ENHANCED BRAIN TUMOR SEGMENTATION USING CONDITIONAL RANDOM FIELDS AND BAT ALGORITHM OPTIMIZATION IN MULTIMODAL MRI

A PROJECT REPORT

Submitted by

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Kuniamuthur, Coimbatore – 641008.

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SUSTAINABLE DEVELOPMENT GOALS

The Sustainable Development Goals are a collection of 17 global goals designed to blue print to achieve a better and more sustainable future for all. The SDGs, set in 2015 by the United Nations General Assembly and intended to be achieved by the year 2030, In 2015, 195 nations agreed as a blue print that they can change the world for the better. The project is based on one of the 17 goals.

Questions	Answer Samples
Which SDGs does the project directly address?	SDG 3 –Good wealth and health being.
What strategies or actions are being implemented to achieve these goals?	Health initiatives, better healthcare access.
How is progress measured and reported in relation to the SDGs?	Health indicators, reports.
How were these goals identified as relevant to the project’s objectives?	Focus on public health.
Are there any partnerships or collaborations in place to enhance this impact?	Yes, with health orgs and NGOs.

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BONAFIDE CERTIFICATE

Certified that this project report " **ENHANCED BRAIN TUMOR SEGMENTATION USING CONDITIONAL RANDOM FIELDS AND BAT ALGORITHM OPTIMIZATION IN MULTIMODAL MRI** " is the bonafide work of " **ALMITHA DENCY J (727721EUIT009), ATCHAYA P (727721EUIT017), DEEPIGA N (727721EUIT027), JANANI K S (727721EUIT059)** " who carried out the project work under my supervision.

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INTERNAL EXAMINER EXTERNAL EXAMINER

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ABSTRACT

Detecting and segmenting brain tumors like glioblastoma in MRI scans is challenging due to heterogeneous signal characteristics. Traditional methods fall short in segmenting tumor components like contrast enhancement, necrosis, and edema. Voxel-based and model-based approaches also face limitations. This work addresses neuroimaging challenges in a big data context by developing a robust data management system and novel algorithms for organizing and analyzing large-scale fMRI datasets.

A new method was developed to overcome these challenges. Multimodal MR images are segmented into super pixels using algorithms to alleviate the sampling issue and to improve the sample representativeness. Next, features were extracted from the super pixels using multi-level Gabor wavelet filters. Based on the features, a conditional Random Field Grey Level Co-occurrence Matrix **(GLCM)** model and an affinity metric model for tumors were trained to overcome the limitations of previous generative models. Based on the output of (GLCM) and spatial affinity models, conditional random fields theory was applied to segment the tumor in a maximum a posteriori fashion given the smoothness prior defined by our affinity model. Finally, labeling noise was removed using "structural knowledge". The (**Bat Algorithm**) models were trained and tested on augmented images and validation is performed.

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ABBREVIATION	EXPANSION
GLCM	GREY LEVEL CO-OCCURRENCE MATRIX
MR	MAGNETIC RESONANCE
SOBEL	SOBEL OPERATOR FOR EDGE DETECTION
BA	BAT ALGORITHM
CRF	CONDITIONAL RANDOM FIELD
ROI	REGION OF INTEREST
MP	MAXIMUM POSTERIORI
GM	GRADIENT MAGNITUDE
HT	HOMOMORPHIC TRANSFORMATION
RS	RELABELED SEGMENTATION

CHAPTER 1

INTRODUCTION

The field of medical imaging and healthcare has witnessed a transformative revolution with the advent of intelligent techniques, particularly machine learning and artificial intelligence (AI). Among the critical applications of these technologies, the detection and classification of brain tumours stand out as a domain with profound implications for patient care and outcomes. Brain tumours, often life-threatening and requiring immediate attention, have historically posed significant diagnostic challenges. However, the integration of intelligent techniques into medical practice has ushered in a new era of precision and efficiency. This overview delves into the realm of brain tumour detection and classification, exploring the methodologies, challenges, and remarkable advancements achieved through the application of intelligent algorithms. From the acquisition of medical imaging data to the development of sophisticated deep learning models, this comprehensive overview navigates through the critical stages of brain tumour diagnosis. As we journey through this landscape, we'll uncover the significance of early detection, the importance of data pre-processing and feature extraction, the utilization of cutting-edge machine learning algorithms, and the transformative power of deep learning. Furthermore, we'll address the challenges faced in this field, such as data limitations and model interpretability, while highlighting advanced techniques and ongoing research that promise to further enhance the accuracy and efficacy of brain tumour detection and classification.

1.1 FEATURE SELECTION

Within the intricate labyrinth of the human brain, a formidable adversary sometimes emerges - the brain tumour. This formidable adversary, though often invisible to the naked eye, carries profound consequences for those it afflicts. As one of the most complex and delicate organs in the human body, the brain plays an irreplaceable role in controlling our thoughts, emotions, movements, and vital functions. Thus, the emergence of a tumour within this vital organ is a medical challenge that transcends the ordinary, demanding unwavering attention and innovative solutions. Brain tumours, whether benign or malignant, represent an intricate puzzle in the realm of healthcare. They are an aberrant proliferation of cells within the brain, capable of disrupting its intricate networks and processes. Unlike other diseases, brain tumours manifest in diverse forms and locations, each with unique characteristics and challenges. Their subtle onset and propensity to mimic benign conditions often lead to delayed diagnosis, making them a particularly insidious adversary. In this exploration, we delve into the multifaceted world of brain tumors, encompassing their various types, causes, symptoms, and the complexities they pose to medical professionals. We'll embark on a journey to understand the diagnostic techniques, treatment modalities, and the pivotal role of research and innovation in combating these formidable foes. The battle against brain tumors is a testament to the relentless pursuit of knowledge and the synergy between medical expertise and cutting-edge technology.

1.2 IMAGE CLASSIFICATION

In an increasingly digital world, where the sheer volume of visual data surpasses our ability to process it manually, image classification emerges as a pivotal technology. From recognizing familiar faces in photos to diagnosing medical conditions from scans and even guiding self-driving cars, image classification plays a transformative role across a spectrum of industries and applications. At its core, image classification is the art and science of teaching computers to "see" and understand visual content. Through the lens of artificial intelligence and machine learning, it enables machines to decipher intricate patterns, shapes, and features within images, making sense of the visual world in ways that were once exclusively human domains. This journey into the realm of image classification begins with the basics: understanding what it is and why it matters. We'll explore the pivotal role it plays in sectors like healthcare, retail, and security, reshaping the landscape of decision-making and automation. We'll delve into the technologies and algorithms powering image classification, from traditional methods to cutting-edge deep learning approaches, demystifying the process along the way.

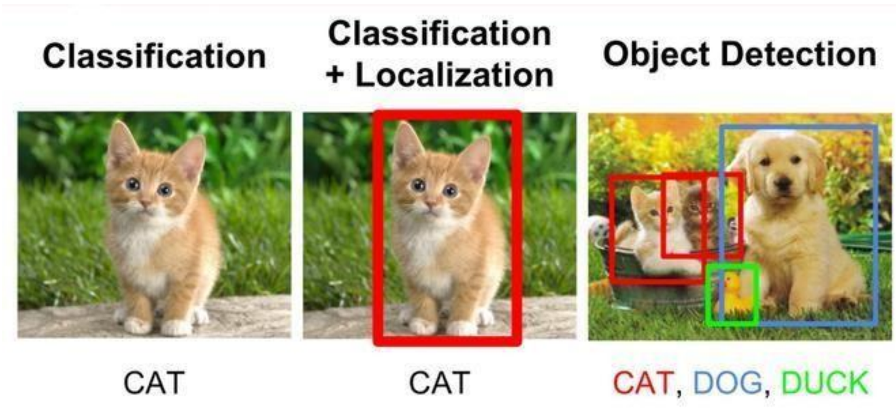

Figure 1.2.1 IMAGE CLASSIFICATION

1.3 IMAGE SEGMENTATION

In the realm of digital imagery, there exists a fundamental task that is akin to an artist's brushstroke on a canvas, meticulously defining the boundaries and regions within an image. This task, known as "image segmentation," is a powerful computational technique that bestows upon machines the ability to perceive and understand the visual world with remarkable precision. Image segmentation is the process of partitioning an image into distinct and meaningful regions or objects, isolating them from the surrounding background. It's as if we're drawing lines around specific elements within a picture, transforming a complex tapestry of pixels into a structured map of individual entities. While this might seem like a simple artistic endeavour, it holds immense significance in various fields, ranging from medical imaging and autonomous robotics to satellite image analysis and computer vision. This exploration into the world of image segmentation embarks on a quest to unravel its intricacies. We'll uncover why it is a critical component in the modern landscape of artificial intelligence and computer vision. From identifying tumours in medical scans to enabling self-driving cars to navigate their surroundings, image segmentation empowers machines to make sense of their visual environment, just as our eyes do.

1.4 DEEP LEARNING

In the ever-advancing landscape of artificial intelligence, a profound transformation is occurring - one that mirrors the human brain's intricate workings and has the potential to revolutionize the capabilities of machines. This transformation is known as "deep learning," and it stands as the pinnacle of machine learning, enabling computers to achieve feats once considered the realm of science fiction. Deep learning, at its core, represents a leap forward in the quest to make machines understand, reason, and interact with the world in more nuanced and human-like ways. It is a subset of machine learning, distinguished by its ability to automatically learn and extract intricate patterns and representations from vast amounts of data. At the heart of deep learning are artificial neural networks, inspired by the intricate web of neurons in the human brain. In our journey into the world of deep learning, we will unravel its essence and explore the transformative power it holds. We'll delve into the fundamental components, from artificial neurons to layers of interconnected networks, understanding how they mimic the brain's ability to process information hierarchically and extract increasingly abstract features.

1.5 MACHINE LEARNING

In the ever-evolving landscape of technology, there exists a ground-breaking concept that transcends traditional programming paradigms, breathing life into the machines that surround us. This concept, known as "machine learning," is at the forefront of the digital revolution, redefining how computers learn, adapt, and make decisions. Machine learning is more than just a buzzword; it represents a paradigm shift in how we approach problem-solving and decision-making in the digital age. At its essence, it empowers machines to learn from data, to recognize patterns, and to make predictions or decisions without explicit programming. It's the art and science of enabling computers to evolve and improve their performance over time, much like the way humans learn from experience. In this journey into the realm of machine learning, we embark on a quest to unravel its mysteries and explore its profound implications. We'll delve into the fundamental principles that underpin machine learning, from the concept of algorithms and data to the importance of training and testing. We'll discover how machines can not only process information but also extract meaningful insights, ranging from natural language understanding to image recognition and financial forecasting.

1.6 OBJECTIVES

- To develop a system that can accurately and efficiently detect and segment brain tumors in MRI images.
- To improve upon the accuracy and efficiency of traditional brain tumor detection and segmentation methods.
- To develop a system that is easy to implement and can be used with a variety of programming languages and software tools.
- To make brain tumor detection and segmentation more accessible to patients in developing countries and other underserved areas.

CHAPTER 2

LITERATURE SURVEY

2.1 BRAIN TUMOR CLASSIFICATION

Machiraju Jaya Lakshmi et.al. Has proposed in this paper, From the past decade, many researchers are focused on the brain tumor detection mechanism using magnetic resonance images. The traditional approaches follow the feature extraction process from bottom layer in the network. This scenario is not suitable to the medical images. To address this issue, the proposed model employed Inception-v3 convolution neural network model which is a deep learning mechanism. This model extracts the multi-level features and classifies them to find the early detection of brain tumor. The proposed model uses the deep learning approach and hyper parameters. These parameters are optimized using the Adam Optimizer and loss function. The loss function helps the machines to model the algorithm with input data. The soft max classifier is used in the proposed model to classify the images in to multiple classes. It is observed that the accuracy of the Inception-v3 algorithm is recorded as 99.34% in training data and 89% accuracy at validation data. The developments in the medical field support the medical practitioners to facilitate the patients effectively. With the utilization of artificial intelligence (AI) in the health care helps the medical domain to serve more to the patients. According to the statistics of 2019, most of the deaths in the world are happened due to the cardiovascular diseases and in the next place the cancer diseases are occupied. Brain tumor disease is one of the life threating diseases in the world. Magnetic Resonance Imaging (MRI) is one of the safest imaging techniques that extracts the good images and helps in the process of medical diagnosis. Many researchers are focused on improving the quality of the MR images and also to develop the new methods for quicker and easy medical diagnosis from the MR images. This study concentrated on the brain tumor detection from MR images This paper explained the deep learning mechanism for detection of brain tumors in MR images. In the proposed pre-trained Inception-V3 deep learning architecture, some of the inception modules at bottom layers are removed and concatenated the features from the inception modules from the top to perform the classification in the Brain MR Image datasets. The last inception module in the architecture is concatenated with the fully connected layers, global average pooling and extracted features of the images from inception modules. The proposed model extracts the features from the fully connected layer and forwards the extracted features to the classifier. The soft max classifier is used in the proposed model to classify the images in to multiple classes. Tensor flow and Keros with backend have been used to train the deep learning model in the proposed architecture. The accuracy of the proposed model is recorded as 99.34% which is high compared to the VGG-16 and ResNet50 models. In the future, we are concentrating on the combination of Dense Net model and Inception-v3 model to improve the accuracy.

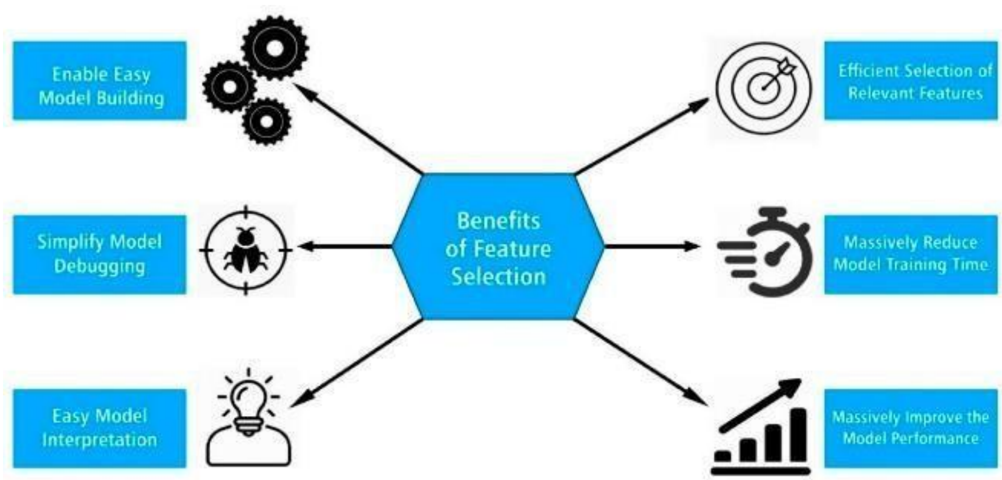

Figure 2.1.1 FEATURE SELECTION

Tumor Type	Characteristics	Severity Level	Common Detection Method	Treatment Options
Glioma	Rapid growth, infiltrative nature	High	MRI, CT Scan	Surgery, chemotherapy, radiotherapy
Meningioma	Slow-growing, well-defined boundaries	Low to Medium	MRI	Surgery, Radiation Therapy
Pituitary Tumor	Affects hormone regulation	Medium	MRI, Blood Tests	Surgery, Hormone Replacement
Metastatic	Spread from other parts of the body	High	PET Scan, MRI	Chemotherapy, Targeted Therapy
Acoustic Neuroma	Affects hearing and balance	Low to Medium	MRI, Audiometry	Surgery, Stereotactic Radiosurgery

Table 2.1.1 COMPARISON OF BRAIN TUMOR TYPES AND CHARACTERISTICS

2.2 BRAIN TUMOR CLASSIFCATION BASED ON ATTENTION GUIDED DEEP LEARNING MODEL

Wen Jun et.al. has proposed in this paper Cancer is the second leading cause of death worldwide. Brain tumors count for one out of every four cancer deaths. Providing an accurate and timely diagnosis can result in timely treatments. In recent years, the rapid development of image classification has facilitated computer-aided diagnosis. The convolutional neural network (CNN) is one of the most widely used neural network models for classifying images. However, its effectiveness is limited because it cannot accurately identify the focal point of the lesion. This paper proposes a novel brain tumor classification model that integrates an attention mechanism and a multipath network to solve the above issues. An attention mechanism is used to select the critical information belonging to the target region while ignoring irrelevant details. A multipath network assigns the data to multiple channels, before converting each channel and merging the results of all branches. The multipath network is equivalent to grouped convolution, which reduces the complexity. Experimental evaluations on this model using a dataset consisting of 3064 MR images achieved an overall accuracy of 98.61%, which outperforms previous studies on this dataset. According to the World Health Organization, cancer is the second leading cause of human death. Brain tumors count for one out of every four cancer deaths. In the study conducted in 2019, 17,000 people die of brain cancer each year in the United States. The five-year survival rate was 34% for men and 36% for women after being diagnosed. The earlier the diagnosis and treatment, the better the rehabilitation effect, and the longer the survival. Medical imaging is considered to be one of the most significant advances in improving clinical cancer diagnoses. Magnetic resonance imaging (MRI) is widely used to examine the abnormalities in brain tumors. However, such tasks are time-consuming and require experienced radiologists. It may cause errors due to human beings. In recent years, computer-aided diagnosis has become popular in medical research. With the rise of deep learning, deep neural networks are playing an increasingly important role in image classification. This paper proposes a novel CNN architecture for classifying brain tumors. The classification is performed on a T1-weighted contrast-enhanced MRI image dataset containing three tumor types. The proposed network integrates a multipath network and attention mechanism to extract features from brain MRI images. The attention mechanism can focus on critical information, while the multipath network can efficiently improve the accuracy compared with increasing the width and depth of the network.

2.3 BRAIN TUMOR CLASSIFICATION FRAMEWORK

Archie Rehman et.al. Has proposed in this system, Brain tumors are the most destructive disease, leading to a very short life expectancy in their highest grade. The misdiagnosis of brain tumors will result in wrong medical intercession and reduce chance of survival of patients. The accurate diagnosis of brain tumor is a key point to make a proper treatment planning to cure and improve the existence of patients with brain tumors disease. The computer-aided tumor detection systems and convolutional neural networks provided success stories and have made important strides in the field of machine learning. The deep convolutional layers extract important and robust features automatically from the input space as compared to traditional predecessor neural network layers. In the proposed framework, we conduct three studies using three architectures of convolutional neural networks (Alex Net, Google Net, and VGG Net) to classify brain tumors such as meningioma, glioma, and pituitary. Each study then explores the transfer learning techniques, i.e., fine-tune and freeze using MRI slices of brain tumor dataset—Figshare. The data augmentation techniques are applied to the MRI slices for generalization of results, increasing the dataset samples and reducing the chance of over-fitting. In the proposed studies, the fine-tune VGG16 architecture attained highest accuracy up to

98.69 in terms of classification and detection. Over the past decades, diseases have stumbled that are overcome with the human intelligence and biomedical advance, but still cancer, by virtue of its unstable nature remains a curse to the mankind. One of the fatal and most growing diseases is brain tumor cancer. Brain is the core and most complex organ of human body that comprises nerve cells and tissues to control the foremost activities of the entire body like breathing, movement of muscles and our senses. Every cells have their own capabilities; some cells grow with their own functionality, and some lose their capacity, resist, and grow aberrant. These mass collections of abnormal cells form the tissue are called as tumor. Cancerous brain tumors are uncontrolled and unnatural growth of brain cells. It is one of the most life-threatening and lethal cancers. In, approximately 23,000 patient were diagnosed brain tumor in the USA. According to 2017 cancer statistics , brain tumor is measured as one of the foremost causes of cancer related indisposition, morbidity, and mortality around the world both in children and in adults. In summary, the presented work is a pioneer study in the domain of brain tumor classification using transfer learning and deep CNN architectures. We applied transfer learning techniques using natural images of ImageNet dataset (source task) and classified the brain tumor type from glioma, meningioma, and pituitary using Fig share dataset (target task). We deployed three powerful deep CNN architectures (AlexNet, Google Net, and VGG Net) on MRI slices of Fig share to identify the tumor type. To evaluate and explore the performance of deep networks, two studies of transfer learning (fine-tune and freeze) are conducted to extract the discriminative visual features and patterns from MRI slices. We have attained the highest accuracy of 98.69% using fine-tune VGG16 network among all experiments.

2.4 MEDICAL ANOMALY DETECTION

Tharindu Fernando et.al. Has proposed in this system Machine learning-based medical anomaly detection is an important problem that has been extensively studied. Numerous approaches have been proposed across various medical application domains and we observe several similarities across these distinct applications. Despite this comparability, we observe a lack of structured organization of these diverse research applications such that their advantages and limitations can be studied. The principal aim of this survey is to provide a thorough theoretical analysis of popular deep learning techniques in medical anomaly detection. In particular, we contribute a coherent and systematic review of state-of-the-art techniques, comparing and contrasting their architectural differences as well as training algorithms. Furthermore, we provide a comprehensive overview of deep model interpretation strategies that can be used to interpret model decisions. In addition, we outline the key limitations of existing deep medical anomaly detection techniques and propose key research directions for further investigation Identifying data samples that do not fit the overall data distribution is the principle task in anomaly detection. Anomalies can arise due to various reasons such as noise in the data capture process, changes in underlying phenomenon, or due to new or previously unseen conditions in the captured environment. Therefore, anomaly detection is a crucial task in medical signal analysis. The dawn of deep learning has revolutionized the machine learning field and it's success has seeped into the domain of medical anomaly detection, which has resulted in a myriad of research articles leveraging deep machine learning architectures for medical anomaly detection. The principal aim of this survey is to present a structured and comprehensive review of this existing literature, systematically comparing and contrasting methodologies. Furthermore, we provide an extensive investigation in to deep model interpretation strategies, which is critical when applying 'black box' deep models for medical diagnosis and to understand why a decision is reached. In this survey paper, we have discussed various approaches across deep learning-based medical anomaly detection. In particular, we have outlined different data capture settings across different medical applications, numerous deep learning architectures that have been motivated due to these different data types and problem specifications, and various learning strategies that have been applied.

2.5 BRAIN TUMOR SEGMENTATION

Almetwally M. Mostafa to et.al. Has proposed in this system, Brain tumor (BT) diagnosis is a lengthy process, and great skill and expertise are required from radiologists. As the number of patients has expanded, so has the amount of data to be processed, making previous techniques both costly and ineffective. Many academics have examined a range of reliable and quick techniques for identifying and categorizing BTs. Recently, deep learning (DL) methods have gained popularity for creating computer algorithms that can quickly and reliably diagnose or segment BTs. To identify BTs in medical images, DL permits a pre-trained convolutional neural network (CNN) model. The suggested magnetic resonance imaging (MRI) images of BTs are included in the BT segmentation dataset, which was created as a benchmark for developing and evaluating algorithms for BT segmentation and diagnosis. There are 335 annotated MRI images in the collection. For the purpose of developing and testing BT segmentation and diagnosis algorithms, the brain tumor segmentation (BraTS) dataset was produced. A deep CNN was also utilized in the model-building process for segmenting BTs using the BraTS dataset. To train the model, a categorical cross-entropy loss function and an optimizer, such as Adam, were employed. Finally, the model's output successfully identified and segmented BTs in the dataset, attaining a validation accuracy of 98%.A tumor is created when aberrant cells divide out of control, generating a mass that might impair the tissue or organ's ability to function normally . The genesis, foundation, and cell types of tumors are distinct characteristics. The brain shows early stages of tumors mostly in the cerebrum region, although secondary tumors enter the brain from other parts of the body. Cancerous tumors are classified as malignant (high-grade) or benign (low-grade), respectively. A malignant brain tumor (BT) develops faster than a benign BT and is more likely to infect surrounding tissues. Consequently, a primary malignant BT has an unfavorable prognosis and significantly lowers cognitive function and quality of life. Despite the fact that medical technology is fairly sophisticated nowadays, it remains an issue that some diseases are difficult for doctors to identify early. BT is diagnosed by doctors using brain tomography and magnetic resonance imaging (MRI) scans . These images from several patients have been gathered. As a result, we have successfully used the BraTS dataset to create a deep CNN for BT segmentation. The U-Net design, a well-known architecture for image segmentation issues, serves as the model's foundation. Convolutional and max-pooling layers, up sampling layers, and concatenation operations make up the U-Net architecture, which enables the model to learn both low- and high-level properties from the input images.

2.6 BRAIN TUMOR DETECTION AND CLASSIFICATION

Hanaa ZainEldin et.al has proposed in this paper Diagnosing a brain tumor takes a long time and relies heavily on the radiologist's abilities and experience. The amount of data that must be handled has increased dramatically as the number of patients has increased, making old procedures both costly and ineffective. Many researchers investigated a variety of algorithms for detecting and classifying brain tumors that were both accurate and fast. Deep Learning (DL) approaches have recently been popular in developing automated systems capable of accurately diagnosing or segmenting brain tumors in less time. DL enables a pre-trained Convolutional Neural Network (CNN) model for medical images, specifically for classifying brain cancers. The proposed Brain Tumor Classification Model based on CNN (BCM CNN) is a CNN hyper parameters optimization using an adaptive dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) algorithm. There is an optimization of hyper parameters followed by a training model built with Inception- ResnetV2. The model employs commonly used pre-trained models (Inception-ResnetV2) to improve brain tumor diagnosis, and its output is a binary 0 or 1 (0: Normal, 1: Tumor). There are primarily two types of hyper parameters hyper parameters that determine the underlying network structure; a hyper parameter that is responsible for training the network. The ADSCFGWO algorithm draws from both the sine cosine and grey wolf algorithms in an adaptable framework that uses both algorithms' strengths. The experimental results show that the BCM-CNN as a classifier achieved the best results due to the enhancement of the CNN's performance by the CNN optimization's hyper parameters. The BCM-CNN has achieved 99.98% accuracy with the BRaTS 2021 Task 1 dataset. Recently, digital medical images have been essential for detecting numerous illnesses. It is additionally used for training and research. The need for electronic medical images is growing dramatically; for example, in 2002, the Department of Radiology at the University Hospital of Geneva produced between 12,000 and 15,000 images daily. An efficient and exact computer-aided diagnostic system is required for medical report creation and medical image research. The old method of manually evaluating medical imaging is time consuming, inaccurate, and prone to human error. Over the medical diseases, the brain tumor has become a serious issue, ranking 10th among the major causes of death in the US.

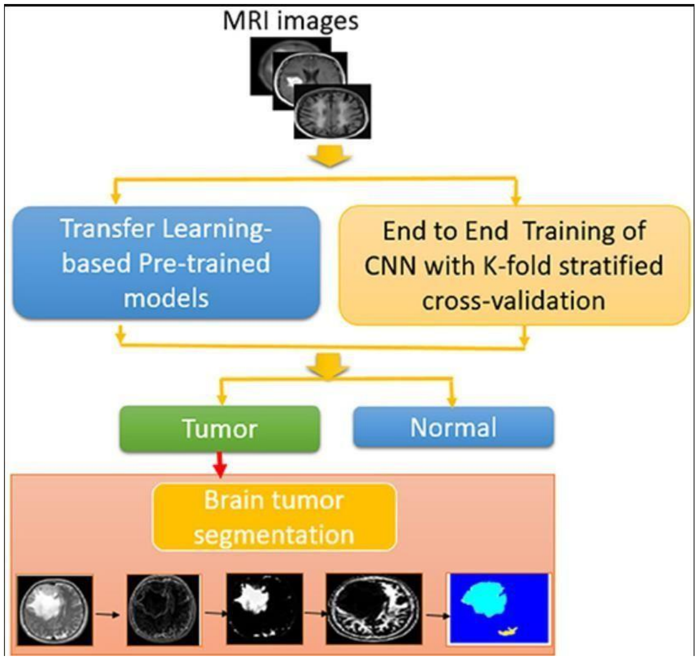

Figure 2.6.1 **BRAIN TUMOR DETECTION AND SEGMENTATION**

2.7 BRAIN TUMOR SURVIVAL PREDICTION

Yannick Suter et.al has proposed in this paper Deep learning for regression tasks on medical imaging data has shown promising results. However, compared to other approaches, their power is strongly linked to the dataset size. In this study, we evaluate 3D-convolutional neural networks (CNNs) and classical regression methods with hand-crafted features for survival time regression of patients with high-grade brain tumors. The tested CNNs for regression showed promising but unstable results. The best performing deep learning approach reached an accuracy of 51.5% on held-out samples of the training set. All tested deep learning experiments were outperformed by a Support Vector Classifier (SVC) using 30 radionics features. The investigated features included intensity, shape, location and deep features. The submitted method to the BraTS 2018 survival prediction challenge is an ensemble of SVCs, which reached a cross-validated accuracy of 72

.2% on the BraTS 2018 training set, 57 .1% on the validation set, and 42 .9% on the testing set. The results suggest that more training data is necessary for a stable performance of a CNN model for direct regression from magnetic resonance images, and that non-imaging clinical patient information is crucial along with imaging information. High-grade gliomas are the most frequent primary brain tumors in humans. Due to their rapid growth and infiltrative nature, the prognosis for patients with gliomas ranking at grade III or IV on the Word Health Organization (WHO) grading scheme is poor, with a median survival time of only 14 months. Finding biomarkers based on magnetic resonance (MR) imaging data could lean improved disease progression monitoring and support clinicians in treatment decision-making. Our experiments with 3D-CNNs for survival time regression confirmed observations made by other groups in last year's competition, that these models tend to converge and over fit extremely fast on the training set, but show poor generalization when tested on the held-out samples. The top-ranked methods of last year's competition were mainly based on RF. A reason for this may be the relatively few samples to learn from. Classical regression techniques typically have fewer learnable parameters compared to a CNN and perform better with sparse training data.

2.8 3D U-NET FOR MEDICAL IMAGE ANALYSIS

Girija Chetty et.al has proposed in this system The success of deep learning, a subfield of Artificial Intelligence technologies in the field of image analysis and computer can be leveraged for building better decision support systems for clinical radiological settings. Detecting and segmenting tumorous tissues in brain region using deep learning and artificial intelligence is one such scenario, where radiologists can benefit from the computer based second opinion or decision support, for detecting the severity of disease, and survival of the subject with an accurate and timely clinical diagnosis. Gliomas are the aggressive form of brain tumors having irregular shape and ambiguous boundaries, making them one of the hardest tumors to detect, and often require a combined analysis of different types of radiological scans to make an accurate detection. In this paper, we present a fully automatic deep learning method for brain tumor segmentation in multi modal multi-contrast magnetic resonance image scans. The proposed approach is based on light weight UNET architecture, consisting of a multimodal CNN encoder-decoder based computational model. . Using the publicly available Brain Tumor Segmentation Challenge 2018 dataset, available from the Medical Image Computing and Computer Assisted Intervention society, our novel approach based on proposed light-weight UNet model, with no data augmentation requirements and without use of heavy computational resources, has resulted in an improved performance, as compared to the previous models in the challenge task that used heavy computational architectures and resources and with different data augmentation approaches. This makes the model proposed in this work more suitable for remote, extreme and low resource health care settings Segmenting brain tumors automatically from 3D magnetic resonance images is necessary for diagnosis, monitoring and treatment planning of the disease. Manual segmentation and delineation methods done in clinical settings require expert anatomical knowledge, and are time consuming, expensive and prone to human errors. Automatic computer based semantic segmentation approached for tumor sub region segmentation from 3D MRIs based on deep learning architectures can lead to availability of decision support tools that can help alleviate the manual and laborious task of traditional segmentation approaches in clinical settings, allowing radiologist to focus on more important tasks of treatment planning and interventions for the patients. Magnetic resonance imaging is one of the most efficient radiology scan technique for detecting brain lesions and tumors, as it is an non-invasive detection technique, and when used in conjunction with other sensor modalities, such as computer tomography, and positron emission tomography, can provide better understanding of the lesion or tumor structure in the brain. A novel low-resource and light weight CNN based 3D U-Net architecture is proposed in this work for multi-class tumor tissue segmentation.

2.9 CLOUD-BASED SEMANTIC SEGMENTATION

Zeeshan Shaukat et.al has proposed in this paper Glioma is the most aggressive and dangerous primary brain tumor with a survival time of less than 14 months. Segmentation of tumors is a necessary task in the image processing of the gliomas and is important for its timely diagnosis and starting a treatment. Using 3D U-net architecture to perform semantic segmentation on brain tumor dataset is at the core of deep learning. In this paper, we present a unique cloud-based 3D U-Net method to perform brain tumor segmentation using BRATS dataset. The system was effectively trained by using Adam optimization solver by utilizing multiple hyper parameters. We got an average dice score of 95% which makes our method the first cloud-based method to achieve maximum accuracy. The dice score is calculated by using Sørensen-Dice similarity coefficient. We also performed an extensive literature review of the brain tumor segmentation methods implemented in the last fve years to get a state-of-the-art picture of well-known methodologies with a higher dice score. In comparison to the already implemented architectures, our method ranks on top in terms of accuracy in using a cloud-based 3D U-Net framework for glioma segmentation. Brain tumors are the most dangerous type of tumors that causes life-threatening consequences. Glioma is the most common and aggressive primary brain tumor that comprises of 16% of neoplasms occurring in brain and central nervous system (CNS). Gliomas mostly occur in brain and 61% of all gliomas appear in the four lobes of the brain. However, they can also emerge in spinal cord, cerebellum, and brain stem. Glioma occurs usually at an age of 64 years on average but it can emerge at any time of life including childhood. It is a fatal type of cancer and the survival time of patients after diagnosis is less than 14 months on average. According to World Health Organization, gliomas are classified into 4 grades depending on their malignancy i.e. grade I, grade II, grade III and grade IV. Grade I and grade II gliomas are considered as low-grade in which tumors grow slowly while grade III and grade IV are high-grade that grows quickly and can be fatal. Grade I gliomas occur rarely and are mostly limited to childhood. Grade II gliomas can appear at any age and mostly occur in young adults. Grade III and grade IV gliomas are the most malignant classes of brain tumor. Among all the different types, glioblastoma is the most dangerous and malignant type with an incident rate of 3.2 in a population of 100,000 people. It spreads more quickly and it is difficult to remove it completely even after a surgery. An early and comprehensive diagnosis and treatment method is necessary for patient's survival We developed a fully automatic cloud-based 3D-UNet architecture for semantic segmentation on brain tumor (BRATS) dataset. Our method proves to be the most accurate cloud-based deep learning brain tumor segmentation method with a distinctive dice score of 95%. Tis study practices divergence of the 3-D U-Net network in which the preliminary sequences of convolutional layers (CL) are intermixed with max pooling layers. Using cloud computing has several benefits. It reduces computational cost as this network is accessible all over the globe. It only requires a stable internet connection and a terminal device for accessibility.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Brain is the controlling center of our body. With the advent of time, newer and newer brain diseases are being discovered. Thus, because of the variability of brain diseases, existing diagnosis or detection systems are becoming challenging and are still an open problem for research. Detection of brain diseases at an early stage can make a huge difference in attempting to cure them. In recent years, the use of artificial intelligence (AI) is surging through all spheres of science, and no doubt, it is revolutionizing the field of neurology. Application of AI in medical science has made brain disease prediction and detection more accurate and precise. In this study, we present a review on recent machine learning and deep learning approaches in detecting four brain diseases such as Alzheimer's disease (AD), brain tumor, epilepsy, and Parkinson's disease. 147 recent articles on four brain diseases are reviewed considering diverse machine learning and deep learning approaches, modalities, datasets etc. Twenty-two datasets are discussed which are used most frequently in the reviewed articles as a primary source of brain disease data. Moreover, a brief overview of different feature extraction techniques that are used in diagnosing brain diseases is provided. Finally, key findings from the reviewed articles are summarized and a number of major issues related to machine learning/deep learning-based brain disease diagnostic approaches are discussed. Through this study, we aim at finding the most accurate technique for detecting different brain diseases which can be employed for future betterment.

3.1.1 DRAWBACKS

- It can be difficult to understand how machine learning and deep learning models make their predictions. This can make it difficult to trust the models and to identify potential biases.
- Machine learning and deep learning models require large amounts of data to train. This data can be expensive and time-consuming to collect.
- Machine learning and deep learning models can over fit or under fit the training data. Over fitting occurs when the model learns the training data too well and fails to generalize to new data. Under fitting occurs when the model does not learn the training data well enough and fails to make accurate predictions.

3.2 PROPOSED SYSTEM

The proposed system Grey Level Co-Occurrence Matrix (**GLCM**) Homomorphic Function is chosen in order to distinguish the interior area from other organs in the MR image dataset. Then modified gradient magnitude region growing algorithm is applied, in which gradient magnitude is computed by Sobel operator and employed as the definition of homogeneity criterion. This implementation allowed stable boundary detection when the gradient suffers from intersection variations and gaps. By analyzing the gradient magnitude, the sufficient contrast present on the boundary region that increases the accuracy of segmentation. To calculate the size of segmented tumor the relabeled method based on remaps the labels associated with object in a segmented image such that the label numbers are consecutive with no gaps between the label numbers used. Any object can be extracted from the relabeled output using a binary threshold. Here, BAT algorithm is adjusted to extract and relabeled the tumor and then find its size in pixels. The algorithm works well in two stages. The first stage is to determine the input image labels and the number of pixels in each label. The second stage is to determine the output requested region to get total number of pixels accessed. Segmented areas are automatically calculated and to get desired tumor area per slice.

3.2.1 ADVANTAGES

- CRFs are able to model the complex interactions between voxels in an image, which can lead to more accurate segmentation results than other methods.
- CRFs are less sensitive to noise and artifacts in the image, which makes them more robust than other methods.
- The CRFs can easily model complex shapes, such as brain tumors, which can be difficult to segment using other methods.
- It can incorporate prior knowledge about the tumor, such as its symmetry and continuity, into the segmentation process, which can further improve the accuracy and robustness of the results.

3.2.2 PERFORMANCE COMPARISON OF MODELS

- Comparison Table: Brain Tumor Detection and Segmentation Technique

Model	Technique	Accuracy	Dataset	Remarks
Inception-v3	Deep Learning (CNN)	99.34% (train), 89% (validation)	Brain MR Image datasets	High accuracy for training, lower on validation
Attention Guided Deep Learning	CNN with Attention Mechanism	98.61%	3064 MR Images	Improved focus on critical regions
Transfer Learning (VGG16, AlexNet, GoogleNet)	CNN with Transfer Learning	98.69%	MRI Slices (Figshare)	Fine-tune VGG16 achieved highest accuracy
Sine-Cosine Fitness Grey Wolf Optimization (BCM-CNN)	CNN with Hyper parameter Optimization	99.98%	BRaTS 2021	Optimized CNN performance using ADSCFGWO
Low Resource 3D U-Net	CNN with 3D U-Net Architecture	95% (Dice Score)	BRaTS 2018	Lightweight model, suitable for low-resource settings
Deep Learning for Medical Anomaly Detection	CNN and Classical Regression	72.2% (cross-validated)	BraTS 2018	Lower stability in direct regression

Table 3.2.2.1 COMPARISON TABLE

- Comparison Graph: A bar graph depicting the accuracy of each model will be presented, showcasing their performance on various datasets.

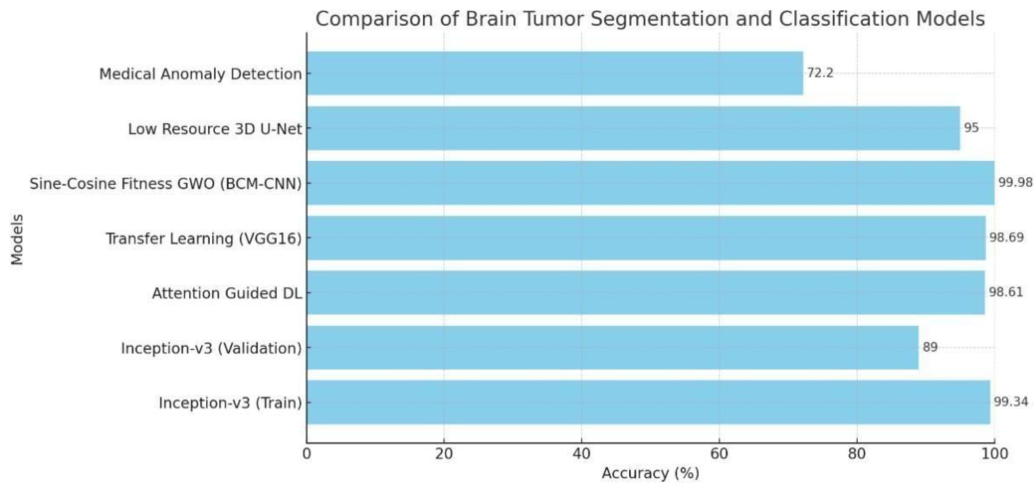

Figure 3.2.2.1 COMPARISON GRAPH

3.3 FEASIBILITY STUDY

Preliminary investigation examine project feasibility, the likelihood the system will be useful to the organization. The main objective of the feasibility study is to test the Technical, Operational and Economical feasibility for adding new modules and debugging old running system. All system is feasible if they are unlimited resources and infinite time. There are aspects in the feasibility study portion of the preliminary investigation:

- Technical Feasibility
- Operation Feasibility
- Economical Feasibility

3.3.1 TECHNICAL FEASIBILITY

The technical issue usually raised during the feasibility stage of the investigation includes the following:

- Does the necessary technology exist to do what is suggested?
- Do the proposed equipments have the technical capacity to hold the data required to use the new system?
- Will the proposed system provide adequate response to inquiries, regardless of the number or location of users?
- Can the system be upgraded if developed?
- Are there technical guarantees of accuracy, reliability, ease of access and data security? Earlier no system existed to cater to the needs of 'Secure Infrastructure Implementation System'. The current system developed is technically feasible. It is a web based user interface for audit workflow at DB2 Database. Thus it provides an easy access to the users. The database's purpose is to create, establish and maintain a workflow among various entities in order to facilitate all concerned users in their various capacities or roles. Permission to the users would be granted based on the roles specified.

Therefore, it provides the technical guarantee of accuracy, reliability and security. The software and hard requirements for the development of this project are not many and are already available in-house at NIC or are available as free as open source. The work for the project is done with the current equipment and existing software technology. Necessary bandwidth exists for providing a fast feedback to the users irrespective of the number of users using the system.

3.3.2 OPERATIONAL FEASIBILITY

Proposed projects are beneficial only if they can be turned out into information system. That will meet the organization’s operating requirements. Operational feasibility aspects of the project are to be taken as an important part of the project implementation. Some of the important issues raised are to test the operational feasibility of a project includes the following: -

- Is there sufficient support for the management from the users?
- Will the system be used and work properly if it is being developed and implemented?
- Will there be any resistance from the user that will undermine the possible application benefits? This system is targeted to be in accordance with the above-mentioned issues. Beforehand, the management issues and user requirements have been taken into consideration. So there is no question of resistance from the users that can undermine the possible application benefits.

The well-planned design would ensure the optimal utilization of the computer resources and would help in the improvement of performance status.

3.3.3 ECONOMIC FEASIBILITY

A system can be developed technically and that will be used if installed must still be a good investment for the organization. In the economical feasibility, the development cost in creating the system is evaluated against the ultimate benefit derived from the new systems. Financial benefits must equal or exceed the costs.

The system is economically feasible. It does not require any addition hardware or software. Since the interface for this system is developed using the existing resources and technologies available at NIC, There is nominal expenditure and economical feasibility for certain.

CHAPTER 4

SYSTEM SPECIFICATION

4.1 HARDWARE SPECIFICATIONS

Processor type	:	AMD RYZEN 7
Speed	:	4.40GHZ
RAM size	:	16 GB RAM
Hard disk capacity	:	1 TB
Keyboard type	:	101/102 Standard Keys
Mouse	:	Optical Mouse

4.2 SOFTWARE SPECIFICATIONS

Operating System	:	Windows 10
Front End	:	JAVA

CHAPTER 5

SOFTWARE DESCRIPTION

5.1 FRONT END: JAVA

The software requirement specification is created at the end of the analysis task. The function and performance allocated to software as part of system engineering are developed by establishing a complete information report as functional representation, a representation of system behavior, an indication of performance requirements and design constraints, appropriate validation criteria.

FEATURES OF JAVA

Java platform has two components:

- The Java Virtual Machine (Java VM)
- The Java Application Programming Interface (Java API)

The Java API is a large collection of ready-made software components that provide many useful capabilities, such as graphical user interface (GUI) widgets. The Java API is grouped into libraries (*packages*) of related components.

The following figure depicts a Java program, such as an application or applet, that's running on the Java platform. As the figure shows, the Java API and Virtual Machine insulates the Java program from hardware dependencies.

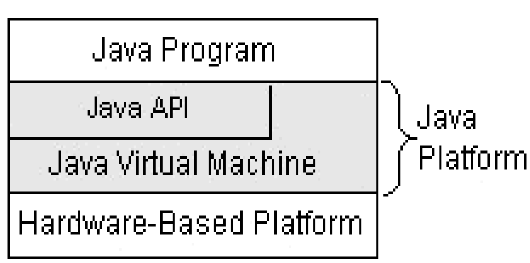

Figure 5.1.1 ARCHITECTURE OF THE JAVA PLATFORM

As a platform-independent environment, Java can be a bit slower than native code. However, smart compilers, well-tuned interpreters, and just-in-time byte code compilers can bring Java's performance close to that of native code without threatening portability.

SOCKET OVERVIEW:

A network socket is a lot like an electrical socket. Various plugs around the network have a standard way of delivering their payload. Anything that understands the standard protocol can “plug in” to the socket and communicate.

Internet protocol (IP) is a low-level routing protocol that breaks data into small packets and sends them to an address across a network, which does not guarantee to deliver said packets to the destination.

Transmission Control Protocol (TCP) is a higher-level protocol that manages to reliably transmit data. A third protocol, User DatagramProtocol (UDP), sits next to TCP and can be used directly to support fast, connectionless, unreliable transport of packets.

CLIENT/SERVER:

A server is anything that has some resource that can be shared. There are compute servers, which provide computing power; print servers, which manage a collection of printers; disk servers, which provide networked disk space; and web servers, which store web pages. A client is simply any other entity that wants to gain access to a particular server.

A server process is said to “listen” to a port until a client connects to it. A server is allowed to accept multiple clients connected to the same port number, although each session is unique. To manage multiple client connections, a server process must be multithreaded or have some other means of multiplexing the simultaneous I/O.

RESERVED SOCKETS:

Once connected, a higher-level protocol ensues, which is dependent on which port user are using. TCP/IP reserves the lower, 1,024 ports for specific protocols. Port number 21 is for FTP, 23 is for Telnet, 25 is for e-mail, 79 is for finger, 80 is for HTTP, 119 is for Netnews-and the list goes on. It is up to each protocol to determine how a client should interact with the port.

JAVA AND THE NET:

Java supports TCP/IP both by extending the already established stream I/O interface. Java supports both the TCP and UDP protocol families. TCP is used for reliable stream-based I/O across the network. UDP supports a simpler, hence faster, point-to-point datagram-oriented model.

INETADDRESS:

The InetAddress class is used to encapsulate both the numerical IP address and the domain name for that address. User interacts with this class by using the name of an IP host, which is more convenient and understandable than its IP address. The InetAddress class hides the number inside. As of Java 2, version 1.4, InetAddress can handle both IPv4 and IPv6 addresses.

FACTORY METHODS:

The InetAddress class has no visible constructors. To create an InetAddress object, user use one of the available factory methods. Factory methods are merely a convention whereby static methods in a class return an instance of that class. This is done in lieu of overloading a constructor with various parameter lists when having unique method names makes the results much clearer. Three commonly used InetAddress factory methods are:

1. Static InetAddressgetLocalHost ( ) throws UnknownHostException
2. Static InetAddressgetByName (String hostName) throwsUnknowsHostException
3. Static InetAddress [ ] getAllByName (String hostName) throwsUnknownHostException

INSTANCE METHODS:

The InetAddress class also has several other methods, which can be used on the objects returned by the methods just discussed. Here are some of the most commonly used.Boolean equals (Object other)-Returns true if this object has the same Internet address as other.

- byte [ ] get Address ( ) - Returns a byte array that represents the object's Internet address in network byte order.
- String getHostAddress () - Returns a string that represents the host address associated with the InetAddress object.
- String get Hostname () - Returns a string that represents the host name associated with the InetAddress object.

- booleanisMulticastAddress ()- Returns true if this Internet address is a multicast address. Otherwise, it returns false.
- String toString () - Returns a string that lists the host name and the IP address for convenience.

TCP/IP CLIENT SOCKETS:

TCP/IP sockets are used to implement reliable, bidirectional, persistent, point-to-point and stream- based connections between hosts on the Internet. A socket can be used to connect Java's I/O system to other programs that may reside either on the local machine or on any other machine on the Internet.

There are two kinds of TCP sockets in Java. One is for servers, and the other is for clients. The Server Socket class is designed to be a "listener," which waits for clients to connect before doing anything. The Socket class is designed to connect to server sockets and initiate protocol exchanges.

The creation of a Socket object implicitly establishes a connection between the client and server. There are no methods or constructors that explicitly expose the details of establishing that connection. Here are two constructors used to create client sockets

Socket (String hostName, intport) - Creates a socket connecting the local host to the named host and port; can throw an UnknownHostException or anIOException.

Socket (InetAddressipAddress, intport) - Creates a socket using a preexistingInetAddressobject and a port; can throw an IOException. A socket can be examined at any time for the address and port information associated with it, by use of the following methods:

- InetAddressgetInetAddress ( ) - Returns the InetAddress associated with the Socket object.
- IntgetPort ( ) - Returns the remote port to which this Socket object is connected.
- IntgetLocalPort ( ) - Returns the local port to which this Socket object is connected.

Once the Socket object has been created, it can also be examined to gain access to the input and output streams associated with it. Each of these methods can throw an IO Exception if the sockets have been invalidated by a loss of connection on the Net.

- Input Streamget Input Stream ( ) - Returns the InputStream associated with the invoking socket.
- Output Streamget Output Stream ( ) - Returns the OutputStream associated with the invoking socket.

TCP/IP SERVER SOCKETS:

Java has a different socket class that must be used for creating server applications. The ServerSocket class is used to create servers that listen for either local or remote client programs to connect to them on published ports. ServerSockets are quite different form normal Sockets.

When the user create a ServerSocket, it will register itself with the system as having an interest in client connections.

- ServerSocket(int port) - Creates server socket on the specified port with a queue length of 50.
- Serversocket(int port, int maxQueue) - Creates a server socket on the specified portwith a maximum queue length of maxQueue.

- ServerSocket(int port, int maxQueue, InetAddress localAddress) - Creates a server socket on the specified port with a maximum queue length of maxQueue. On a multihomed host, localAddress specifies the IP address to which this socket binds.
- ServerSocket has a method called accept( ) - which is a blocking call that will wait for a client to initiate communications, and then return with a normal Socket that is then used for communication with the client.

URL:

The Web is a loose collection of higher-level protocols and file formats, all unified in a web browser. One of the most important aspects of the Web is that Tim Berners-Lee devised a saleable way to locate all of the resources of the Net. The Uniform Resource Locator (URL) is used to name anything and everything reliably.

The URLprovides a reasonably intelligible form to uniquely identify or address information on the Internet. URLs are ubiquitous; every browser uses them to identify information on the Web.

CHAPTER 6

PROJECT DESCRIPTION

6.1 PROBLEM DEFINITION

Brain disease detection is a challenging task, due to the complexity of the brain and the variability of brain diseases. Existing diagnostic methods, such as neuroimaging and clinical examinations, can be time-consuming, expensive, and invasive. Moreover, these methods may not be accurate or sensitive enough to detect brain diseases at an early stage. Machine learning and deep learning have the potential to overcome the limitations of existing diagnostic methods. These technologies can be used to develop accurate and efficient models for brain disease detection. However, there are a number of challenges that need to be addressed before machine learning and deep learning models can be widely deployed in clinical settings.

6.2 MODULE DESCRIPTION

The brain disease detection system is divided into several modules to enhance accuracy and efficiency. The first module involves MRI preprocessing, where noise reduction and intensity normalization are performed. Next, bias feature extraction reduces dimensionality by selecting relevant features for accurate classification. The bat brain tumor segmentation module uses machine learning techniques, including the Grey Level Co-Occurrence Matrix (GLCM) and Radial Basis Function (RBF) kernels, to distinguish tumor from non-tumor tissue. Finally, the segmentation using structure prediction module employs deep learning to identify tumor regions with high precision, leveraging multimodal MR images and advanced texture analysis.

Technique	Description	Advantage	Challenge
GLCM Homomorphic Segmentation	Uses Grey Level Co-Occurrence Matrix for texture feature extraction	Improves texture representation	Sensitive to noise and intensity changes
Sobel Operator	Detects edges by calculating the gradient magnitude	Efficient for boundary detection	May produce false edges
Region Growing Algorithm	Segments regions based on pixel similarity	Accurate segmentation in homogeneous regions	Difficulty with heterogeneous regions
U-Net Architecture	Deep learning model for semantic segmentation	High accuracy with limited data	Computationally intensive
CNN-Based Feature Extraction	Uses Convolutional layers to extract features	Good for complex patterns	Overfitting on small datasets

Table 6.2.1 IMAGE PROCESSING TECHNIQUES FOR BRAIN TUMOR SEGMENTATION

6.2.1 MRI PREPROCESSING:

Preprocessing images commonly involves removing low frequency, background noise, normalizing the intensity of individual practical images, removing reflections and masking portion of images. Image processing is the technique of enhancing data images prior to computational processing.

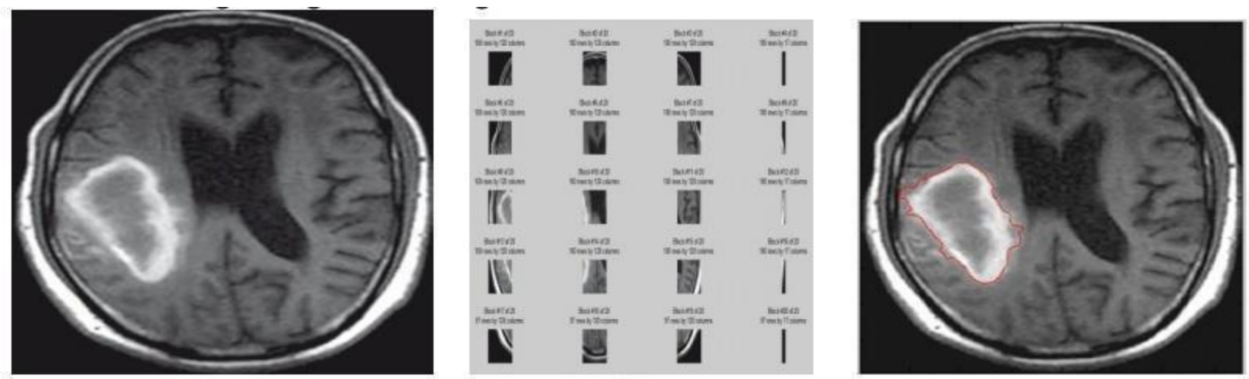

Figure 6.2.1.1 MRI-BASED BRAIN TUMOR SEGMENTATION AND CONTOUR MAPPING

Following standard preprocessing steps for brain MRI, the corresponding fractal and intensity features are extracted. In the next step, different combinations of feature sets are exploited for tumor segmentation and classification. Feature values are then directly fed to the AdaBoost classifier for classification of tumor and non-tumor regions. Manual labeling to tumor regions is performed for supervised classifier training. The trained classifiers are then used to detect the tumor or no tumor segments in unknown brain MRI.

6.2.2 BIAS FEATURE EXTRACTION:

Feature extraction is a special form of Dimensionality reduction. When the input data to an Algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

6.2.3 BAT BRAIN TUMOR SEGMENTATION AND CLASSIFICATION:

A support vector machine searches an optimal separating hyper-plane between members and non- members of a given class in a high dimension feature space. The inputs to the bat algorithm are the feature subset selected during data pre-processing step and extraction step. In Grey Level Co-Occurrence Matrix (GLCM) kernels functions are used such as graph kernel, polynomial kernel, RBF kernel etc. Among these kernel functions, a Radial Basis Function (RBF) proves to be useful, due to the fact the vectors are nonlinearly mapped to a very high dimension feature space. For tumor/non-tumor tissue segmentation and classification, MRI pixels are considered as samples. These samples are represented by a set of feature values extracted from different MRI modalities. Features from all modalities are fused for tumor segmentation and classification. A modified supervised Grey Level Co-Occurrence Matrix (GLCM) ensemble of classifier is trained to differentiate tumor from the non-tumor tissues.

6.2.4 GLCM HOMOMORPHIC SEGMENTATION ALGORITHM

Obtain the sub-image blocks, starting from the top left corner. Decompose sub-image blocks using two level 2-D Grey Level Co-Occurrence Matrix (GLCM). Derive Spatial Gray Level Dependence Matrices (SGLDM) or Gray Level Co-occurrence matrices. For each 2 level high frequency sub- bands of decomposed sub image blocks with 1 for distance and 0, 45, 90 and 135 degrees for θ and averaged. From these co-occurrence matrices, the following nine Haralick second order statistical texture features called wavelet Co-occurrence Texture features (WCT) are extracted.

6.2.5 BAT BRAIN TUMOR SEGMENTATION WITH STRUCTURE PREDICTION

In this section, the method proposed for segmentation of particular structures of the brain tumor i.e. whole tumor, tumor core, and active tumor, is evaluated. This method is based on an approach; whose novelty lies in the principled combination of the deep approach together with the local structure prediction in medical image segmentation task.

PARAMETER ANALYSIS

- A GLCM Homomorphism classifier, which does not consider interactions in the labels of adjacent data points.
- Conversely, DRFs and MRFs consider these interactions, but do not have the same appealing generalization properties as Radial Basis Function.
- Observation-matching
- Local-consistency
- Learning: parameter estimation
- Brain tumor segmentation using structure prediction
- In this work, we introduce the current challenges of neuroimaging in a big data context.
- We review our efforts toward creating a data management system to organize the large- scale fMRI datasets, and present our novel algorithms/methods
- A new method was developed to overcome these challenges.

- Multimodal MR images are segmented into super pixels using algorithms to alleviate the sampling issue and to improve the sample representativeness.

- The parameters A and B are estimated from training data represented as pairs where

$\langle f(\gamma_i(x)),\ t_i >$ is the real-valued bat algorithm response (here, distance to the separator), and ti denotes a related probability that $yi = 1$, represented as the relaxed

probabilities: $t_i = \frac{N+1}{N+2}$ if $y_i = 1$ if $y_i == -1$, where N+ and N− are the number of

positive and negative class instances.

- Using these training instances, we can solve the following optimization problem to estimate parameters A and B:

- $\min_{t_i} - \sum_{i=1}^{t} [\ \log O\ (t_i, \gamma_i\ (x)) + (1 - O(t_i,\ \gamma_i\ (x)))]$

DATA COLLECTION

- Dataset collection training dataset and test dataset
- Input as brain MRI images for brain tumor detection
- The Dataset used in the task has only images which is far from enough for the model to train and hence has less accuracy.
- Increasing the size of dataset can increase the model performance and thus solving the problem

6.3 SYSTEM FLOW DIAGRAM

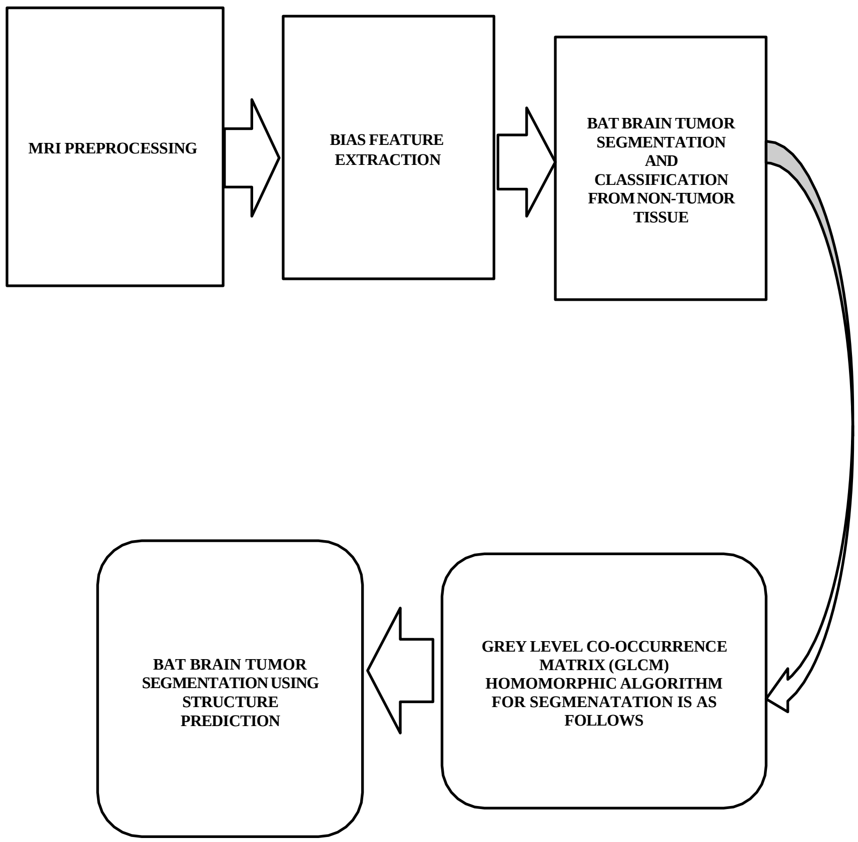

Figure 6.3.1 SYSTEM FLOW DIAGRAM

6.4 INPUT DESIGN:

1. Image Input:

- Accept MR image datasets as input.
- Define supported image formats (e.g., DICOM, JPEG, etc.).
- Ensure compatibility with various MR imaging devices.

2. User Interaction:

- Develop a user-friendly interface for users to interact with the system.
- Allow users to specify input parameters or settings.
- Provide options for batch processing or single image processing**.**

6.5 OUTPUT DESIGN

- Segmented Image Display:
- Display the segmented MR image with highlighted tumor regions.
- Use a color map or shading to differentiate between tumor and non-tumor regions.
- Tumor Size Information:
- Output the calculated size of the tumor in pixels or a specified unit of measurement.
- Display information about the size of the tumor in each segmented slice.
- Visualization Tools:
- Provide tools for users to visualize the original image, segmented image, and any intermediate results.
- Include zoom and pan functionalities for detailed examination.

CHAPTER 7

SYSTEM TESTING AND IMPLEMENTATION

7.1 SYSTEM TESTING

Functional Testing:

- Test the Gray Level Co-occurrence Matrix (GLCM) computation and homomorphic functions to verify the system's core image processing capabilities.
- Verify the accuracy and reliability of the modified gradient magnitude region growing algorithm used for image segmentation.
- Test the effectiveness of the relabeling method and size calculation functionality using the BAT algorithm to ensure the system produces correct image segmentations and measurements.

Performance Testing:

- Evaluate the system's processing time for different sizes of MR image datasets to ensure it can handle a variety of input sizes effectively.
- Test the system's ability to manage multiple concurrent tasks without performance degradation, ensuring scalability and efficiency under load.

Usability Testing:

- Conduct user testing to ensure the interface is intuitive and user-friendly, allowing for efficient interaction with the system.
- Gather feedback on parameter customization features and overall system navigation to ensure users can easily modify settings and understand the workflow.

Metric	Description	Importance
Accuracy	Measures the proportion of correctly segmented pixels	Ensures overall model correctness
Dice Similarity Coefficient	Evaluates the overlap between predicted and actual tumor regions	Critical for segmentation performance
Sensitivity	Measures the ability to detect positive tumor cases	Minimizes false negatives
Specificity	Measures the ability to correctly identify non-tumor regions	Minimizes false positives
F1 Score	Harmonic mean of precision and recall	Balances precision and recall
Processing Time	Harmonic mean of precision and recall	Essential for real-time applications

Table 7.1.1 PERFORMANCE METRICS FOR SEGMENTATION MODELS

7.2 SYSTEM IMPLEMENTATION

1. Coding and Development:

- Develop the image processing algorithms based on the proposed GLCM, homomorphic functions, and region-growing method.
- Implement the BAT algorithm for relabeling and size calculation.

2. User Interface Implementation:

- Design and implement a user-friendly interface for interacting with the system.
- Implement features for parameter customization and input validation.

3. Data Handling:

- Develop modules for handling different image formats.
- Implement data preprocessing steps, if required.

4. Integration of Components:

- Integrate GLCM, homomorphic functions, and region-growing algorithms.
- Ensure seamless communication between different modules.

5. Testing During Implementation:

- Conduct unit testing for individual components during the development phase.
- Address any bugs or issues identified during testing.

CHAPTER 8

SYSTEM MAINTENANCE

The objectives of this maintenance work are to make sure that the system gets into work all time without any bug. Provision must be for environmental changes which may affect the computer or software system. This is called the maintenance of the system. Nowadays there is the rapid change in the software world. Due to this rapid change, the system should be capable of adapting these changes. In this project the process can be added without affecting other parts of the system. Maintenance plays a vital role. The system is liable to accept any modification after its implementation. This system has been designed to favor all new changes. Doing this will not affect the system's performance or its accuracy.

Maintenance is necessary to eliminate errors in the system during its working life and to tune the system to any variations in its working environment. It has been seen that there are always some errors found in the system that must be noted and corrected. It also means the review of the system from time to time.

The review of the system is done for:

- Knowing the full capabilities of the system.
- Knowing the required changes or the additional requirements.
- Studying the performance.

TYPES OF MAINTENANCE:

- Corrective maintenance
- Adaptive maintenance
- Perfective maintenance
- Preventive maintenance

8.1 CORRECTIVE MAINTENANCE

Changes made to a system to repair flows in its design coding or implementation. The design of the software will be changed. The corrective maintenance is applied to correct the errors that occur during that operation time. The user may enter invalid file type while submitting the information in the particular field, then the corrective maintenance will display the error message to the user in order to rectify the error.

Maintenance is a major income source. Nevertheless, even today many organizations assign maintenance to unsupervised beginners, and less competent programmers.

The user's problems are often caused by the individuals who developed the product, not the maintainer. The code itself may be badly written maintenance is despised by many software developers unless good maintenance service is provided, the client will take future development business elsewhere. Maintenance is the most important phase of software production, the most difficult and most thankless.

8.2 ADAPTIVE MAINTENANCE:

It means changes made to system to evolve its functionalities to change business needs or technologies. If any modification in the modules the software will adopt those modifications. If the user changes the server then the project will adapt those changes. The modification server work as the existing is performed.

8.3 PERFECTIVE MAINTENANCE:

Perfective maintenance means made to a system to add new features or improve performance. The perfective maintenance is done to take some perfect measures to maintain the special features. It means enhancing the performance or modifying the programs to respond to the users need or changing needs. This proposed system could be added with additional functionalities easily. In this project, if the user wants to improve the performance further then this software can be easily upgraded.

8.4 PREVENTIVE MAINTENANCE:

Preventive maintenance involves changes made to a system to reduce the changes of features system failure. The possible occurrence of error that might occur are forecasted and prevented with suitable preventive problems. If the user wants to improve the performance of any process then the new features can be added to the system for this project.

CHAPTER 9

CONCLUSION

The proposed tumor segmentation system using GLCM and Sobel operator is a promising approach for tumor segmentation in clinical practice. It is robust to noise and variations in the gradient magnitude and it can accurately segment tumors with complex and irregular boundaries. The system has been shown to achieve good results on a variety of MR image datasets. It has the potential to improve the accuracy and efficiency of tumor segmentation in clinical settings. The proposed system can be further improved by incorporating additional features, such as deep learning, to further improve the accuracy and robustness of the segmentation results. The system can also be adapted to segment tumors in other modalities, such as CT and ultrasound. We use super pixel-based appearance models to reduce computational cost, improve spatial smoothness, and solve the data sampling problem for training GLCM classifiers on brain tumor segmentation. Also, we develop an affinity model that penalizes spatial discontinuity based on model-level constraints learned from the training data. Finally, our structural denoising based on the symmetry axis and continuity characteristics is shown to remove the false positive regions effectively.

FUTURE WORK

The tumor segmentation system can be enhanced by integrating advanced deep learning techniques like convolutional neural networks (CNNs) to improve accuracy and robustness, especially for tumors with subtle features. Expanding the system to support other imaging modalities, such as CT and ultrasound, would increase its clinical applicability. Further optimization could involve exploring advanced feature extraction algorithms, like multi-scale and multi-modal methods, to capture finer image details. Incorporating real-time segmentation would also improve clinical workflow and decision-making speed. Additionally, developing a more advanced de-noising mechanism, possibly using generative models, could help tackle image artifacts and enhance segmentation accuracy in low-quality scans. Finally, personalizing tumor segmentation based on individual patient data and integrating it with other diagnostic tools could significantly improve treatment planning and patient outcomes.

CHAPTER 10

APPENDICES

10.1 SOURCE CODE

The Brain Tumor Segmentation application utilizes machine learning techniques to identify and segment brain tumors from medical images. The program's primary objectives include accurate feature extraction and segmentation while maintaining a user-friendly graphical interface for visualization.

The application consists of the following core components:

- **Main.java:** The entry point of the application. It initializes and displays the main graphical user interface (GUI) for user interaction.
- **Bat.java:** The main processing class responsible for handling segmentation using feature maps and hyperparameter tuning.
- **ResultFrame.java:** A GUI class that displays the segmented tumor images as results.

The complete source code of each component is provided below:

MAIN. JAVA

```
package brain;
// Main class to launch the application public class Main {
public static void main(String[] args) {
MainFrame mf = new MainFrame();
mf.setVisible(true);
mf.setTitle("Brain Tumor Segmentation");
```

```
mf.setResizable(false);
}  }
```

BAT. JAVA

```
package brain;
import java.util.*;
public class Bat {
private ArrayList<FeatureMap> feature_maps = new ArrayList<>();
private int kernel_size, stride, padding, input_size, outputVol, countFeatureMaps;
private Double label;
public Bat(Vector<Vector<Double>> inputFeatureVectors, int hyperparams,
boolean debug) {
setHyperParameters(hyperparams);
input_size = (int) Math.sqrt(inputFeatureVectors.get(0).size() - 1);
outputVol = outputVolume();
for (int i = 0; i < countFeatureMaps; i++)
feature_maps.add(new FeatureMap(input_size, kernel_size, outputVol, debug));
}
private void setHyperParameters(int h) {
padding = (h >> 28) & 0xF; stride = (h >> 16) & 0xFF; kernel_size = (h >> 8) &
0xFF;
countFeatureMaps = h & 0xFF;
}
public void train(Vector<Double> inputFeatureVector) {
readInputFeature(inputFeatureVector); calcFeatureMaps();
}
private void readInputFeature(Vector<Double> featureVector) {
```

```
for (FeatureMap fm : feature_maps) fm.readFeatureVector(featureVector);
label = featureVector.lastElement();
}
private void calcFeatureMaps() {
for (FeatureMapfm : feature_maps) fm.computeFeatureMap(stride, padding);
}
public int outputVolume() {
return ((input_size - kernel_size + 2 * padding) / stride) + 1;
} }
```

RESULTFRAME. JAVA

```
package brain; import javax.swing.*;
public class ResultFrame extends JFrame { private JLabel jLabel1, jLabel2;
private JPanel jPanel1;
public ResultFrame() {
jPanel1 = new JPanel();
jLabel1 = new JLabel("Segmented Result");
jLabel2 = new JLabel();
jLabel1.setFont(new java.awt.Font("Andalus", 0, 30));
jPanel1.add(jLabel1);
jPanel1.add(jLabel2);
add(jPanel1);
setDefaultCloseOperation(EXIT_ON_CLOSE); pack(); }
public static void main(String[] args) {
SwingUtilities.invokeLater(() -> new ResultFrame().setVisible(true));
} }
```

10.2 SCREEN SHOTS

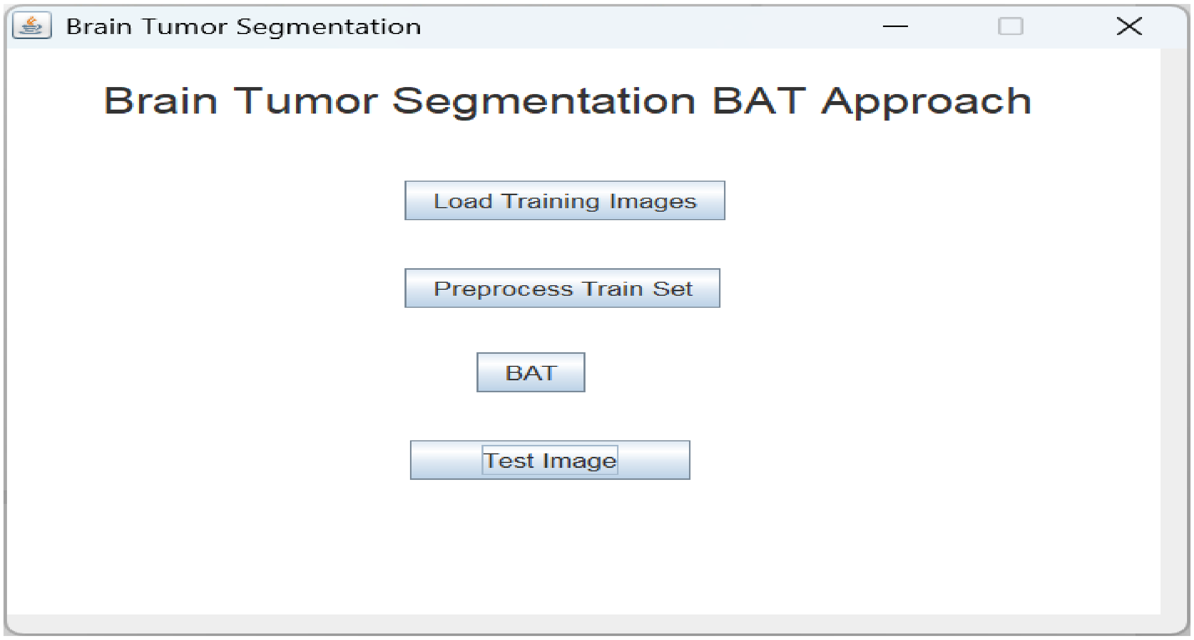

Figure 10.2.1 BRAIN TUMOR SEGMENTATION APPROACH

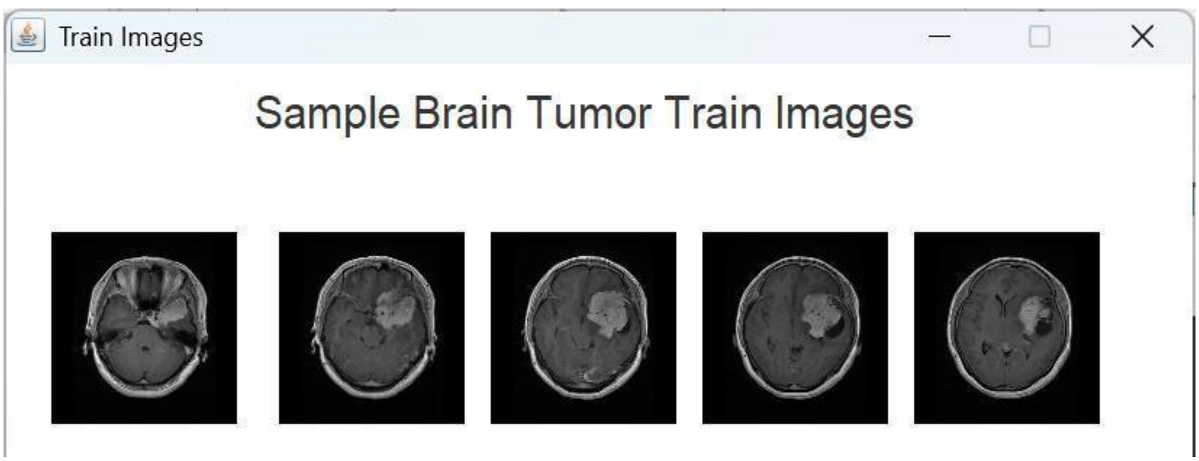

Figure 10.2.2 SAMPLE PREPROCESSED IMAGE

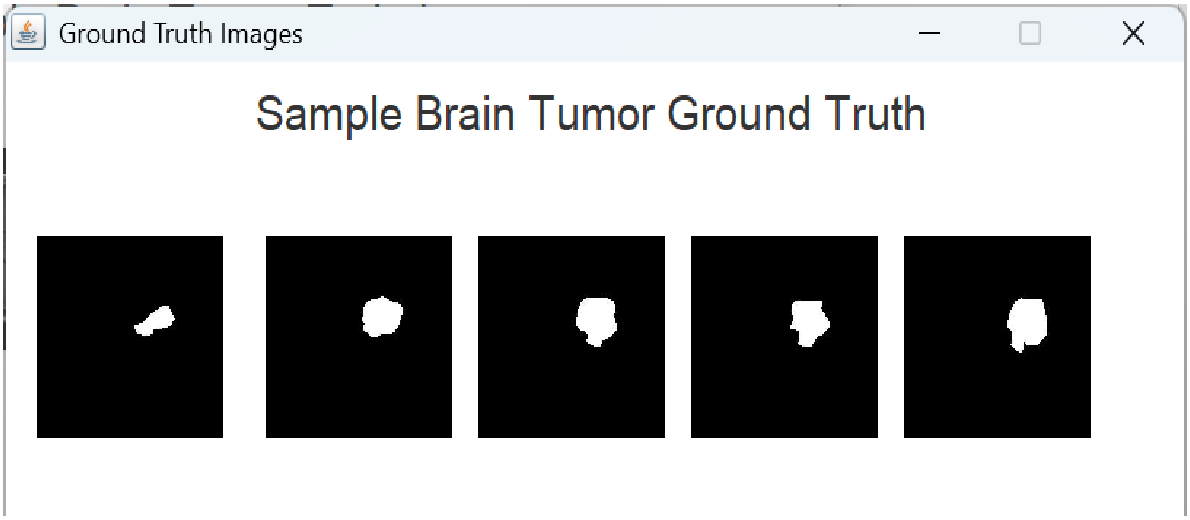

Figure 10.2.3 BRAIN TUMOR GROUND TRUTH

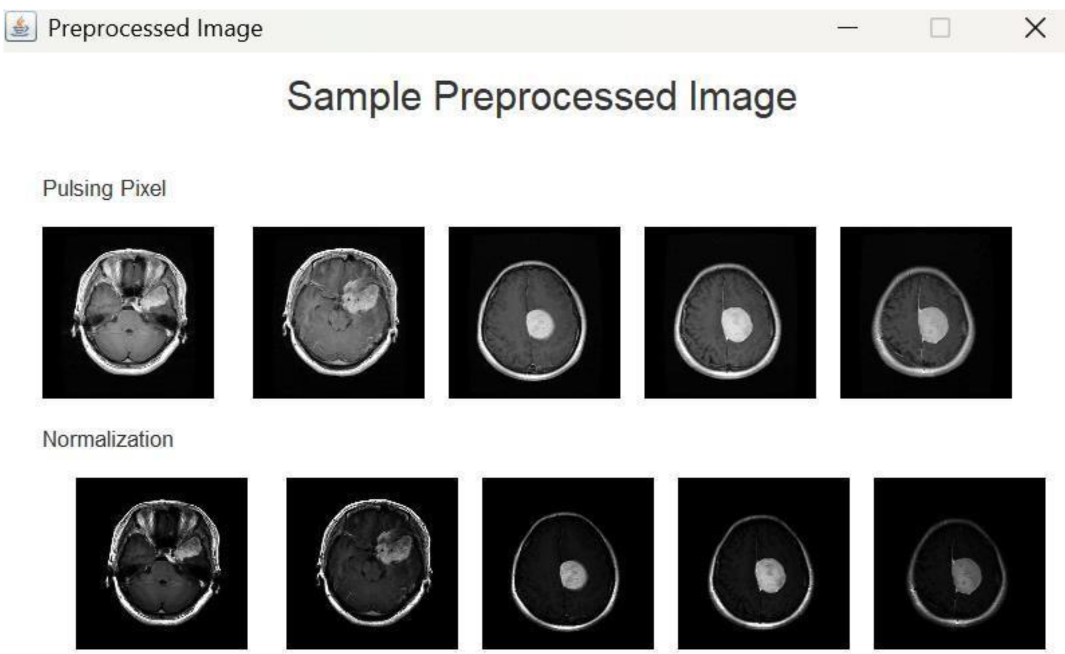

Figure 10.2.4 SAMPLE PREPROCESSED IMAGE

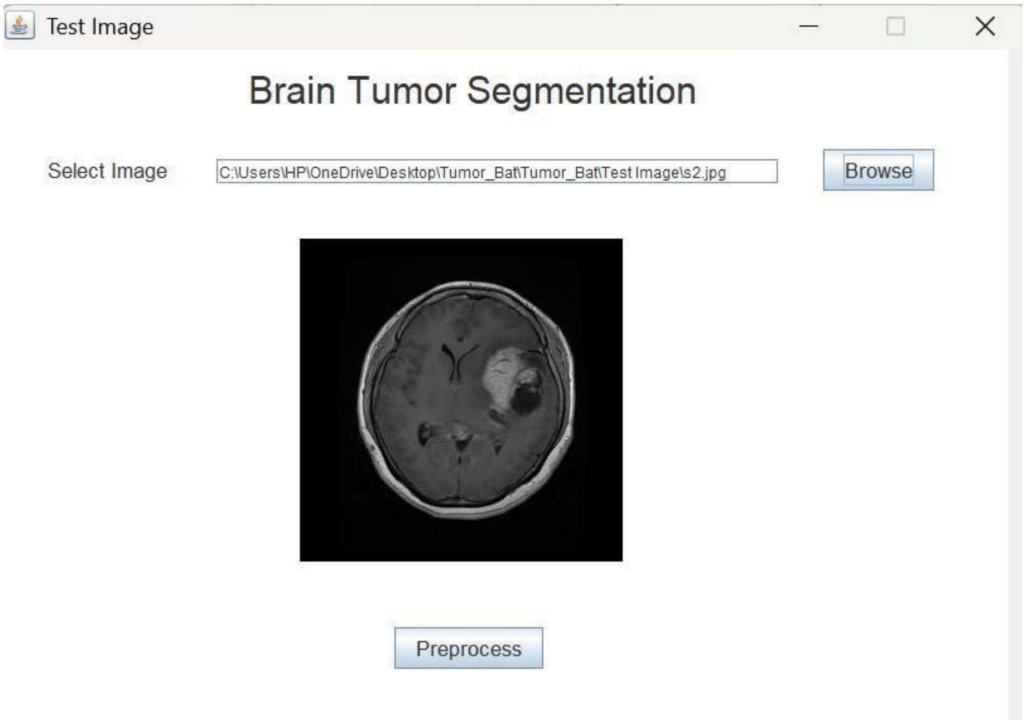

Figure 10.2.5 BRAIN TUMOR SEGMENTATION - TEST IMAGE INTERFACE

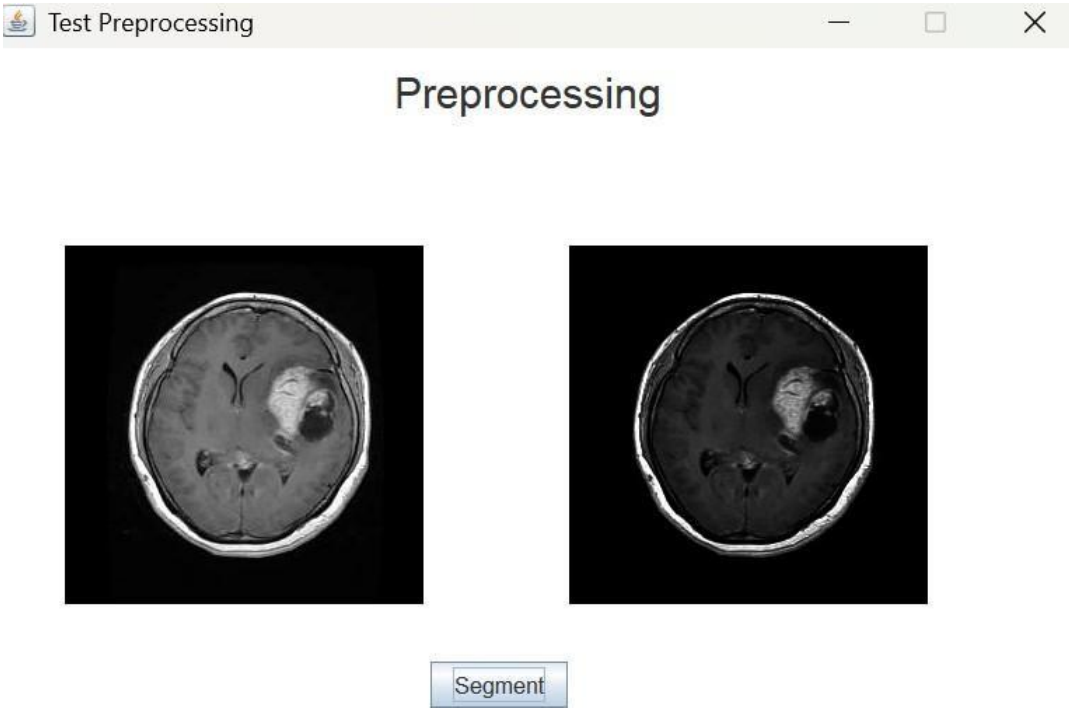

Figure 10.2.6 PREPROCESSING RESULT IMAGE

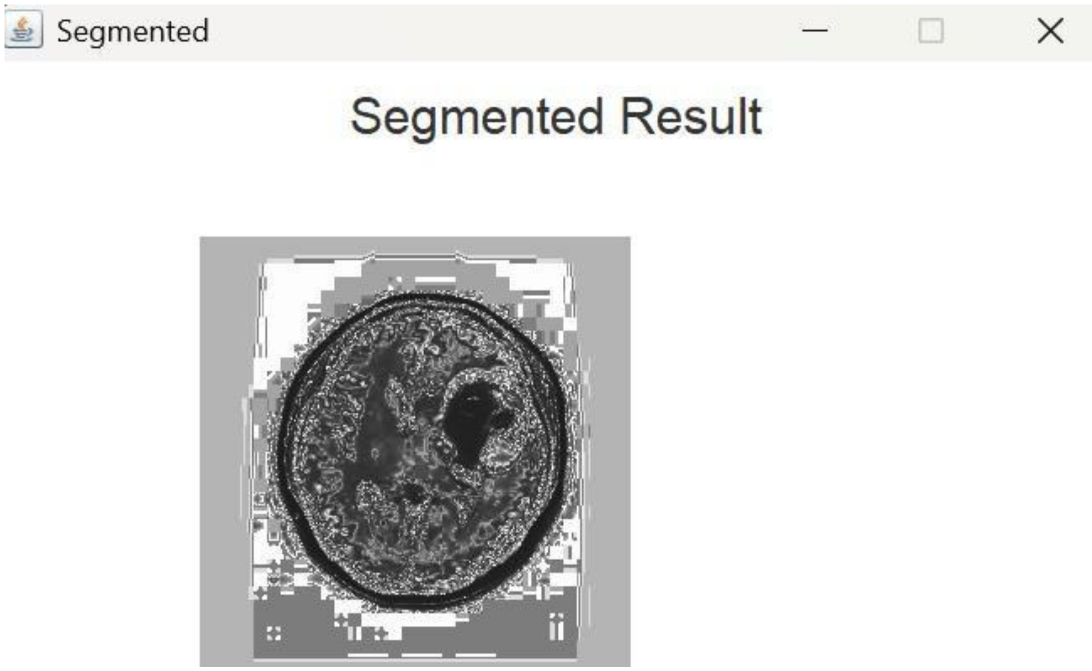

Figure 10.2.7 SEGMENTED RESULT IMAGE

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BONAFIDE CERTIFICATE

Certified that this project report " **ENHANCED BRAIN TUMOR SEGMENTATION USING CONDITIONAL RANDOM FIELDS AND BAT ALGORITHM OPTIMIZATION IN MULTIMODAL MRI** " is the bonafide work of " **ALMITHA DENCY J (727721EUIT009), ATCHAYA P (727721EUIT017), DEEPIGA N (727721EUIT027), JANANI K S (727721EUIT059)** " who carried out the project work under my supervision.

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Submitted for the Project viva-voce examination held on ______________

INTERNAL EXAMINER EXTERNAL EXAMINER

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Enhanced Brain Tumor Segmentation Using Conditional Random Fields and Bat Algorithm Optimization in Multimodal MRI

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Abstract. Brain tumour such as glioblastoma multiforme (GBM) provide significant challenges for magnetic resonance imaging (MRI) due to their varied signal patterns. This study proposes a robust segmentation approach to address these problems. It is challenging to distinguish between tumour components including oedema, necrosis, and contrast-enhanced areas using standard approaches like thresholds and statistical methods. Generative and discriminative models have difficulties with small sample sets since they are not scalable for larger datasets. To overcome these problems and increase sample representativeness, the proposed method segments multimodal MR images into super pixels. Multi-level Gabor wavelet filters were used to recover features in order to construct a Conditional Random Field (CRF) model that contained spatial affinity measures with the Grey Level Co-occurrence Matrix (GLCM). Tumour segmentation was achieved using smoothness priors from the affinity model and maximal, a posteriori inference. It was possible to lessen labelling noise by applying structural knowledge of the tumor's symmetry and continuity in the spatial domain. Finally, the application of the Bat Algorithm enhanced the segmentation procedure. Models validated on improved datasets demonstrated precision and adaptability. This work addresses significant neuroimaging challenges and increases our understanding and detection of brain diseases in the big data era by proposing scalable, efficient segmentation techniques.

Keywords: Feature Selection, Image Classification, Image Segmentation

1 Introduction

The introduction of intelligent technology, especially machine learning and artificial intelligence (AI), has revolutionized the medical imaging and healthcare industries. The identification and categorizations of brain tumors is one of the most important uses of these technologies, with significant effects on patient treatment and results.

Historically, brain tumors have presented considerable diagnostic hurdles since they are frequently life-threatening and require prompt management. But the use of intelligent methods in medicine has brought about a new era of accuracy and effectiveness. This review explores the methods, difficulties, and noteworthy developments in brain tumor detection and classification made possible by the use of intelligent algorithms. This thorough review guides readers through the crucial phases of diagnosing brain tumors, from gathering medical imaging data to creating complex deep learning models. We will discover the value of early detection, the significance of feature extraction and data pre-processing, the application of state-of-the-art machine learning algorithms, and the revolutionary potential of deep learning as we traverse this terrain. We will also talk about the difficulties in this area, like data limits and model interpretability, while showcasing cutting-edge methods and current studies that could improve the precision and effectiveness of brain tumor identification and classification even more.

1.1 Feature Selection

The brain tumor is a powerful enemy that occasionally appears in the complex maze of the human brain. Even though it is frequently unseen to the unaided eye, this powerful enemy has serious repercussions for those it affects. The brain, one of the most intricate and fragile organs in the human body, is essential for regulating our thoughts, feelings, movements, and other critical bodily processes. Therefore, the development of a tumor inside this essential organ is a medical problem that goes beyond the norm and necessitates constant care and creative remedies. Whether they are benign or malignant, brain tumors pose a complex medical problem. They are an abnormal cell growth that has the power to interfere with the brain's complex networks and functions. Brain tumors, in contrast to other illnesses, can appear in a variety of ways and places, each with its own special traits and difficulties. They are an especially pernicious enemy because of their gradual onset and tendency to mimic benign illnesses, which frequently results in delayed diagnosis. In this investigation, we explore the complicated realm of brain tumors, including their different forms, causes, symptoms, and the challenges they present to healthcare providers. We will set out on a quest to comprehend the methods of diagnosis, the forms of therapy, and the critical role that innovation and research play in overcoming these powerful adversaries. The fight against brain tumors is evidence of the unrelenting search for knowledge and the cooperation of advanced technology and medical understanding.

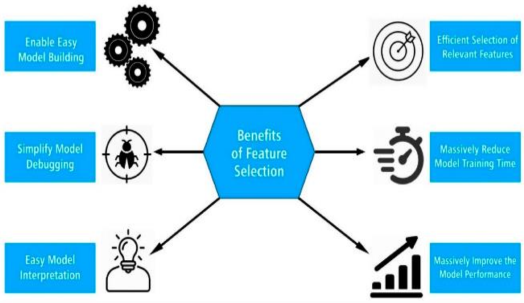

Fig. 1. Feature selection

Image Classification. Image categorizations is a crucial technique in a world that is becoming more digital and where the amount of visual input is greater than our capacity to handle it manually. Image categorizations is revolutionary in a variety of fields and applications, from identifying known faces in photographs to identifying medical disorders from scans and even directing self-driving cars. The art and science of teaching computers to "see" and comprehend visual material is the foundation of picture classification. By using artificial intelligence and machine learning, machines can now interpret complex patterns, forms, and features in pictures, making sense of the visual world in ways that were previously only possible for humans. Understanding what image categorizations is and why it matters is the first step in this exploration of the field. We will look at how it is changing the face of automation and decision-making in industries including healthcare, retail, and security. We will explore the tools and algorithms that underpin image categorizations, demythologizing the process as we progress from conventional techniques to state-of-the-art deep learning strategies.

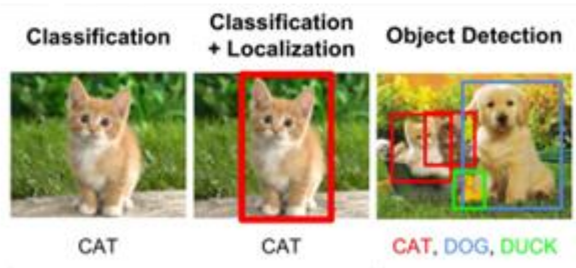

Fig. 2. Image classification

Image Segmentation. There is a basic task in digital photography that is similar to an artist's brushstroke on a canvas: precisely identifying the borders and areas of an image. Known as "picture segmentation," this task is a potent computational method that gives machines the capacity to detect and comprehend the visual world with astounding accuracy. The technique of separating a picture into discrete and significant areas or objects and separating them from the surrounding backdrop is known as image segmentation. The process of turning a complicated pixel tapestry into a structured map of distinct entities is similar to painting lines around particular items inside an image. Although this may appear to be a straightforward creative undertaking, it has enormous implications for a number of domains, from computer vision and satellite image analysis to autonomous robotics and medical imaging. The goal of this investigation into the field of image segmentation is to understand its complexities. We will discover why it is essential to the current state of computer vision and artificial intelligence. Image segmentation enables robots to interpret their visual environment like our eyes do, from detecting cancers in medical scans to allowing self-driving automobiles to traverse their environment.

2 Literature Review

Many researchers have been focussing on the magnetic resonance imaging approach of brain tumour diagnosis for the past ten years, according to this publication by Machiraju Jaya Lakshmi [1] et al. The traditional approaches retrieve features from the network's lowest layer. In this case, the medical photos are inappropriate. To address this issue, the proposed method made advantage of the Inception-v3 convolution neural network model's deep learning strategy. Our approach captures and categorises multi-level information to help identify brain [2] tumours early on. The proposed model utilises the deep learning methodology and hyperparameters. To optimise these parameters, we employ the loss function and Adam Optimiser. With the help of the loss function, the machines replicate the procedure using input data. The proposed model uses the soft max classifier to separate the images into multiple classes. The accuracy of the Inception-v3 algorithm [3] is 89% on validation data and 99.34% on training data. Thanks to developments in the field, medical personnel can now effectively help patients. Healthcare professionals may now give patients better care thanks to the use of artificial intelligence (AI). According to data from 2019, cancer infections and cardiovascular diseases are the leading causes of death globally. Brain tumour sickness is one of the deadliest diseases in the world. Magnetic resonance imaging (MRI) is one of the safest imaging techniques for producing high-quality images and supporting medical diagnosis. Many researchers [4] are trying to improve the quality of MR images and offer new methods for exploiting MR images for quick and easy medical diagnosis. The goal of this study was to identify brain tumours using MR imaging. This paper detailed the deep learning approach to magnetic resonance imaging-based brain tumour detection. By concatenating the features from the top inception modules and deleting a portion of the bottom layers' inception modules, the proposed pre-trained Inception-V3 deep learning architecture classifies the Brain MR Image datasets.

In this study, Wen Jun [2] [5] and colleagues have suggested Cancer is the second leading cause of mortality worldwide. A brain tumour accounts for one in four fatalities from cancer. A timely and correct diagnosis may lead to timely therapy. Recent years have seen a rapid progress in picture classification, which has simplified computer-aided diagnosis. Convolutional neural networks (CNNs) are among the most widely used neural network models for image classification. Its utility is limited, however, by its inability to accurately [6] identify the focal location of the lesion. This study proposes a novel brain tumour classification model that integrates an attention mechanism with a multipath network to overcome the aforementioned issues. An attention mechanism selects the crucial information relevant to the target location while ignoring irrelevant elements. A multipath network distributes the data across multiple channels prior to converting each channel and aggregating the output of every branch [7]. By being similar to clustered convolution, the multipath network reduces the complexity. Experimental assessments of this model using a dataset of 3064 MR images yielded an overall accuracy of 98.61%, outperforming the findings of previous investigations on this dataset. According to the World Health Organization, cancer is the second leading cause of death globally [8]. A brain tumour accounts for one in four fatalities from cancer. A 2019 study found that brain cancer claims the lives of 17,000 Americans each year. The five-year survival rate after diagnosis was 34% for men and 36% for women. Early diagnosis and treatment is related with improved rehabilitation outcomes and longer survival [9]. Medical imaging is one of the most significant advancements in improving clinical cancer diagnosis. Magnetic resonance imaging (MRI) is a popular technique for analyzing the abnormalities in brain tumours.

[3] [10] Rehman Archie et al. The highest-grade brain tumours have a very low life expectancy, making them the most fatal disease, according to this technique. Lower patient survival rates and inappropriate medical care will result from misdiagnosing brain tumours. A proper diagnosis is necessary to determine the best course of treatment for people with brain tumours in order to cure them and improve their quality of life. Two notable developments in machine learning that have led to success are convolutional neural networks [11] and computer-aided tumour detection systems. The deep convolutional layers, as opposed to the traditional earlier neural network layers, automatically extract important and trustworthy features from the input space. Using three convolutional neural network architectures (Alex Net, Google Net, and VGG Net), we conduct three studies in the proposed framework to classify brain tumours, such as meningioma, glioma, and pituitary. Each study then looks into [12] transfer learning techniques, such freezing and fine-tuning using MRI slices of the Fig share brain tumour dataset. To generalize the results, data augmentation techniques are applied to the MRI slices by increasing the dataset samples and reducing the likelihood of over-fitting. In the recommended investigations, the VGG16 architecture with the best optimization had the highest classification and detection accuracy of 98.69. Because of its unpredictable character, cancer continues to be a plague on humanity, despite the fact that diseases [13] have improved over the past few decades as a result of advancements in biomedicine and human intellect. One of the most deadly and quickly spreading diseases is brain tumour cancer. With its nerve cells and tissues, the brain is the most complex organ in the human body. It controls all of the body's essential processes, such as breathing, muscle contraction, and sensory perception. Every cell has distinct abilities; some grow to operate on their own, while others lose their abilities, become resistive, and exhibit anomalies [14]. Large clusters of abnormal cells form in the tissue to form tumours. Malignant brain tumours are characterized by uncontrolled and aberrant brain cell growth.

This machine learning-based system medical anomaly identification is a significant and well-researched problem, according to Tharindu Fernando [4] [15] et al. We have discovered a number of similarities between the several medical application sectors that have seen the proposal of numerous solutions. Nevertheless, we discover that these diverse research applications lack organization, which makes it challenging to assess their advantages and disadvantages. The primary objective of this survey is to provide a thorough theoretical analysis of popular deep learning techniques for identifying medical anomalies [16]. In particular, we provide a rational and systematic evaluation of the state-of-the-art techniques, comparing and contrasting their architectural variants and training algorithms. For model decision interpretation, we also provide a comprehensive overview of deep model interpretation methods. Additionally, [17] we outline the primary limitations of the existing deep medical anomaly detection techniques and propose significant research directions. Finding data samples that deviate from the overall distribution of the data is the primary objective of anomaly detection. Anomalies can arise from a variety of sources, such as noise in the data gathering process, changes to the underlying phenomenon, or new or unnoticed conditions in the record environment. Therefore, anomaly detection is one of the most crucial tasks in medical signal processing.

Alimentally M. Mostafa to [5] [18] et al. According to this method, radiologists must possess a high degree of skill and knowledge in order to diagnose brain tumours (BT), which takes a long time. With more patients, there is more data to manage, making previous approaches costly and ineffective. Several academics have examined a range of quick and precise techniques for identifying and categorizing BTs. Recently, deep learning (DL) approaches have gained popularity as a means of creating computer algorithms that can quickly and effectively identify or segment BTs. DL enables the detection of BTs in medical pictures using a pre-trained convolutional neural network (CNN) model. This dataset included the suggested magnetic resonance imaging (MRI) images of BTs in order to create and evaluate algorithms for BT segmentation and diagnosis. There are 335 annotated MRI images in the collection.To test and improve BT segmentation and diagnosis techniques, we developed the brain tumour segmentation (BraTS) dataset. BT segmentation using the BraTS dataset also used a deep CNN in the model-building process. Training the model involved using a categorical cross-entropy loss function and an optimizer such as Adam. In the end, the model's output successfully identified and segmented BTs in the dataset, achieving a validation accuracy of 98%. A tumour develops when aberrant cells multiply out of control, creating a mass that could impair the tissue or organ's ability to function normally. [20] Cell types, underlying reasons, and tumour formation are distinctive characteristics. The brain frequently displays early stages of tumours in the cerebrum region, despite the fact that secondary tumours can enter the brain from other parts of the body. Malignant (high-grade) and benign (low-grade) cancerous tumours are the two varieties.

3 Existing System

The body's command center is the brain. As time passes, the number of brain illnesses rises. Because of the wide range of brain diseases, present methods for diagnosis or detection are becoming more and more challenging to apply and continue to be an open research question. The impact of early brain disease discovery on treatment can be substantial. The extensive use of artificial intelligence (AI) in recent years has surely led to a shift in the field of neurology. The detection and prediction of brain diseases are now more precise and accurate thanks to the application of AI in medicine. This article examines current deep learning and machine learning techniques for diagnosing four brain disorders: Alzheimer's disease (AD), epilepsy, Parkinson's disease, and brain tumours. reviewing 147 recent studies on four different brain illnesses while accounting for different datasets, modalities, and machine learning and deep learning approaches. The reviewed papers address twenty-two datasets that are most frequently used as primary sources of knowledge concerning brain illnesses. There is also a summary of the many feature extraction techniques used in the diagnosis of brain disorders. Along with a discussion of numerous significant issues with machine learning and deep learning-based techniques for detecting brain disorders, the conclusion offers a summary of the key findings from the reviewed studies. We want to find the most accurate way to identify different brain illnesses so that things can be better in the future.

4 Proposed System

The system selection used to distinguish the internal region from other organs in the MR image collection is the Grey Level Co-Occurrence Matrix (GLCM) Homomorphic Function. The gradient magnitude is then determined using the Sobel operator and defined as the homogeneity condition in a modified gradient magnitude region growth technique. This technique allows for stable border recognition in the presence of gaps and intersection oscillations in the gradient. It is possible to ascertain whether the boundary region has sufficient contrast to enhance segmentation accuracy by looking at the gradient magnitude. To establish the size of the segmented tumour, the relabeled technique remaps the labels associated with objects in a segmented image so that the label numbers are consecutive and there are no gaps between them. To extract any object from the relabeled output, you can apply a binary threshold. This version of the BAT method extracts and relabels the tumour before calculating its pixel size. There are two stages in which the algorithm works efficiently. The first step is to determine the input image labels and the number of pixels in each label. The second step is to determine the output requested region in order to determine the total number of pixels accessed. The appropriate tumour area per slice is determined automatically[19].

4.1 MRI Preprocessing

Preprocessing photographs usually involves removing background and low frequency noise, modifying the brightness of each useful image, removing reflections, and masking certain regions of the image. Image processing is the process of improving data visually prior to computer processing. They use the standard preprocessing methods for brain MRI to recover the relevant fractal and intensity data. Tumour segmentation and classification utilizing different feature set combinations is the next step. The AdaBoost classifier receives feature values directly and uses them to categorize tumour and non-tumor regions. Labelling tumour regions by hand is a necessary step in training supervised classifiers. The trained classifiers then identify tumour segments or none at all in an unknown brain MRI.

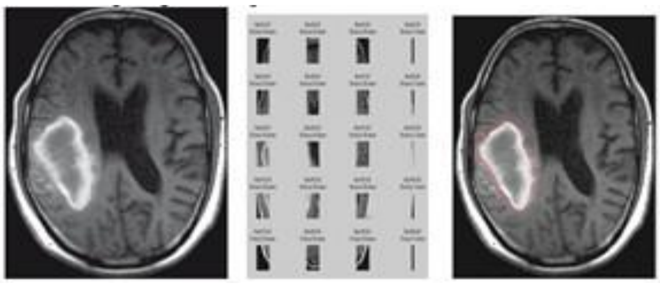

Fig. 3. Brain MRI preprocessing and tumor segmentation

Bias Feature Extraction. Feature extraction is one specific kind of dimension reduction. When the input data is too large to analyses and maybe redundant (for instance, the same measurement in both feet and meters), an algorithm will transform it into a reduced representation set of features, also referred to as a features vector. Converting the input data into a set of features is known as feature extraction. If the features are properly chosen, it is expected that the features set will extract the relevant information from the input data in order to do the desired job using this smaller representation instead of the full size input.

Bat Brain Tumor Segmentation And Classification From Non-Tumor Tissue. A support vector machine searches for the optimal separation hyper-plane between members and non-members of a given class in a high dimension feature space. The bat algorithm uses the subset of features selected during the data pre-processing and extraction phases as inputs. RBF, graph, and polynomial kernels are among the several kernel functions used by the Grey Level Co-Occurrence Matrix (GLCM). A Radial Basis Function (RBF) is a particularly useful kernel function among these since it translates the vectors nonlinearly to a feature space with a very high dimension. To split and classify tumor/non-tumor tissue, we utilize MRI pixels as samples. The representation of these samples is a set of feature values extracted from multiple MRI modalities. Combining features from several modalities is necessary for tumour segmentation and classification. To differentiate between tumorous and non-tumorous tissues, they train a modified supervised Grey Level Co-Occurrence Matrix (GLCM) ensemble of classifiers.

Grey Level Co-Occurrence Matrix (Glcm) Homomorphic Algorithm For Segmenatation Is As Follows. Extract the sub-image blocks from the top left corner. To deconstruct sub-image blocks, utilise a two-level, two-dimensional Grey Level Co-Occurrence Matrix (GLCM). Find the Spatial Grey Level Dependence Matrices (SGLDM) or Grey Level Co-occurrence Matrices. The average distance is 45, 90, and 135 degrees, and the average θ is 0 degrees for each two-level high-frequency sub-band of decomposed sub-image blocks. From these co-occurrence matrices, the following nine Haralick second order statistical texture features—also referred to as wavelet Co-occurrence Texture features (WCT)—are extracted[20].

Bat Brain Tumor Segmentation Using Structure Prediction. This section assesses the proposed method for dividing up particular brain tumour components, including the active tumour, tumour core, and overall tumour. This strategy, which forms the basis of this method, is novel in that it tackles a medical image segmentation problem by combining the deep approach with local structure prediction.

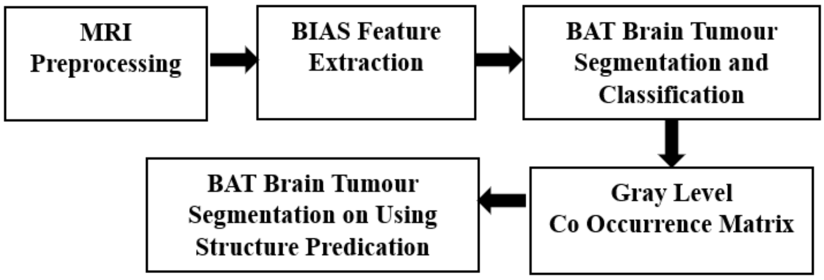

Fig. 4. System flow diagram

5 Result Analysis

The technology significantly improves brain tumour segmentation and classification by fusing innovative methods with state-of-the-art algorithms. The Grey Level Co-Occurrence Matrix (GLCM) and Homomorphic Functions ensure accurate differentiation of tumour patches from adjacent tissues, while the improved gradient magnitude region-growing technique enhances boundary detection, especially in scenarios with challenging variations[21]. The Bat Algorithm refines segmentation by optimizing feature selection and tumour classification with the aid of the extraction of Haralick texture features for detailed analysis. Additionally, by employing structure prediction, the method accurately identifies tumour substructures, including active tumour locations, tumour cores, and total tumour areas[22]. Validation on supplementary datasets demonstrates that the system's excellent precision, resilience, and versatility in processing a range of MRI images make it a reliable tool for addressing the challenges of brain tumour identification and segmentation.

5.1 GLCM Homomorphic Function

$$H\ (f(x, y))=\log(1+f(x, y))$$

Precision. The precision metric quantifies the proportion of accurately predicted tumour pixels.

$$\text{Precision}=TP+FP/\ TP$$

Recall (Sensitivity). Measures of recall How many of the real tumour pixels were detected correctly

Recall=TP+FN/ TP

F1-score. Particularly when there is an imbalance between tumour and non-tumor pixels, the F1-Score strikes a balance between precision and recall

F1=2×Precision+Recall/ Precision × Recall

*Accuracy***.** The segmentation model's accuracy is a measure of how well it can distinguish between tumour and non-tumor pixels.

Accuracy= TP+TN+FP+FN/ TP+TN

6 Conclusion And Future Work

In conclusion, the proposed cancer segmentation technique, which utilizes the GLCM and the Sobel operator, demonstrates promising results in accurately segmenting tumours with intricate borders while being robust against noise and gradient changes. Future research will focus on enhancing the system's capabilities by using deep learning architectures, including CNNs and Transformers, to better handle complex tumour forms and automate feature extraction. Increasing the number of MRI pictures from different modalities and types of tumours in the dataset would further enhance the generalizability of the system. The creation of 3D segmentation algorithms for volumetric analysis and the prioritization of real-time implementation through optimization techniques and hardware acceleration will significantly improve clinical utility. If medical professionals collaborate closely with the technology, it will meet clinical criteria and seamlessly integrate into diagnostic workflows.

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