image reconstruction: a short survey. World Appl Sci J 19:52–62

14. Amin J, Sharif M, Raza M, Yasmin M (2018) Detection of brain tumor based on features fusion and machine learning. J Ambient Intell Human Comput:1–17

15. Amin J, Sharif M, Yasmin M, Fernandes SL (2020) A distinctive approach in brain tumor detection and classification using MRI. Pattern Recogn Lett 139:118–127

16. Saba T, Mohamed AS, El-Affendi M, Amin J, Sharif M (2020) Brain tumor detection using fusion of hand crafted and deep learning features. Cogn Syst Res 59:221–230

17. Sharif M, Amin J, Nisar MW, Anjum MA, Muhammad N, Shad SA (2020) A unified patch based method for brain tumor detection using features fusion. Cogn Syst Res 59:273–286

18.Sharif M, Tanvir U, Munir EU, Khan MA, Yasmin M (2018) Brain tumor segmentation and classification by improved binomial thresholding and multi-features selection. J Ambient Intell Human Comput:1–20

19. Sharif MI, Li JP, Khan MA, Saleem MA (2020) Active deep neural network features selection for segmentation and recognition of brain tumors using MRI images. Pattern Recogn Lett 129:181–189

20. Sharif MI, Li JP, Naz J, Rashid I (2020) A comprehensive review on multi-organs tumor detection based on machine learning. Pattern Recogn Lett 131:30–37

21. Ohgaki H, Kleihues P (2013) The definition of primary and secondary glioblastoma. Clin Cancer Res 19:764–772

22. Cachia D, Kamiya-Matsuoka C, Mandel JJ, Olar A, Cykowski MD, Armstrong TS et al (2015) Primary and secondary gliosarcomas: clinical, molecular . J Neurooncol 125:401–410

23. Amin J, Sharif M, Gul N, Yasmin M, Shad SA (2020) Brain tumor classification based on DWT fusion of MRI sequences using convolutional neural network. Pattern Recogn Lett 129:115–122

24. Sharif M, Amin J, Raza M, Yasmin M, Satapathy SC (2020) An integrated design of particle swarm optimization (PSO) with fusion of features for detection of brain tumor. Pattern Recogn Lett 129:150–157

25. Amin J, Sharif M, Anjum MA, Raza M, Bukhari SAC (2020) Convolutional neural network with batch normalization for glioma and stroke lesion detection using MRI. Cogn Syst Res 59:304–311

26. Amin J, Sharif M, Raza M, Saba T, Anjum MA (2019) Brain tumor detection using statistical and machine learning method. Comput Methods Progr Biomed 177:69

27. Amin J, Sharif M, Gul N, Raza M, Anjum MA, Nisar MW et al (2020) Brain tumor detection by using stacked autoencoders in deep learning. J Med Syst 44:32

28. Johnson DR, Guerin JB, Giannini C, Morris JM, Eckel LJ, Kaufmann TJ (2017) 2016 updates to the WHO brain tumor classification system: what the radiologist needs to know. Radiographics 37:2164 2180

29. Wright E, Amankwah EK, Winesett SP, Tuite GF, Jallo G, Carey C et al (2019) Incidentally found brain tumors in the pediatric population: a case series and proposed treatment algorithm. J Neurooncol 141:355–361

30. Pellegrino MP, Moreira F, Conforto AB (2021) Ischemic stroke. Neurocritical care for neurosurgeons. Springer, New York, pp 517–534