BRAIN TUMOR SEGMENTATION AND CLASSIFICATION USING IMAGE PROCESSING

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH

July 2024

APPROVAL

This Project titled “Brain Tumor Segmentation and Classification Using Image Processing”, submitted by **Md. Rakibul Islam Shanto** and **Samsun Naher Asme** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 14-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Narayan Ranjan Chakraborty, Associate Professor and Associate Head, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ACKNOWLEDGEMENT

First, we express our heartiest thanks and gratefulness to almighty for His divine blessing making it possible for us to complete the final year project successfully.

We are grateful and wish our profound indebtedness to **Narayan Ranjan Chakraborty**, **Associate Professor and Associate Head**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of "Computer Vision" to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartiest gratitude to the **Head of the Department of CSE**, for his kind help in finishing our project and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

In this study, we propose an automated approach for brain tumor segmentation and classification from MRI images which is a leading sector in medical imaging research because of the importance they have for patient diagnosis and therapy. This project does a comprehensive literature review and provides approaches to improve the accuracy and efficiency of brain tumor detection. The dataset, sourced from Kaggle, consists of 4237 MRI images categorized into four classes: No Tumor, Glioma, Meningioma, and Pituitary tumors. Corresponding segmentation masks are also included for precise delineation of tumor regions. The detection system's performance is improved through the use of techniques such as feature extraction, image resizing, and grayscale conversion. Several segmentation and classification methods, including Convolutional Neural Networks (CNNs), Artificial Neural Network (ANN), Graph Neural Network (GNN) are evaluated. The segmentation task is performed using a customized CNN, achieving an impressive accuracy of 96.32%. For the classification task, a variety of machine learning models were tested, including Random Forest, Extra Trees, Logistic Regression, Gradient Boosting, Support Vector Machine, Decision Tree, Naive Bayes, ANN, and GNN. Among these, the Graph Neural Network (GNN) demonstrated superior performance, achieving an accuracy of 99.65%. The project also involves developing a web application where users can upload MRI images to receive automatic tumor detection and classification. This application aims to assist medical professionals by providing quick and accurate diagnoses, potentially improving patient outcomes. The project aims to overcome existing obstacles in brain tumor identification while also contributing to the development of accurate and trustworthy diagnostic tools for healthcare professionals.

Keywords: Brain Tumor, Segmentation, CNN, Classification, MRI images.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Tumors in the brain is a big health threat globally, for individuals of all ages. Because the brain is an important part of our health. Brain tumor ranks as the 2nd leading cause of cancer among with the children under the age of 15. It is the second fastest-growing problem causing cancer among individuals even over the age of 65. In the USA, this problem is growing at an alarming rate. There more than 100,000 people will receive a diagnosis of a brain tumor in the next upcoming year. Now it is a very urgent need for advancements in the detection, diagnosis, and of course the treatment of brain tumors to minimize the devastating impact on individuals and worldwide.

Nowadays, to improve the detection of brain tumors using MRI images have benefited from advance technologies like neural network and deep learning. Many researchers have been trying out different methods to find tumors earlier and more accurately and also the place where the tumor is situated. They're using things like neural networks, clustering algorithms, segmentation techniques and other techniques to improve the images before analyzing on them. By making some mix methods, they are making big projects that can find brain tumors.

However, there are still some challenges exits to overcome the problem, like making sure the models work well with different types of data specially the MR Images and avoiding the mistakes. Overall, these advance technologies are helping the doctors to find out and treatment the brain tumors faster and more accurately. In recent years, the field of brain tumor segmentation and classification using MRI images have experienced a big transformation, including the technologies such as neural network and deep learning. By achieving the power of neural networks, clustering algorithms, and other advanced image processing techniques, scientists and researchers have made significant strides in automating the detection of brain tumors, enabling earlier detection and more accurate treatment planning.

Although these obstacles, research efforts, and technological advancements are driving a quick evolution in brain tumor detection and classification. By expanding the frontiers of medical imaging and artificial intelligence, every new study adds a layer of understanding and knowledge.

1.2 Background and Present State

Brain tumors are abnormal cell growths inside the brain that can be either harmless or dangerous. They represent serious risks to health and need to be diagnosed and treated as soon as possible. Because of its high-resolution imaging capabilities, MRI (Magnetic Resonance Imaging) is the primary method used to diagnose brain cancers, however, CT (Computed Tomography) scans are also utilized. Our study focuses on four groups of brain tumors: no brain tumors, glioma tumors, pituitary tumors, and meningioma tumors. Precisely dividing and categorizing these neoplasms is crucial for efficient treatment scheme development and enhanced patient results.

Radiologists manually analyze images to find brain tumors using traditional procedures, which can be laborious, subjective, and prone to error. Automated methods utilizing deep learning and machine learning techniques have been developed to get beyond these restrictions. These cutting-edge techniques use neural networks to evaluate CT and MRI images, resulting in more precise and effective tumor detection. In particular, our study makes use of various machine learning models including deep learning models like Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) to attain accurate tumor segmentation and classification.

The accuracy of detecting brain tumors has greatly increased due to recent advances in deep learning. Neural network models now perform better because to techniques including feature extraction, data augmentation, transfer learning, and model tuning. By using CNNs and GNNs, which have shown better results than conventional machine learning models, our study seeks to build on these gains. By concentrating on these cutting-edge techniques, we hope to create a dependable instrument that will help physicians identify and treat brain tumors more successfully, thereby enhancing patient care and results.

1.3 Problem Statement

Every project has obstacles that it must overcome in order to correctly accomplish its goals. It can be difficult to find and compile high-quality MRI datasets for deep learning model testing and training. Strong model performance depends on preserving enough variance and diversity in the datasets, which can be difficult and expensive to do while gathering

MRI data. Moreover, there is a dearth of labeled data for brain tumor classification and segmentation, necessitating rigorous annotation and validation processes to ensure reliability and accuracy.

Second, a major barrier to developing algorithms is the variety and complexity of brain tumors. It is difficult to create a treatment that works for all tumors since they can occur in the brain in a variety of shapes, sizes, and locations. Maintaining high accuracy while modifying models to function well across various tumor kinds and patient characteristics is still a challenging problem. Moreover, integrating recently created technologies with current clinical practices and medical imaging systems presents a distinct set of challenges. Ensuring data security, smooth dependability, and legal compliance are top considerations. Similarly, the application needs to be easy to use and intuitive for medical professionals with varying levels of technical proficiency, which calls for careful design and usability testing.

It's also important to think about the ethical and legal ramifications of employing automated tools in beneficial situations. The protection of patient privacy, informed consent, and autonomy in making decisions are critical concerns that need to be taken care of in order to win over patients' and healthcare professionals' support. Ultimately, it is imperative to meticulously confirm and test the created models' practical performance and adaptability. It will take research and validation experiments involving a range of patient populations and healthcare facilities to assess the security, efficacy, and safety of the proposed methodology.

1.4 Objectives

Our main goal is to create a robust and easy-to-use technology that will help medical professionals correctly identify and treat brain tumors. Convolutional Neural Networks (CNNs) are one of the cutting-edge deep learning techniques that we want to use to greatly enhance the segmentation and classification of brain cancers from MRI images. Our objective is to proficiently hone these algorithms on huge MRI datasets in order to outperform current measures and set new norms for accuracy. By using techniques like transfer learning and normalization, we want to improve the models' capacity for prediction over a variety of datasets, guaranteeing reliable results and generalizability.

Additionally, we're dedicated to making this tool user-friendly and implementing their comments into it so that it fits effortlessly into the daily workflow of medical professionals. Our goal is to produce a useful tool that seamlessly integrates into the everyday routines of physicians, rather than just coming up with a technical answer. Our goal is to assist medical professionals in recognizing and treating brain tumors more effectively by creating a tool that interfaces directly with them.

Our ultimate goal is to positively influence patient care by giving medical professionals a useful tool for brain tumor detection and therapy. We think that by fusing cutting-edge technology with the ideas of human-centered design, we can revolutionize the field of brain scans and enhance patient outcomes everywhere. With this research, we hope to significantly improve the quality of life and survival rates of patients globally by providing physicians with a powerful ally in the fight against brain tumors.

1.5 Scope and Limitations

Our study focuses on applying deep learning techniques to develop an effective tool for brain tumor classification and segmentation using MRI scans. Benign or malignant brain tumors carry significant dangers to a patient's health and need to be properly diagnosed and treated. Our objective is to develop an intuitive tool that can effectively distinguish between various brain tumor types, including gliomas, meningiomas, pituitary tumors, and non-tumor cases. We will use deep learning algorithms to examine MRI images from training and testing data in order to do this. Each dataset will undergo meticulous processing to guarantee thorough coverage of tumor variants and shapes. Our project intends to aid in the early diagnosis and precise categorization of brain tumors by combining cutting-edge deep learning techniques with high-quality MRI images. This will ultimately enable better patient care and knowledgeable professional decision-making.

There are several restrictions in place, despite the project's goals and progress. A noteworthy constraint of the tool is that it might not yield precise forecasts if an alternative MRI scan that was not part of the training or testing dataset is supplied as input. This problem emphasizes how much more model improvement and generalization are required. Furthermore, our CNN model achieves 96.32% segmentation accuracy, which is still behind the accuracy reported in several previous research works, although being noteworthy. These drawbacks point to areas in need of development and the necessity of continuing study to increase the precision and dependability of the instrument.

1.6 Report Organization

This study investigates brain tumor segmentation and classification, focusing on deep learning to enhance accuracy. Chapter One: Introduction outlines the research questions, objectives, motivations, and the overall framework. Chapter Two: Literature Review provides a detailed literature review on CNNs, machine learning, and brain tumor detection, along with a comparative analysis of existing works and open issues. Chapter Three: Methodology describes the proposed methodology, including hardware and software requirements, project management, and financial analysis. Chapter Four: Implementation details the training of models and their evaluation. Chapter Five: Result and Analysis presents experimental results and comparative analysis, supported by graphical and statistical data. Chapter Six: Impact on Society, Environment, and Sustainability explores the broader implications for healthcare, ethical aspects, and sustainability plans. Chapter Seven: Conclusion and Future Work summarizes the main findings, offers practical applications, and suggests avenues for further research, ensuring a comprehensive understanding of the research's impact on brain tumor classification and segmentation using image processing.

1.7 Summary

Our work addresses the fundamental need for accurate and useful brain tumor detection. Since brain tumors are one of the main causes of cancer-related deaths globally, developments in deep learning and neural networks present promising opportunities to enhance MRI scan-based brain tumor detection techniques. The project's objective is to automate tumor identification using deep neural networks, providing experts with a reliable tool for early detection and precise treatment planning.

Driven by the pressing need to improve patient care, the project intends to apply deep learning methods to develop a robust application that can accurately identify and classify brain cancers from MRI images. By merging deep learning techniques and gathered datasets, our initiative seeks to aid in the precise definition and early identification of various tumor forms, such as gliomas, meningiomas, pituitary tumors, and non-tumor instances. Through rigorous verification methodologies and broad teamwork, the initiative aims to remove roadblocks and pave the way for major advancements in brain tumor diagnosis and treatment.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Tumors in the brain is a big health threat globally, for individuals of all ages. Because the brain is an important part of our health. Brain tumor ranks as the 2nd leading cause of cancer among with the children under the age of 15. It is the second fastest-growing problem causing cancer among individuals even over the age of 65. In the USA, this problem is growing at an alarming rate. There more than 100,000 people will receive a diagnosis of a brain tumor in the next upcoming year. Now it is a very urgent need for advancements in the detection, diagnosis, and of course the treatment of brain tumors to minimize the devastating impact on individuals and worldwide.

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However, there are still some challenges exits to overcome the problem, like making sure the models work well with different types of data specially the MR Images and avoiding the mistakes. Overall, these advance technologies are helping the doctors to find out and treatment the brain tumors faster and more accurately. In recent years, the field of brain tumor segmentation and classification using MRI images have experienced a big transformation, including the technologies such as neural network and deep learning. By achieving the power of neural networks, clustering algorithms, and other advanced image processing techniques, scientists and researchers have made significant strides in automating the detection of brain tumors, enabling earlier detection and more accurate treatment planning.

Although these obstacles, research efforts, and technological advancements are driving a quick evolution in brain tumor detection and classification. By expanding the frontiers of medical imaging and artificial intelligence, every new study adds a layer of understanding and knowledge.

2.2 Related Works

Several researches have shown the successful performance of convolutional neural networks in classification and segmentation tasks. Researchers achieve impressive accuracy rates using advanced deep learning architectures such as ResNet101v2 and VGG-16, researchers achieve remarkable accuracy rates, with CNNs consistently outperforming other algorithms [11] (Khan et al., 2022), [12] (Chattopadhyay & Maitra, 2022), [13] (Mittal & Tayal, 2021), [9] (Kumar et al., 2021).

Pre-processing steps, including resizing, rotation, and geometric corrections, are employed to enhance image quality and aid in feature extraction [1] (Methil, 2021), [2] (Sravanthi et al., 2021). Additionally, segmentation techniques such as support vector machines (SVM) and self-organizing maps (SOM) are utilized for accurate delineation of tumor boundaries [2] (Sravanthi et al., 2021), [3] (Suresha et al., 2020).

Other studies focus on the integration of multiple image processing steps, such as noise removal, grayscale conversion, and edge detection, to refine segmentation results [4] (Abd Khalid et al., 2020), [14] (Mittal & Tayal, 2021), [15] (Thayumanavan & Ramasamy, 2021). The application of sophisticated algorithms like watershed transform and fuzzy C means clustering further improves segmentation accuracy [14] (Mittal & Tayal, 2021), [15] (Thayumanavan & Ramasamy, 2021).

Moreover, feature extraction techniques like histogram of oriented gradients (HOG) and discrete wavelet transform (DWT) are employed alongside traditional machine learning classifiers such as random forest and SVM to classify tumor regions [6] (Sahaai, 2021), [15] (Thayumanavan & Ramasamy, 2021).

Innovative approaches such as genetic algorithms and deep learning architectures demonstrate promising results in both segmentation and classification tasks [8] (Amin et al., 2022), [10] (Budati & Katta, 2022). These methods leverage the power of evolutionary computation and complex neural network architectures to achieve high accuracy rates.

Leveraging advanced architectures such as ResNet18 and VGG-19, researchers achieve significant accuracy rates, with CNNs consistently outperforming traditional approaches

[21] (Tang & Teoh, 2023), [22] (Periasamy et al., 2023), [25] (Siddaiah et al., 2022). Pre-processing steps, including cropping, RGB to grayscale conversion, and image blurring, are employed to enhance image quality and facilitate subsequent analysis [16] (Koshti et al., 2022), [17] (Malik et al., 2021).

Additionally, segmentation techniques such as clustering-based approaches and data reduction methods play a crucial role in accurately delineating tumor boundaries [16] (Koshti et al., 2022), [20] (Soomro et al., 2022).

Moreover, feature extraction techniques such as thresholding, area filtering, and boundary tracing are utilized alongside sophisticated algorithms like Gaussian filter and morphological operations to refine segmentation results [18] (Sethy et al., 2022), [19] (Ugale et al., 2022).

Another innovative approaches, including deep learning architectures and transfer learning, demonstrate promising results in both segmentation and classification tasks [26] (Kalra et al., 2023), [27] (Selcuk & Serif, 2023). These methods harness the power of complex neural network architectures to achieve high accuracy rates.

Furthermore, data augmentation techniques, normalization, and balancing the dataset are crucial steps in improving model robustness and generalization [21] (Tang & Teoh, 2023), [22] (Periasamy et al., 2023). Studies like [29] (Konar et al., 2023) and [30] (Nikhil et al., 2023) delve into deep learning frameworks, particularly YOLOv7 and YOLOv3, showcasing their effectiveness in brain tumor detection with impressive mean average precision (mAP) scores. Image manipulation techniques and data augmentation play a pivotal role in enhancing model performance. Techniques such as resizing, rotation, flipping, and shearing, as demonstrated in [30] (Nikhil et al., 2023), contribute to model robustness and generalization.

Furthermore, transfer learning with pre-trained CNN models emerges as a powerful tool in brain tumor classification, as highlighted in [30] (Nikhil et al., 2023). Leveraging architectures like VGG-19, ResNet101, and Inception-ResNet-v2, researchers achieve high accuracy rates, with a hybrid Inception ResNet model yielding exceptional performance.

On the hardware front, studies like [31] (Prasad et al., 2023) delve into the design and evaluation of ultrawideband (UWB) patch antennas for brain tumor detection. In the realm of image processing, techniques such as grayscale conversion, filtering, and resizing continue to be instrumental in pre-processing MRI images for accurate detection. Notably, studies like [34] (Mahajan & Chavan, 2023) and [35] (Fathima et al., 2023) employ CNN architectures alongside traditional classifiers like KNN and SVM, achieving commendable accuracies in multiclass classification tasks.

Moreover, advanced deep learning models, including hybrid architectures and gradient-weighted class activation mapping (Grad-CAM), demonstrate enhanced performance in brain tumor detection and diagnosis [32] (Pikulkaew, 2023), [36] (Dharshini et al., 2023). Watershed transform, fuzzy C means clustering, and clustering-based techniques are prominent segmentation algorithms used to precisely delineate tumor boundaries. For classification tasks, convolutional neural networks (CNNs) emerge as the preferred choice, regularly outperforming classical classifiers.

In some final papers, CNN architectures such as ResNet, VGG, and Inception-ResNet-v2, along with advanced variants like ResNet101v2 and VGG-16, achieve remarkable accuracy rates in classifying tumor regions. These CNNs leverage feature extraction techniques like histogram of oriented gradients (HOG) and discrete wavelet transform (DWT) alongside traditional machine learning classifiers such as random forest and support vector machines (SVM) to accurately classify tumor regions.

Overall, the use of segmentation techniques for accurate boundaries and CNN-based classification algorithms for accurate classification shows the power of merging image processing and deep learning methodologies to advance brain tumor segmentation and classification.

2.3 Comparative between Existing Works

The literature review on brain tumor segmentation and classification includes an in-depth review of 40 research papers that include segmentation, classification, and other related approaches. The paper highlights the importance of convolutional neural networks (CNNs) in achieving high accuracy rates across a variety of applications. Researchers frequently beat standard algorithms by using advanced deep-learning models such as ResNet101v2, VGG-16, ResNet18, and VGG-19.

Some papers focus just on segmentation techniques [2], [3], [4], [14], and others on classification using CNNs, [6], [8], [10], [21], [22], [25], [26], [27], there is a significant gap in research that successfully brings together segmentation and classification methodologies. Future research could look into hybrid techniques that combine the benefits of segmentation algorithms for accurate tumor delineation and CNN-based classifiers for strong classification, to improve the overall diagnostic accuracy. Although some papers use transfer learning with pre-trained CNN models, [30], there is still a need to evaluate the effectiveness of various transfer learning strategies, such as fine-tuning and feature extraction. Analysis of various transfer learning algorithms might offer information on how to best use pre-trained models for improved categorization performance.

Despite great progress, some gaps and opportunities for further research are recognized. These include integrating segmentation and classification techniques, evaluating transfer learning methodologies, developing novel feature extraction methods, and defending data imbalance and generalization issues.

TABLE 2.3.1: Comparative Analysis Table

Rf No	**Pre-processing**	**Classification/ Segmentation**	**Used Algorithm**	**Best Algorithm**
[1]	Resizing, Rotation, Horizontal shift, Vertical shift, Shearing, Zooming, Horizontal flip, ImageDataGenerator, Erosion and dilation, Opening, Closing, Histogram Equalization	Classification: CNN	CNN, ResNet101v2	98% after preprocessing
[2]	MRI image transformation, Geometric corrections, Non-brain element removal, Grayscale conversion, Image filtering, Binary thresholding	Segmentation: SVM, Self-Organizing Maps	SVM, SOM	97% (classification based segmentation)
[3]	CT filter, MRI filter, EEG	Segmentation: K-means clustering, Binary Thresholding Classification: SVM	Binary Thresholding, K-means clustering, SVM	Testing 0.96, figure out the type also
[4]	Grayscale Conversion, Mean/Median Filter (noise removal) Sobel & Canny	Segmentation: Grayscale conversion, Noise removal	Sobel algorithm Canny algorithm	Accuracy 0.76

	(Edge Detection), Global Threshold	(median/mean filtering), Image enhancement, Edge detection (Sobel, Canny), Global thresholding		
[5]	Grayscale, Dilation & Erosion, Gaussian Blur Technique, Contour Detection	Classification: CNN, VGG-16	CNN, VGG-16	CNN = 91.6% VGG = 91.9%
[6]	Image acquisition, Image enhancement, Histogram equalization, Binarization, Feature extraction	Classification: DNN, Stacked Autoencoders, Softmax Layer	HOG GLCM DNN PC Softmax CNN LSTM	DNN (50 epochs) = 95.3%
[7]	<u>Noise Removal Filters</u>: Median Filter, Wiener Filter, Mean Filter <u>Contrast Enhancement</u>: Bi-histogram equalization, Histogram equalization, Optimization <u>Feature Selection</u>: PCA, PSO, Wrapper Method	Classification: NN, SVM, Bayesian Networks, KNN, Gaussian Mixture Model, Dirichlet Process, Q Learning, R Learning, TD Learning, Pattern Net Segmentation: Adaptive K-means Clustering, CNN based on U-net Architecture	Deep L (DNN, CNN, RNN), Machine L (KNN, SVM, CART), Image class (Pattern Net),	Pattern Net = 98.9%
[9]	Median filtering Thresholding method Region growing method	Segmentation: Thresholding Region Growing Watershed Algorithm Classification: CNN Architecture ReLU Pooling Fully Connected Layer Genetic Algorithm (GA)	Thresholding Method Region Growing Method Watershed Algorithm CNN Genetic Algorithm (GA)	validation accuracy = 92%

[10]	Gaussian filter, Median filter	Segmentation: Skull-stripping procedure Median filter Chan-vese model Level set method Classification: KNN SVM Naïve Bayes Logistic Regression Random Forest Decision Tree	CVS LSS GLCM KNN SVM NB LR RF DT	SVM = 96.48%
[11]	Image extraction, Labeling	Classification: SVM Sigmoid Softmax Segmentation: (Manual, Semi-automatic, Absolute automatic) segmentation methods	SVM RMSProp (Root Mean Square Propagation) AdaMax CNN	CNN = 99.74%, Softmax RMSProp optimizer.
[12]	Image extraction, Labeling	Classification: CNN, VGG-16	23 layers CNN + VGG-16	2 datasets, 97.8% &100% accuracy
[13]	Image filter (Convolution, pooling, fully connected layers), Function (ReLU, Tanh, sigmoid function)	Classification: CNN	three layers of CNN architecture	f-score = 97.3% mean accuracy = 96.08%
[14]	Median filtering Thresholding Grayscale conversion Image segmentation Morphological reconstruction Edge detection Watershed transform Filtration Measurement parameter calculation	Segmentation Watershed transform K-means clustering Thresholding Fuzzy C Means Clustering	Watershed transform K-means clustering Thresholding Fuzzy C Means Clustering Otsu's segmentation technique	highest entropy = 6.2372 by watershed segmentation technique

[15]	Intensity Normalization Image Resizing (128x128) DWT HOG Noise Removal (Median Filter) Brain Image Normalization Brain Extraction Otsu’s Segmentation Morphological Operations Overlay-Based Fusion	Classification: RFC SVM DT	RFC SVM DT DWT HOG Fuzzy C means clustering Markov Gibbs random field Otsu’s segmentation method PCA	RFC = 98.37%
[16]	Cropping RGB to grayscale conversion Image blurring Skull and brain part detection in MRI images Clustering-based approaches: SOM and Fuzzy C Means, Data reduction: LE / ICA, K-means clustering / AHC	Segmentation: Clustering-based approach (Self Organizing Map), Fuzzy C Means clustering, LE, ICA, K-means clustering, AHC Classification: Custom architecture of CNN, DWAE Model, Transfer Learning with CNN, Model evaluation function	SOM FCM LE ICA K-means AHC CNN DWAE Model Transfer Learning	DWAE = 99.3% accuracy of 97% is the best
[17]	Grayscale (SVD), Noise reduce, Thresholding, Edge detection, Sobel operation, Canny operation, Segmentation.	Segmentation: Region-based technique, Thresholding (boundary-based) technique, Edge-based technique	Grayscale conversion using SVD Noise removal through filtering approaches Skull & scalp separation using morphological operations	successfully extracted the neoplasm
[18]	Thresholding, area filter, boundary tracing, region merging, image subtraction	Segmentation: Thresholding Area filtering Boundary tracing	Skull stripping Thresholding Area filtering Boundary tracing	successfully detects the position of glioma, meningioma, and pituitary brain tumors using T1-

				weighted MRI images
[19]	Gaussian Filter, noise removal, image enhancement, thresholding (binary inversion, Otsu), morphological operation (Erosion + Dilation), segmentation (Watershed),	Segmentation: Gaussian filter, thresholding, contour detection, morphological operations, and watershed segmentation	Fuzzy C-means, SVM, CRF, MRF, K-means, CNN, Watershed Algorithm	CNN + Otsu = 97.87%
[20]	denoising, thresholding, Canny edge detection, intensity statistical features, texture-based features, GLCM, TTBM, Gabor filters, GAC, region-growing, watershed, CRF, decision forest, meanshift, K-means, fuzzy C-means, SOM, KNN, and SVM	Segmentation: thresholding, GLCM, TTBM, GAC, watershed, region-growing, Conditional Random Field, Meanshift, K-means, Fuzzy C-means, SOM, and KNN	DensNet201, Inception-v3, VGG-16, CNN, F-CNN, E-CNN, U-Net, GANs	DensNet21 = 99.51%
[21]	Data augmentation Resizing images to 224x224 pixels. Converting images to 3 channels. Balancing the dataset.	Classification: GoogLeNet CapsNet CNN ResNet18	ResNet18 model, CapsNet architecture, CNN, GoogLeNet	ResNet18 => accuracy = 0.88 sensitivity = 0.86 specificity = 0.90 precision = 0.896
[22]	Image re-sizing Image cropping Image processing Data augmentation Normalization of images	Classification: SVM, ACNN, CNN with three layers	Convolutional Neural Network (CNN) VGG-19 ResNet-50	ResNet-50, accuracy: 89.46 (training data)
[23]	Grayscale conversion Gaussian blurring Erosion followed by Dilation Data Augmentation	Classification: ResNet50 EfficientNet B1 DenseNet	ResNet50 EfficientNet B1 DenseNet	EfficientNet B1, accuracy: 99.31%,
[24]	Data processing Image enhancement	Classification: CNN VGG19 Architecture General CNN ResNet 50 EfficientNet B0	TensorFlow Keras CNN VGG 19 EfficientNet B0 ResNet 50	EfficientNet B0 accuracy 96.5%

[25]	Image resizing Data augmentation Gaussian blurring Erosion and dilation Feature extraction	Classification: FFBPNN HADA SVM ANN KNN Spiral RBF NN SMO	VGG-19 FFBPNN HADA SVM ANN KNN KSVM SOMNN BPN RBFN	ResNet50, Accuracy: 89%
[26]	Noise removal Image scaling Normalization Image loading	Classification: Deep Learning based Tumor Detector Threshold-based segmentation algorithm	MobileNetv2 Efficientnetb4 VGG16 Efficientnetv2B1 Mobile Net ResNet50	MobileNetv2 accuracy: 99.67%
[27]	Scaling down raw photos Normalization Bounding box placement Training epochs Utilization of specific dataset	Segmentation	YOLOv2 YOLOv8 CRF CNN YOLOv8s	YOLOv8 – mean average precision (mAP)=97.6%
[28]	-Determination of antenna materials and dimensions. -Creation of the antenna using CST Studio.	(no specific method) Antenna analysis and electromagnetic parameters.	(no algorithm) S-parameter analysis Far-field radiation pattern analysis VSWR calculation Specific absorption rate (SAR) calculation	Resonance frequency: 12.96 GHz
[29]	Resizing Flip Rotation Cropping	Classification: YOLOv7 YOLOv3	YOLOv7 YOLOv3	YOLOv7 (640x640) with a mAP of 94%
[30]	Resizing images to dimensions (224,224), Image manipulation techniques: Rotation Width & height shift Horizontal & vertical flipping	Classification: Transfer learning with pre-trained CNN models (VGG-19, ResNet101, Inception-ResNet-v2)	VGG-19 Resnet101 Inception-Resnet-v2 Custom Inception-ResNet-v2 model	Inception-ResNet Hybrid 99.30%

	Shearing Zooming			
[31]	Not mentioned	(No specific methods) Design, simulation, evaluation, and comparison of antenna performance	(Process) 1 Design and simulation using CST Microwave Studio (MS) 2 Evaluation of antenna performance 3 Comparison of radiation characteristics 4 Compliance with safety standards	SAR value for brain with tumor: 9.5 W/Kg SAR value for healthy brain: 1.54 W/Kg
[32]	-Standardization of MRI scan image intensities -Resizing images to 246 by 310 pixels -Data augmentation: 1 Random rotation 2 Random flipping 3 Random shifting	Classification	DCNN based on the ResNet-50 architecture Grad-CAM	ResNet-50 97%
[33]	Re-sizing Normalizing Removing background artifacts	Classification: ResNet101	ResNet-101 Contrastive learning	ResNet-101, accuracy = 97%, precision = 97.05 %, recall = 97%, and F1 score 96.99%
[34]	Grayscale conversion Resizing of images to 150 x 150 pixels	classification, focuses on detecting & classifying brain tumors into Glioma, Meningioma, Pituitary, No tumor.	CNN VGG16 KNN SVM Multilayer Perceptron (MLP) Naïve Bayes Logistic Regression Random Forest	CNN 88%
[35]	Filtering Contrast augmentation Skull stripping	Classification CNN	CNN Decision Tree (DT) classifier Radial Basis Function (RBF) classifier	CNN 98.67%

[36]	Conversion to Grayscale Median Filtering Edge Detection	Classification: CNN RNN SVM DT RF NB	CNN BAT algorithm	CNN 98.67%
[37]	Image resizing	Classification:	CNN VGG-16 MobileNetV2 InceptionV3	VGG-16 => training accuracy of 99%
[38]	Wiener filter for smoothing. Canny edge detection for edge identification.	Classification	Decision Trees (DT) SVM Logistic Regression (LR) KNN Naïve Bayes (NB) ANN	DT = 99%
[39]	Data Wrangling and Preprocessing Data Segmentation into Training and Testing sets	Classification	CNN KNN SVM Random Forest	CNN accuracy of 94.82%
[40]	Normalizing intensity Resizing to 128x128	Classification: CNN, DNN	2D CNN Deep Neural Network	CNN = 98.2%

2.4 Open Issues

The acquisition of high-quality MRI datasets for the purpose of training and testing our deep learning models is a primary problem in the "Brain Tumor Segmentation and Classification Using Image Processing" research. Since MRI data collection is costly and time-consuming, it can be challenging to obtain a sufficient amount of different and varied data for a robust model. Furthermore, brain tumor segmentation and classification lack labeled data, which makes correct annotation and validation very difficult. This issue is exacerbated by the intricacy and variety of brain tumors, which can have a variety of sizes, forms, and locations inside the brain. It's challenging to create models that are highly accurate and function effectively across these various sorts and attributes.

There are additional difficulties when integrating new technology with current clinical workflows and medical imaging systems. It is essential to make sure that everything functions well, protects data, and complies with laws. Careful design and usability testing are also necessary to ensure that the application is user-friendly for medical professionals with varying technical skill levels. In order to earn the trust of patients and healthcare professionals, it is imperative to address ethical and legal concerns such as safeguarding patient privacy and guaranteeing informed consent. To make sure the created models are trustworthy, safe, and efficient, they must also be tried and tested in actual clinical settings with various patient populations and facilities. Making a website with a web framework to provide easy access to the segmentation and classification results presents another challenge. In addition to web development expertise, this calls for the seamless integration of the backend algorithms, creating a complex task that addresses both the project's practical and technological components.

2.5 Summary

An extensive analysis of 40 research publications that use segmentation, classification, and other related techniques is part of the literature study on brain tumor segmentation and classification. The study emphasizes how crucial convolutional neural networks (CNNs) are to obtaining high accuracy rates in a range of applications. Researchers often use advanced deep-learning models, such ResNet101v2, VGG-16, ResNet18, and VGG-19, to outperform ordinary techniques.

Expansion, rotation, and scaling are examples of pre-processing techniques that are widely employed to enhance image quality and facilitate feature extraction. Tumor boundaries can be precisely identified with the use of support vector machines (SVM), self-organizing maps (SOM), clustering-based algorithms, and data reduction techniques. CNNs perform better than other techniques in tumor area classification when paired with SVM and random forest. Cutting edge methods like deep learning architectures, transfer learning, and evolutionary algorithms combine complex neural network topologies with computational evolution to attain high accuracy rates. These methods yield promising results.

To improve model robustness and generalizability, dataset balance, standardization, and data augmentation are essential components. Even with the tremendous improvement, there are still certain gaps and areas that warrant more study. These include creating new feature extraction techniques, assessing transfer learning approaches, integrating segmentation and classification techniques, and addressing generalization and data imbalance concerns.

CHAPTER 3
METHODOLOGY

3.1 Overview

This chapter describes the process of identifying and classifying brain cancers from MRI scans. The first step involves prepping the photographs, which includes converting them to black and white, ensuring that they are the correct size, and extracting the most significant elements. Next, an advanced computer algorithm known as a Convolutional Neural Network (CNN) meticulously annotates the locations of the tumors on the MRI images. This is an important phase since it sets up the next step, which is the identification of the type of tumor (gliomas or meningiomas) using various computer models (SVM, DT, KNN, NB), and sophisticated neural networks (ANN and GNN). These models are selected due to their ability to efficiently process and forecast large amounts of complicated data.

Techniques like employing pre-trained models and adding more data are utilized to improve the models' performance even further. To educate the computer more about tumors, further examples must be created in order to add more data. Utilizing trained models facilitates faster learning. The chapter concludes with an assessment of the whole system's performance using metrics such as sensitivity and accuracy. These experiments indicate that the technique is dependable and can effectively assist physicians in more precisely identifying brain cancers from MRI scans, hence enhancing patient care and medical imaging diagnosis.

3.2 Proposed Methodology

The proposed methodology uses a combination of machine learning and advanced image processing techniques for the segmentation and classification of brain tumors from MRI data. Preprocessing the MRI images to improve their quality is the first step in the procedure. In order to do this, the photos must be converted to grayscale, resized to a standard size, and pertinent features that support precise analysis must be extracted. Preprocessing operations are essential to guarantee consistent and meaningful data input into the models, which enhances the performance of subsequent segmentation and classification tasks.

To efficiently identify tumor borders for the segmentation task, a customized Convolutional Neural Network (CNN) is employed. correct tumor region identification is ensured by this method, which is essential for correct classification. Following the segmentation of the tumor regions, several machine learning models are evaluated as part of the classification phase: Support Vector Machine (SVM), Decision Tree (DT), Classification and Regression Trees (CART), K-Nearest Neighbors (KNN), and Naïve Bayes (NB). Advanced neural network models, such Artificial Neural Networks (ANN) and Graph Neural Networks (GNN), are used in addition to these conventional machine learning models to classify the segmented tumor locations into groups like gliomas, meningiomas, pituitary tumors, and non-tumor cases.

Methods including data augmentation, transfer learning, and standardization are used to improve the performance of the model even further. Through a variety of modifications, data augmentation produces more training samples, giving the models access to a more varied dataset for learning. By utilizing pre-trained models and expanding on prior information, transfer learning increases accuracy and efficiency. By ensuring that the data is suitably scaled, normalization helps the models learn and forecast more accurately. The efficacy of these models is validated through a thorough review of statistical measures. The ultimate goal is to enhance the precision and efficiency of brain tumor identification and classification, thereby making a substantial contribution to medical imaging and patient care.

3.3 Hardware Requirement

We used the Google Colab environment's Keras library to conduct experiments for this investigation. The decision was taken because Google Colab makes machine learning techniques in Python easy to use and accessible. The foundation of our machine learning projects was TensorFlow, which is widely recognized as one of the best deep learning libraries.

Google Colab offers a strong platform with substantial cloud computing capabilities for doing machine learning experiments. We utilized Tesla graphics processing units (GPUs) through Google Colab to expedite our deep learning model training. We were fortunate to have Google Colab generously give us with up to 16GB of random-access memory (RAM) for use in our research.

Google Colab provides a range of GPU configurations, such as Tesla K80, T4, P4, and P100 GPUs. These GPUs are essential for managing the computational complexity of deep learning tasks, which makes it possible for our models to be trained and evaluated effectively.

It is crucial to emphasize that our research initiatives are made possible in large part by the computing infrastructure that Google Colab provides, especially with regard to GPU availability. These tools enable academics to quickly design novel solutions across a range of domains and efficiently tackle challenging machine learning challenges.

3.4 Project Management and Financial Analysis

There are several cost items for this project. A table is given below for the individual analysis.

TABLE 3.4.1. Estimated Cost for Deep Learning base project

SN	Components	Estimated Cost (BDT)
1.	Hardware	30,000-40,000
2.	Visiting Stakeholders	5000-6000
3.	Software and Tools	1000-1500
4.	Data Collection and Processing	10,000-15,000
5.	Documentation and Report Writing	1000-1500
6.	Contingency	5000-5500
Total Estimated Cost		52,000-59,500

3.5 Summary

Using MRI images, the suggested approach for brain tumor segmentation and classification involves pre-processing the images to enhance their quality using methods like scaling and grayscale conversion. By using feature extraction, we may obtain important tumor traits that will help with precise analysis of the MRI picture. Tumor boundaries are precisely outlined by a specific Convolutional Neural Network (CNN) used in segmentation tasks.

Our classification approach combines many machine-learning models, including SVM, DT, ANN, and GNN, to classify tumors into distinct kinds, such as meningioma and glioma. Novel methods like transfer learning and evolutionary algorithms enhance accuracy, whereas standardization and data augmentation guarantee the robustness of the model. Classification and segmentation integration, as well as transfer learning assessment, are still difficult tasks. Lastly, data collection projects comprise acquiring hardware components and MRI images, with a project management and financial budget of about 50,000 BDT.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

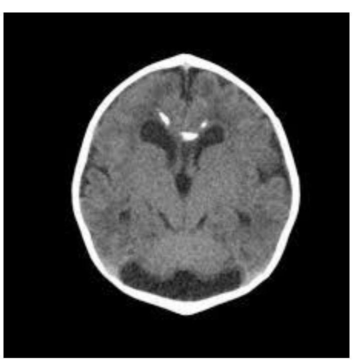
In the implementation of our project on "Brain Tumor Segmentation and Classification Using Image Processing," the first thing comes about our dataset.

A. Datasets

The dataset utilized in this study is sourced from the Kaggle platform, specifically the "Brain Tumor Segmentation Dataset" curated by Atika Akter. This dataset comprises MRI images of brain scans along with corresponding masks delineating tumor regions. The images are categorized into four classes: "No Tumor," "Glioma," "Meningioma," and "Pituitary," each representing different types of brain tumors.

In the "Image" folder, a total of 4237 MRI images are available, distributed across the different tumor categories. Specifically, there are 1595 images labeled as "No Tumor," 649 images labeled as "Glioma," 999 images labeled as "Meningioma," and 994 images labeled as "Pituitary." Corresponding to these images, the "Mask" folder contains segmentation masks indicating the tumor regions. Each mask aligns with the respective image category, totaling to 4239 masks in the dataset.

A thorough training and assessment of segmentation and classification models is made possible by the availability of a variety of tumor types and their matching masks. The models are exposed to a variety of tumor features thanks to the dataset's balanced distribution across classes, which helps to produce reliable and accurate predictions.



A. No Tumor

The mask of the No Tumor is nothing but a black image.

B. Glioma

C. Meningioma

D. Pituitary

Figure 4.1.1: Some Raw Image & Mask of Datasets

All things considered, the "Brain Tumor Segmentation Dataset" is a useful tool for furthering medical image analysis research, especially in the area of brain tumor identification and categorization. Its thorough coverage of tumor kinds and related masks makes it easier to design efficient diagnostic systems that have practical uses in the medical field.

Here the dataset link_ [Brain Tumor Segmentation Dataset] | Kaggle

TABLE 4.1.1: Images Used in the Train, Test and Validation Sets

	No Tumor	**Glioma**	**Meningioma**	**Pituitary**
Image	1595	649	999	994
Mask	1595	650	1000	994

4.2 Train Model

There are different stages for the training model for our project that starts with the image processing techniques which is very important for the any kind of image.

Image Preprocessing:

To ensure consistency and improve model performance, the images were preprocessed with grayscale conversion to standardize the input data, simplifying the processing pipeline. Then the important part came which was resizing. All the images and masks were resized to 256x256 pixels to ensure uniformity in input size for the CNN model. The preprocessing step involved reading the images and masks, converting them to grayscale, and resizing them to the desired dimensions.

Feature Extraction:

The offered code focuses on taking pictures of brain tumors and extracting and categorizing information from them. Images are first read from a designated directory and preprocessed by converting them to grayscale. The binary thresholded images are found to have contours, and the bounding rectangle's aspect ratio, solidity, and circularity are examined for the largest contour. The SIFT technique detects key points in order to record texture complexity. The contours are fitted with an ellipse, and the area ratio between the ellipse and the contour is computed. The number of corners, which indicates the complexity of the image, is quantified using Harris corner detection. To offer a complete feature set, further features including the compactness index, color variation, and asymmetry score are computed.

For additional analysis, these extracted features are exported into CSV files and kept in a

Pandas DataFrame. To properly classify brain tumors, machine learning models need to be trained on this structured data. The code ensures that the generated models have a strong foundation for differentiating between different types of brain tumors by recording a wide range of picture features, which eventually helps with accurate diagnosis and treatment planning.

Data Loading and Splitting:

Following preprocessing, a methodical and controlled procedure was followed to load the images and masks into arrays. In order to make sure that every image and mask combination was correctly matched by matching filenames, the images and masks were first read from their respective directories. In order to preserve uniformity in the input dimensions, 256x256 pixels were the new size for both images and masks. In order to standardize the inputs for the ensuing neural network training, this scaling step was essential. First, the loaded data was organized into lists in Python: the `image_dataset} list contained the grayscale images, and the `mask_dataset} list contained the associated masks. Then, in order to use the array operations and computational efficiency offered by the NumPy library, these lists were transformed into NumPy arrays for more effective processing and manipulation.

Next, a 90/10 split ratio was used to divide the dataset into training and testing sets. This was accomplished by using the train_test_split function from the sklearn.model_selection module, which set a random seed to guarantee a random yet repeatable split. 90% of the data made up the training set, which was used to train the CNN model; the remaining 10% made up the testing set, which was used to assess how well the model performed on untested data. By carefully dividing the data, the model is trained on a wide range of images, which improves its robustness and accuracy in real-world applications as well as its capacity to generalize to new, unknown data.

Training:

Creating a convolutional neural network (CNN) model specifically for segmentation tasks marked the beginning of the training phase. The architecture made use of the U-Net framework, which is well-known for working well on picture segmentation assignments. With the help of this architecture, which included an encoder and a decoder path, features at different levels of abstraction could be extracted and then upsampled to create segmentation maps. The input layer of the model was initially configured to receive 256x256 pixel images. This was followed by a sequence of convolutional blocks that were in charge of extracting features and encoding spatial information. Two convolutional layers with batch normalization and ReLU activation functions made up each convolutional block, which encouraged feature learning and non-linearity in the network.

Specifically designed for binary segmentation tasks, the U-Net model was constructed using the binary cross-entropy loss function and the Adam optimizer. The network's accuracy in defining tumor regions was optimized by using the binary cross-entropy loss function, and the Adam optimizer made use of the default hyperparameters. In order to minimize the specified loss function, the model updated its weights iteratively over epochs during training. To avoid overfitting and guarantee ideal convergence, early stopping callbacks were incorporated to track model performance and terminate training once the validation loss plateaued.

The U-Net model was trained by feeding it preprocessed training data, which included grayscale images of brain tumors and the masks that went with them. The model was trained across a number of epochs, where gradients and weight updates were computed by making forward and backward passes through the network during each epoch. In order to precisely segregate tumor locations from input images, the model's parameters were optimized throughout the training phase. After training, the model's performance was assessed on a different validation set to determine whether it could generalize to data that had not yet been seen. The goal of this rigorous training procedure was to provide the model the ability to accurately segment tumors for clinical applications by helping to define tumor boundaries in brain MRI imaging.

4.3 Model Evaluation

There are two important part of our project which is segmentation and classification.

Segmentation:

A convolutional neural network (CNN) architecture inspired by the U-Net model was specifically created for the segmentation task using brain magnetic resonance imaging (MRI) scan data to identify tumor locations. With its encoder-decoder structure, our customized CNN architecture made it easier to extract features and locate them spatially both of which are essential for precise segmentation. The model architecture was composed of a series of convolutional blocks, each with two convolutional layers, rectified linear unit (ReLU) activation functions, batch normalization, and so on. In order to restore spatial details lost during down-sampling, the encoder path gradually down-sampled the input image while the decoder path up-sampled the feature maps.

The U-Net-inspired design improved its capacity to define complex tumor borders by utilizing a sequence of convolutional and transpose convolutional layers to collect hierarchical features at various scales. Tumor locations inside MRI scans can be precisely located thanks to the decoder path's reconstruction of spatial details after the encoder path retrieved high-level semantic characteristics. To enable information flow across various network levels, the model made use of skip connections between corresponding encoder and decoder blocks. This allowed for effective feature reuse and helped to mitigate the vanishing gradient issue during training.

Using a binary cross-entropy loss function and the Adam optimizer, the customized CNN model was optimized during training. With the help of the matching tumor masks and preprocessed MRI images, the model was trained for 100 epochs. In order to maximize the model's capacity to precisely detect tumor locations, the training procedure entailed iteratively modifying the model parameters to reduce the difference between predicted segmentation maps and ground truth masks. Additionally, to avoid overfitting and improve the model's generalization performance, dropout regularization was used, using a 0.07 dropout rate. The goal of the training phase was to provide the CNN model the ability to precisely segment tumor locations within unseen MRI data, so that doctors could examine and assess tumor shape.

Classification:

Several machine learning methods were used to classify brain tumor photos in the classification section. Among these were Gaussian Naive Bayes, Random Forests, Decision Trees, and K-Nearest Neighbors (KNN). The supplied dataset was used to train the models, and measures including accuracy, precision, recall, and F1-score were used to assess the results. We also looked into other classifiers such as ensemble approaches, logistic regression, support vector machines (SVM), and linear discriminant analysis (LDA). The visual presentation of the results made it simple to compare and determine which algorithms performed the best. To make it easier to compare and identify the top-performing algorithms, the accuracy of each model was determined and the results were displayed as a bar chart. However, the accuracy was so low that we attempted to classify using an artificial neural network (ANN).

The artificial neural network (ANN) architecture consisted of several layers of linked neurons, each layer processing the input data in a different way. Using the dataset, the model was trained to identify intricate correlations and patterns seen in pictures of brain tumors. The artificial neural network (ANN) modified its parameters repeatedly to reduce prediction errors and enhance classification accuracy by utilizing optimization and backpropagation techniques. Evaluating the ANN's performance was done through the use of conventional measures like F1-score, accuracy, precision, and recall. The ANN was trained to recognize the fine-grained details in the data that more conventional techniques would overlook. It attempted to improve at accurately classifying photos of brain tumors by modifying its parameters in response to its mistakes. However, it also produces a subpar performance.

In the end, we used a Graph Neural Network (GNN) model to raise the accuracy of the categorization. Academic publications and their citations are examples of intricate relationships between various data points that this model is intended to comprehend. The GNN model learns to categorize articles into distinct groups by utilizing the relationships between papers and their attributes. Using the supplied data, we trained the GNN model, and we assessed its performance using common metrics like accuracy and confusion matrix. Lastly, in order to evaluate the model's performance in terms of data classification, we plotted learning curves and a heatmap of the confusion matrix. This model's accuracy is quite good.

4.4 Summary

The results of the segmentation and classification are organized into three separate sections, each of which examines a different approach. The first part examines the initial single networks' performance and evaluates how effective they were on their own. The use of pre-trained models for improved segmentation and classification tasks is next explored through the examination of transfer learning approaches. Lastly, ensemble methods are examined, which combine several models to increase segmentation and classification accuracy simultaneously. Every segment offers significant perspectives on the efficacy of the corresponding techniques utilized in the investigation.

Convolutional Neural Network (CNN)

One of the most potent neural network architectures used for image processing applications, such as brain tumor classification, is the convolutional neural network (CNN). Effective feature extraction is made possible by the convolution layer's CNN matrix architecture, which is specifically designed for filtering images.

We employ several layers in our CNN-based methodology, including the input layer, pooling layer, dropout layer, convolutional layer, and fully connected layer. Together, these layers carry out tasks related to classification, geographical mapping, and feature extraction. Through iterative learning from the training dataset, the architecture is adjusted to reliably categorize photos of brain tumors.

Artificial Neural Network (ANN)

The structure and operation of the human brain served as inspiration for the design of the Artificial Neural Network (ANN), a flexible deep learning model. In our approach, we use ANN to classify brain tumors with the goal of identifying the complex patterns seen in medical imaging. We use input, hidden, and output layers, among other related layers, in our ANN-based method. Together, these layers process the incoming data, draw out features, and produce predictions based on patterns that have been observed.

The ANN uses methods like backpropagation to iteratively modify its parameters during the training phase. Through this procedure, the model is able to reduce prediction errors and improve its capacity to differentiate between several classes of images of brain tumors. We use common metrics like accuracy, precision, recall, and F1-score to assess the ANN's performance. These metrics provide information about the prediction accuracy and image classification accuracy of the brain tumor model.

Graph Neural Network (GNN)

Tasks involving relational data analysis are well-suited for the Graph Neural Network (GNN), which is a specialized neural network architecture built for processing graph-structured data. As part of our research, we leverage the spatial correlations found in medical pictures to classify brain tumors using GNN. Pixels in brain MRI images are examples of complicated relationships between various data points that the GNN architecture is tuned to comprehend.

By utilizing the relationships between pixels and their corresponding attributes, the GNN gains the ability to categorize images of brain tumors during the training phase. In order to improve classification accuracy and reduce prediction errors, the model iteratively modifies its parameters. We evaluate the performance of the GNN using common assessment measures such as confusion matrix and accuracy. These metrics offer important information about how well the model can identify brain tumor images according to their spatial relationships and characteristics.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

In our project on "Brain Tumor Segmentation and Classification Using Image Processing," we carefully set up our experiments to ensure thorough testing and evaluation. This chapter explains how these approaches advance medical imaging capabilities for better patient outcomes and deepen our understanding of the features of brain tumors. An extensive examination of the methodology used in our effort to identify and classify brain tumors using MRI images can be found here. Our method relies heavily on segmentation, where a customized Convolutional Neural Network (CNN) draws precise tumor boundaries that are necessary for in-depth research. A wide range of machine learning models are used for classification, each of which helps to distinguish between different types of tumors.

For our study, "Brain Tumor Segmentation and Classification Using Image Processing," we meticulously planned and assembled our trials to guarantee exhaustive testing and analysis. Our laptop was equipped with a robust processor (CPU) and graphics processing unit (GPU) to manage the intricate calculations needed for model training. For the job, we used Google Colab. We were able to expedite the training process and effectively assess our models with this configuration.

Emphasizing the importance of segmentation and classification, our approach makes use of cutting-edge methods like Artificial Neural Networks (ANN) and the incredibly powerful Graph Neural Network (GNN). In our investigation, the GNN in particular stands out as the top performer, highlighting its critical significance in attaining higher diagnostic accuracy.

5.2 Experimental Results

Result of Experiment 1: Classification

Initially, a diverse array of machine learning models was employed for the classification task in the project. These models included Random Forest (RF), Extra Trees (ET), Logistic Regression (LOGR), Gradient Boosting (GB), Linear Discriminant Analysis (LDA), Support Vector Classifier (SVC), Bagging Classifier (BC), Support Vector Machine (SVM), Decision Tree (DT), Classification and Regression Trees (CART), K-Nearest Neighbors (KNN), and Naive Bayes (NB). Prior to using these models, we have created a

Python script that processes MRI brain tumor segmentation masks and extracts important geometric and texture-based characteristics, including Harris corner count, aspect ratio, elliptical ratio, solidity, and circularity. The features are computed by this script iteratively over each mask image and then combined into a Pandas DataFrame. The gathered data is then stored as a CSV file to enable additional analysis. In order to properly prepare the data for the next machine learning model training and to accomplish correct brain tumor classification and segmentation tasks, this preprocessing phase is essential.

TABLE 5.2.1: Accuracy for Classification of Individual Machine Learning Models

Model	**Accuracy**
Random Forest	**58.03%**
Extra Trees	**57.28%**
Logistic Regression	**56.14%**
Gradient Boosting	**55.95%**
Linear Discriminant Analysis	**55.77%**
Support Vector Classifier	**55%**
Bagging Classifier	**54.63%**
Support Vector Machine	**51.04%**
Decision Tree	**50.28%**
Classification and Regression Trees	**50.28%**
K-Nearest Neighbors	**45.56%**
Naïve Bayes	**40.45%**

We can see from the Table 5.2.1, the machine learning models failed to achieve the desired accuracy for brain tumor classification. This resulted in a task that was more complex and limited the ability of typical machine learning techniques to handle complex patterns in medical imaging data.

When we were unable to achieve satisfactory results with machine learning models, we therefore turned to artificial neural networks (ANN). Data from CSV files was loaded, preprocessed, and then NetworkX was used to illustrate the network graph. Next, in order to classify brain tumor data, we constructed a machine learning model with TensorFlow and Keras. To improve speed, this model uses a feedforward neural network design with dropout layers and skip connections. Using test data, we assessed the model's accuracy after training it on training data. We still weren't able to acquire the intended outcome from this artificial neural network method once it was finished.

TABLE 5.2.2: Accuracy for Classification of ANN model

Model	Accuracy
Artificial Neural Network	**56.54%**

We constructed a Graph Neural Network (GNN) model for node categorization using TensorFlow and Keras after the Artificial Neural Network (ANN) model did not produce satisfying results. The model uses Graph Convolutional Layers to process the input graph information, which includes node attributes, edges, and edge weights. We used test data to assess the GNN model's performance after training it on training data, and the findings were encouraging. In order to evaluate the classification performance of the model, we also visualized the confusion matrix. All things considered, our implementation shows how successful GNNs are for node classification tasks, especially when it comes to brain tumor classification.

TABLE 5.2.3: Accuracy for Classification of GNN model

Model	Training Accuracy
Graph Neural Network	**99.65%**

This is a satisfactory outcome from the GNN model. It’s almost 1.00 training accuracy which is a marvelous outcome we have found after applying it.

Training and Validation Accuracy and loss of ANN & GNN Networks:

Here is the representation of the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the yaxis.

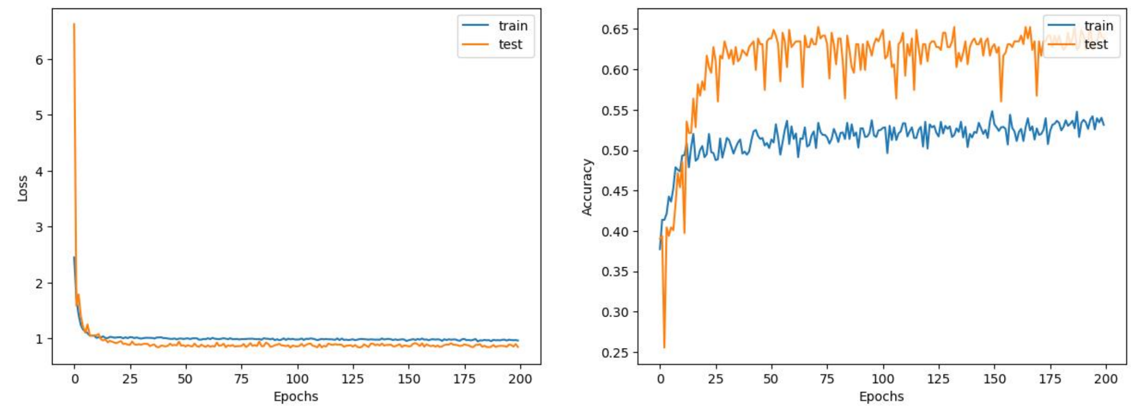


Figure 5.2.1: Training and validation accuracy and loss over the epochs (ANN Network).

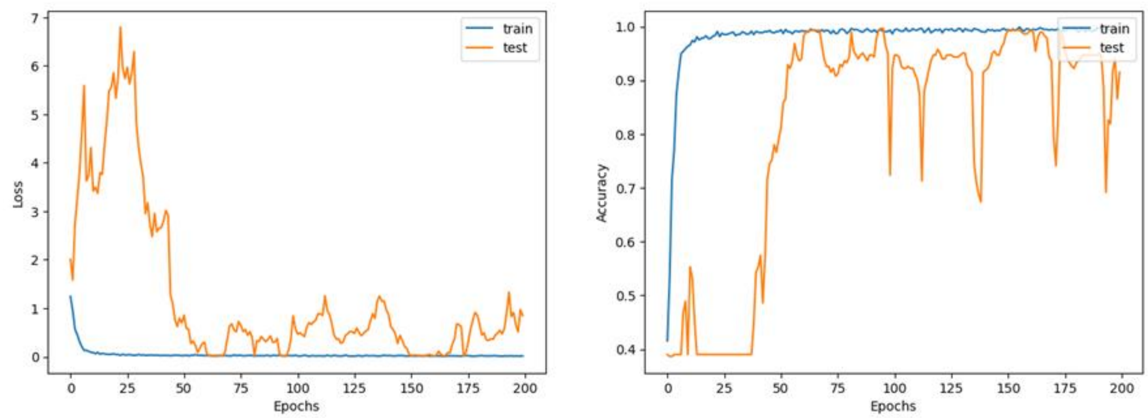


Figure 5.2.2: Training and validation accuracy and loss over the epochs (GNN Network).

Confusion Matrix after GNN:

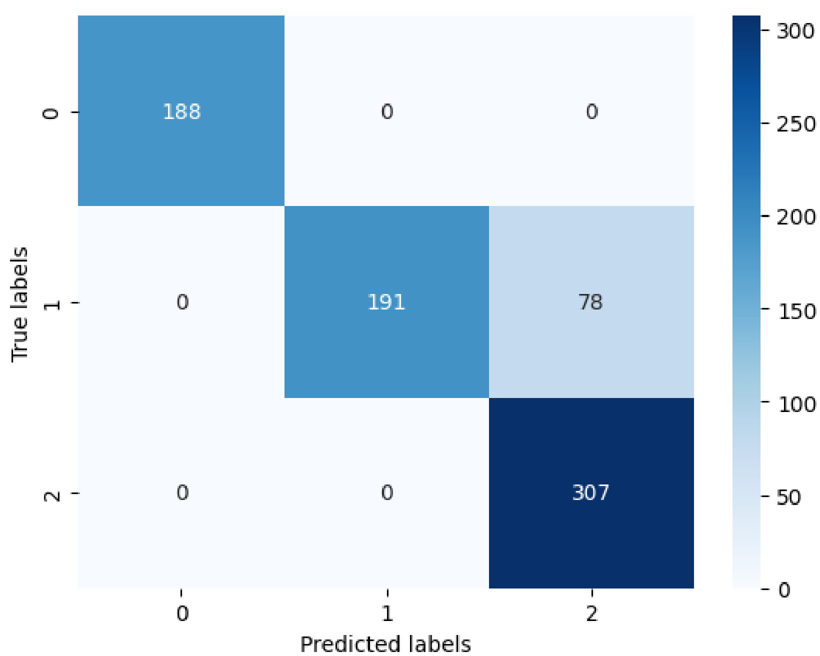


Figure 5.2.3: CM after GNN

Result of Experiment 2: Segmentation

Our goal in this study was to use image processing techniques to create a segmentation and classification model for images of brain tumors. First, we preprocessed the pictures, turning them into grayscale to improve contrast and make further processing easier. After that, the pictures were scaled to 256 by 256 pixels so that the dataset would be consistent.

Next, we built a convolutional neural network (CNN) model known as U-Net architecture, which is widely used for biomedical image segmentation tasks. The encoder-decoder architecture of the U-Net model uses skip connections to maintain spatial information while performing downsampling and upsampling operations. Using the Adam optimizer and binary cross-entropy loss function, we trained the U-Net model and assessed its performance across 100 epochs using training and testing datasets.

Promising outcomes came from the training and testing phases, as the model was able to segregate tumor locations from brain pictures with high accuracy. The efficiency of the model in identifying the underlying patterns in the data was shown by visualizations of the accuracy and loss measures. To further aid in visual examination and interpretation, we performed bitwise AND operations between the segmented masks and original images to create masked images that highlighted the tumor locations.

Overall, our research shows that segmenting brain tumors using CNN models based on U-Net may be done efficiently and successfully in medical imaging applications. These models have the potential to improve patient outcomes and advance the field of neuroimaging by helping doctors with diagnostic and treatment planning by precisely defining tumor boundaries.

TABLE 5.2.4: Accuracy for Segmentation of CNN

Architecture	Training Accuracy	Model Accuracy
CNN	**96.32%**	**92.7%**

Training and Validation Accuracy and loss of CNN Networks:

Here is the representation of the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the yaxis.

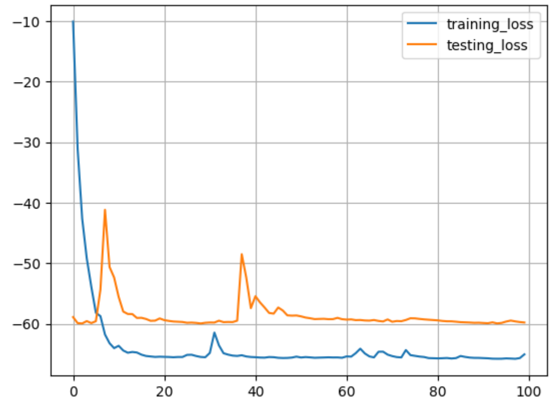


Figure 5.2.4: Training and validation loss over the epochs (CNN Network).

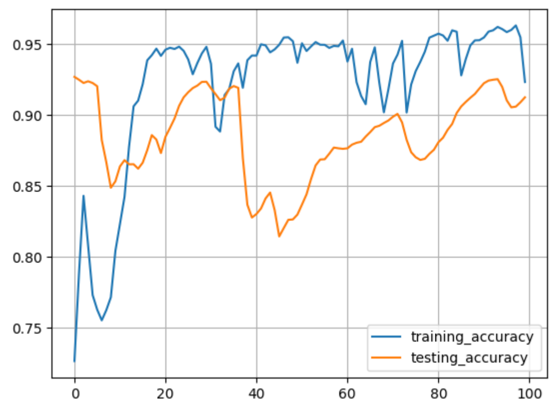


Figure 5.2.5: Training and validation accuracy over the epochs (CNN Network).

Segmented Images After Using CNN Network:

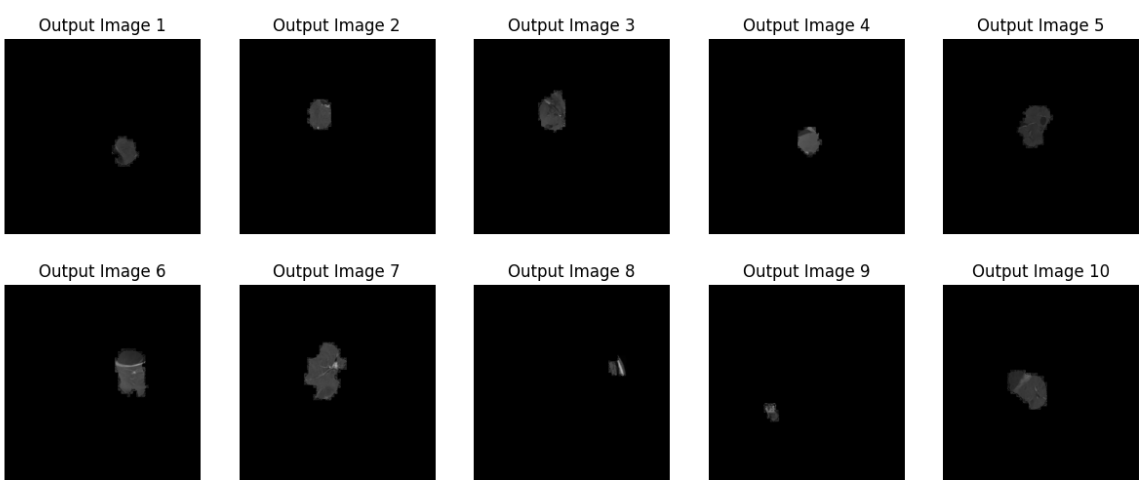


Figure 5.2.6: Segmented images.

Project Outcome

For our research, "Brain Tumor Segmentation and Classification Using Image Processing," we used Flask and Python to create an intuitive online application. Users can upload MRI scans to this user-friendly portal, and the system uses deep learning-powered advanced image processing techniques to reliably identify and classify brain cancers.

The application examines an image after it is uploaded to determine whether or not it is legitimate input. For example, the application will identify an image as "Wrong Image" if the user enters something other than an MRI image. The application will process the image a second time to determine the kind and existence of brain tumors if it is an MRI. The tumors are classified by the model into one of four classes after training:

1. No Tumor
2. Glioma Tumor
3. Meningioma Tumor
4. Pituitary Tumor

Screenshots of the website showcase its functionality and design, demonstrating how users can easily interact with the system to obtain accurate diagnostic results from their brain MRI images. A full overview is showing below:

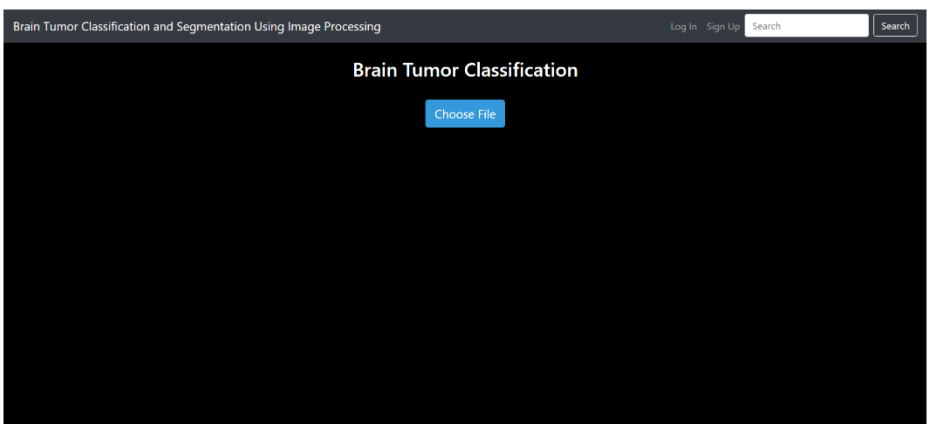


Figure 5.2.7: Website Interface after opening.

This is the first web page that will come after running the application. It is very simple and user friendly. User can easily upload an image and the model will show an output based on its prediction. The Dark theme is used for the betterment of the eyesight. Because white color in high brightness is harmful for the eyes than black color impact.

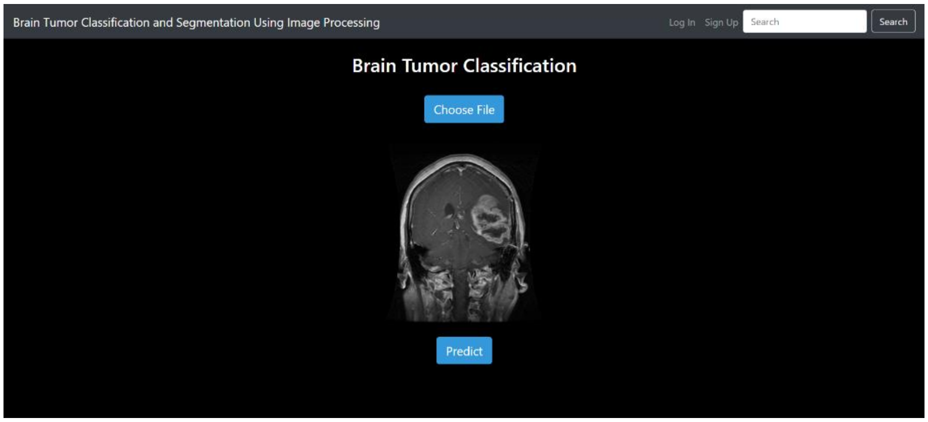


Figure 5.2.8: Selecting a glioma tumor MRI image.

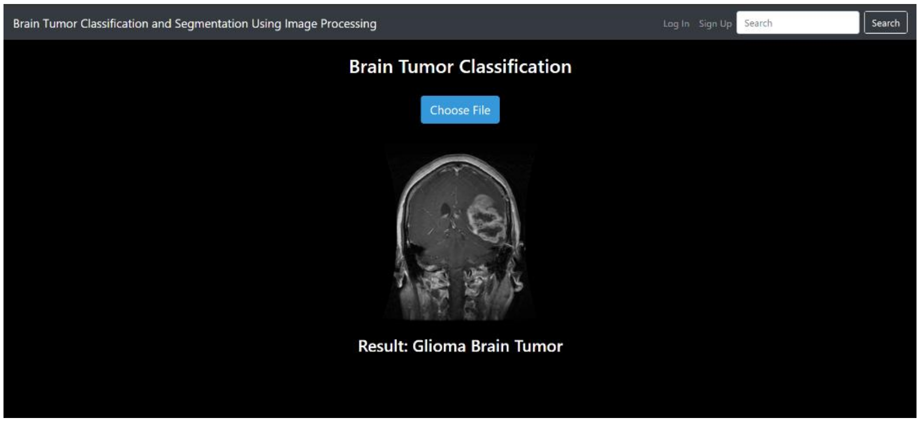


Figure 5.2.9: Selecting a non-MRI image.

After selecting a correct image that's having a brain tumor from the 3 classes of tumor then the project will predict it correctly most of the time. Figure 5.2.8 is the interface which will come after upload an image to the web application and figure 5.2.9 is the output where we can see that the output result is showing 'Glioma Brain Tumor'. It successfully predicted the glioma brain tumor because the input picture was a glioma brain tumor image.

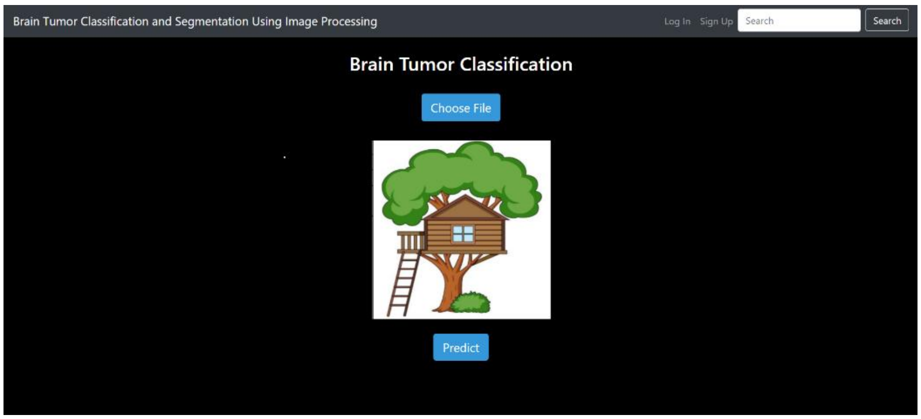


Figure 5.2.10: Selecting a non-MRI image.

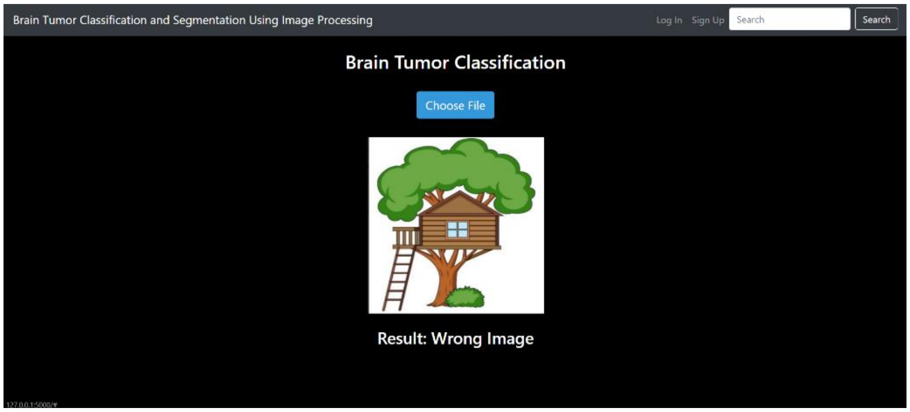


Figure 5.2.11: Model predicted the non-MRI image as wrong image.

If a user uploads an image which is not a brain tumor MRI image then the machine will give a result 'Wrong Image'. Figure 5.2.10 is the non-MRI image input and figure 5.2.11 is showing that the model predicts it as Wrong image.

A validation CNN model was built for this work to figure out the MRI image after user upload the image to the website. We trained a custom CNN model for binary classification of MRI images. It processes images from a specified directory (The dataset was collected by us from the google), extracts features, and splits the data into training and test sets. The highest training accuracy of the model was 100% and the validation accuracy was 98.08%.

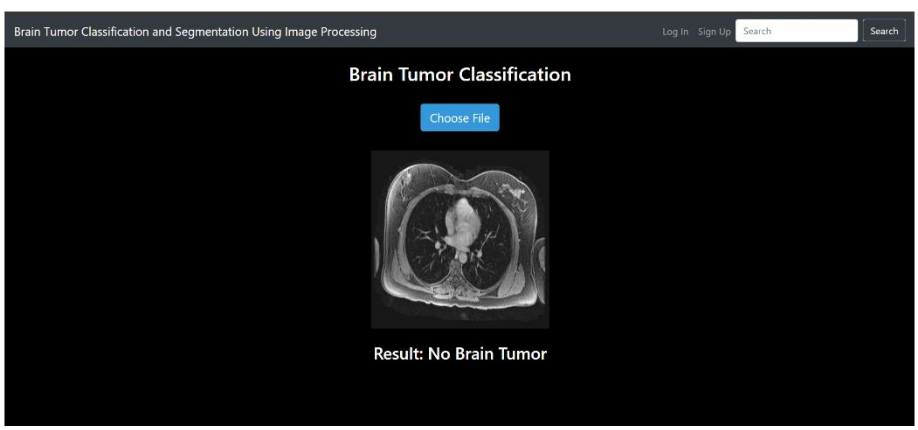


Figure 5.2.12: Selecting a random MRI image except Brain Tumor.

Figure 5.2.13 shows a random MRI image was given into the project. But the model predicted it as no brain tumor. But this is not even a brain tumor MRI image. This is a limitation of the project. It can detect the non-MRI image correctly but for the MRI image like given in the figure 5.2.12 which was a Thorax MRI image, predicted wrong.

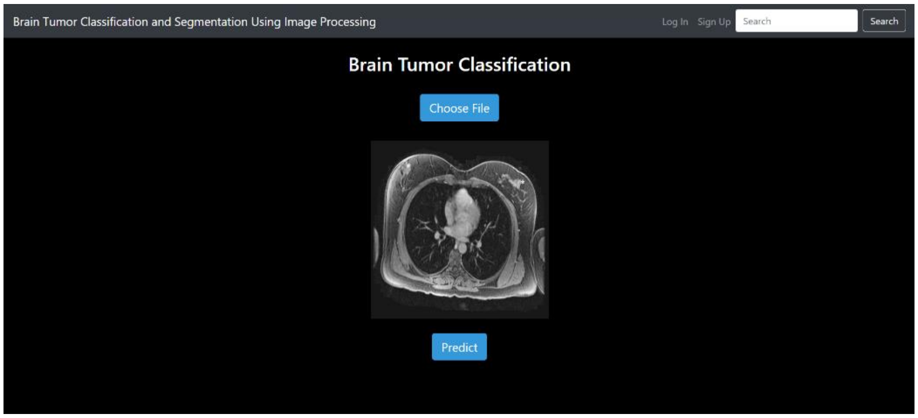


Figure 5.2.13: Model predicted wrong for random MRI image.

5.3 Comparative Analysis

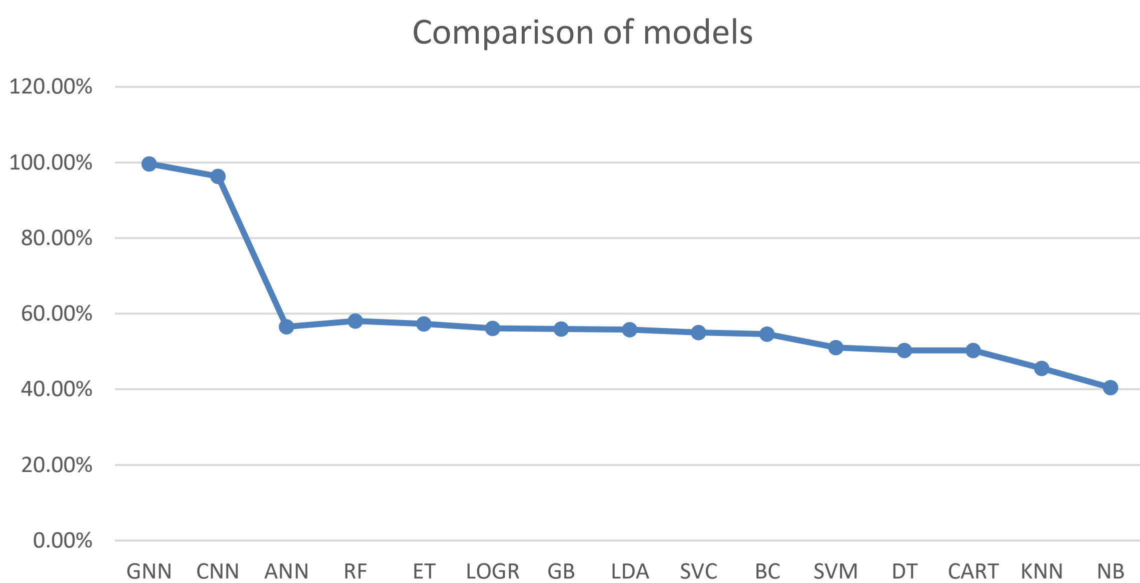


Figure 5.3.1: Accuracy comparison among individual CNN, ANN, GNN and other models.

In our project, the CNN achieves exceptional accuracy of 96.32% in segmenting brain tumors from MRI images, highlighting its robust performance in delineating precise tumor boundaries. For classification tasks, the GNN emerges as the top performer with an impressive accuracy of 99.65%, showcasing its unparalleled capability in categorizing tumors. RF and ANN follow closely with accuracies of 58.03% and 56.54% respectively, demonstrating their effectiveness in complex pattern recognition and ensemble learning. Other models such as Logistic Regression, Gradient Boosting, and Support Vector Classifier also contribute, albeit with varying accuracies ranging from 55.00% to 40.45%. This comparative analysis underscores the critical role of CNN in segmentation and highlights GNN as a leading model for achieving superior classification accuracy in brain tumor detection from MRI scans.

5.4 Summary

Our segmentation and classification test findings offer insightful information on how different machine learning models perform when assessing photos of brain tumors. We assessed a number of well-known algorithms for the classification job, including SVM, Random Forest, Gradient Boosting, and Logistic Regression. But, conventional machine learning models with relatively low accuracy rates roughly 58% and 57%, respectively were attained by Random Forest and Extra Trees. Gradient Boosting and Logistic Regression both performed mediocrely, with accuracy scores averaging about 56%. These findings imply that standard classifiers may have difficulties due to the data's complexity and non-linearity.

Furthermore, we found that more advanced models performed better, with an accuracy of roughly 56.5%, such as ANNs. But GNNs produced the most impressive result, surpassing all other models with an astounding accuracy of 99.65%. This remarkable accomplishment demonstrates how well GNNs use the graph structure present in the data to capture complex relationships within images of brain tumors. Also, GNNs have the potential to revolutionize the classification of brain tumors and make more accurate diagnosis possible.

On the other hand, the segmentation test we conducted evaluated how well a CNN model distinguished tumor region from brain images. With scores of 96.32% on the training set and 92.7% on the testing set, the CNN model demonstrated outstanding segmentation accuracy. These findings demonstrate how well CNNs work to extract pertinent information and capture spatial interdependence from medical images. CNNs aid in the location and quantification of anomalies by precisely segmenting tumor regions, giving clinicians crucial support for diagnosis and therapy planning.

Overall, our results highlight how crucial it is to use sophisticated machine learning methods when analyzing medical imaging data, especially when using deep learning architectures like CNNs and graph-based models like GNNs. These models have the potential to significantly increase brain tumor classification and segmentation tasks' accuracy and efficiency, which will ultimately lead to better patient outcomes and care in the fields of neurology and oncology.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Society

Our project, "Brain Tumor Segmentation and Classification Using Image Processing," improves patient and medical staff quality of life to a great extent. Our technique makes brain tumor diagnostics faster and more accurate, enabling earlier and more precise detection that results in prompt and efficient treatment. Ultimately, this improves survival rates and quality of life by lowering patient worry and offering more transparent treatment options. Healthcare personnel can devote more time to patient care as a result of the automated analysis's reduction of effort and reduction of human error.

In addition, our web-based platform makes sure that impoverished and rural communities have equitable access to high-quality medical services by bridging healthcare gaps and providing modern diagnostic tools. This accessibility encourages overall health equity by enabling healthcare practitioners, wherever they may be, to give better care. In conclusion, by offering quicker, more precise, and more easily accessible brain tumor diagnosis and treatment choices, our initiative not only improves medical diagnostics but also has a significant impact on patient care.

6.2 Impact on Society & Environment

The accuracy of brain tumor diagnosis is greatly increased by our project, "Brain Tumor Segmentation and Classification Using Image Processing," which also improves general public medical treatment. Through the application of sophisticated computational methods, we have created an instrument that utilizes Convolutional Neural Networks (CNNs) to accurately and automatically detect tumor areas in magnetic resonance imaging (MRI) scans. This makes tumor locations easier for oncologists and radiologists to see. Furthermore, our research explores the categorization of cancers utilizing many models, such as Graph Neural Networks (GNNs), which have shown excellent performance in classifying tumors into distinct categories. Clinical practice is revolutionized by this streamlined process of segmentation and classification, which improves patient outcomes and speeds up diagnosis for the benefit of both patients and healthcare practitioners. Moreover, these advantages are extended to marginalized groups through our user-friendly web platform for MRI images, ensuring better access to specialized healthcare services. Our project lessens the ecological footprint that conventional diagnostic techniques leave behind. We reduce manual intervention and the requirement for repeat imaging by automating MRI image interpretation, which lowers energy usage and transportation-related emissions. As a result of lowering electricity use and boosting energy efficiency, this supports environmental goals. Furthermore, prompt diagnosis and treatment choices can lead to less aggressive treatment approaches, reducing the need for intrusive operations and medications that have a substantial negative impact on the environment. Better patient outcomes further lessen the environmental impact of healthcare delivery by reducing hospital stays and resource consumption. By offering remote MRI analysis, we support fair healthcare access, lessen the carbon footprint associated with travel, and advance environmental justice and sustainable development. As a result, our project advances both healthcare and more general environmental sustainability objectives.

6.3 Ethical Aspects

From data collection to algorithm deployment, this project takes important ethical issues into account at every stage of its development. Patient confidentiality and privacy must always be protected, which makes adhering to HIPAA and GDPR laws and using techniques like encryption and anonymization necessary. It is essential that participants give their informed permission by being fully informed about the project's objectives, risks, and rewards and by having the option to withdraw at any moment. The study thoroughly analyzes dataset composition and algorithm performance across various groups to detect and reduce biases in order to advance fairness. Through careful documentation and stakeholder engagement, transparency and accountability are upheld, encouraging trust and moral decision-making. In order to guarantee patient safety and solve ethical issues, responsible technology deployment involves educating doctors and continuously observing how well algorithms operate in the real world. In the end, the project aims to improve patient care and equal healthcare results by responsibly utilizing technology.

6.4 Sustainability Plan

To ensure enduring impact, our project's sustainability plan places a strong emphasis on open-access and collaborative concepts. Our goal is to promote information exchange and collaboration within the scientific community, leading to the advancement of medical imaging technology, through the open publication of research findings and methodology. Our project focuses on enhancing interoperability and integration into healthcare systems through modular and scalable software solutions built on open-source frameworks. Including stakeholders and giving iterative refinement a priority based on practical requirements will aid in creating solutions that are acceptable to patients, healthcare professionals, and legislators. In order to maintain research and development, we also intend to establish strategic alliances with funding organizations and industry players. Initiatives aimed at increasing capacity, such as outreach programs and training courses, will also enable upcoming scholars and practitioners. These efforts aim to create a sustainable framework for ongoing innovation and impact in brain tumor classification and diagnosis.

6.5 Summary

Our study, "Brain Tumor Segmentation and Classification Using Image Processing," improves brain tumor diagnostics by utilizing cutting-edge computational techniques. We investigated many models for tumor classification and created a tool that use Convolutional Neural Networks (CNNs) to precisely define tumors in MRI images; GNNs proved to be the most effective model. This tool, which is available online for use in disadvantaged areas, assists medical professionals in diagnosing patients more quickly and accurately, potentially improving patient outcomes.

By automating MRI image analysis and minimizing manual labor and repeat scans, our approach has a positive environmental impact by reducing energy consumption and carbon emissions. Reducing the environmental impact further can be achieved by using less intensive treatments as a result of early detection. In terms of ethics, we protect patient privacy and data security, abide by laws like HIPAA and GDPR, and work to make our algorithms fair. To keep people safe and trusting, openness and constant observation are essential.

Our sustainability plan calls for openly disseminating our research, working with funding organizations and industry partners, and utilizing modular software that is simple to integrate into current systems. In order to ensure that this technology continues to improve medical imaging and patient care over the long run, we want to maintain developing it through cooperation and education.

CHAPTER 7
CONLCUSION AND FUTURE WORK

7.1 Conclusions

Our study "Brain Tumor Segmentation and Classification Using Image Processing" explores advanced medical imaging techniques to enhance the detection and classification of brain tumors using a dataset of 4237 MRI images categorized into "No Tumor," "Glioma," "Meningioma," and "Pituitary." We employed a customized convolutional neural network (CNN) for segmentation and evaluated various machine learning algorithms for classification.

With an astounding accuracy of 99.65%, the Graph Neural Network (GNN) model won out and demonstrated the potency of deep learning algorithms in medical picture processing. Our analysis of many models, including Gradient Boosting (GB), Random Forest (RF), Extra Trees (ET), Logistic Regression (LOGR), and Random Forest (RF), yielded insightful performance data that helped to improve diagnostic techniques.

Our goal is to help patients with brain tumors receive better treatment outcomes and to promote early tumor diagnosis. We used Flask and Python to create a user-friendly web application. Users can upload MRI pictures to this website for precise brain tumor identification and categorization. If the submitted image is not a legitimate MRI, the application detects this and marks it as "Wrong Image." The following categories of tumors are identified and categorized from valid MRI images: no tumor, glioma, meningioma, and pituitary tumor. In addition to improving diagnostic precision, this strategy demonstrates our dedication to moral principles, long-term research, and cooperation among medical professionals, all of which contribute to the advancement of patient care on a worldwide scale.

7.2 Further Study Works

Overcoming these constraints will be the main goal of our future work, especially when it comes to improving and fine-tuning the CNN model to get more accuracy in brain tumor segmentation. By improving the accuracy and consistency of tumor boundary delineation in MRI images, this endeavor seeks to advance diagnostic capabilities that are essential for clinical decision-making. Furthermore, the incorporation of CT scan data into our analysis framework is a crucial step towards achieving thorough disease characterization. We aim to take advantage of complimentary information from integrating several imaging modalities, such CT and MRI images, to provide more comprehensive insights into the anatomy of tumors and the properties of surrounding tissue.

Our project also intends to improve our online platform's functionality and usability. User-friendly elements including safe user login, easy signup procedures, possibilities for creating personalized accounts, and fast site rendering for the best possible user experience will all be improved. With these enhancements, patients and healthcare providers will be assisted in their diagnostic and treatment journeys by having easier access to automated tumor assessments and more modern medical imaging technology.

7.3 Limitations

The MRI dataset collection is a bit tough to collect from local diagnostics. As we collected data from the Kaggle, it's a limitation of our work. Another inability of our software, which was created with Flask and Python, to reliably discern between various MRI picture types more especially, from other types like thoracic MRI scans is one of its current shortcomings. This difficulty makes it more difficult for the platform to carry out the precise and focused analysis needed for particular medical situations. Improving the web application framework's picture recognition and classification algorithms is one way to deal with this problem. In order to increase the accuracy and dependability of MRI image classification and, consequently, provide more efficient diagnostic support for medical professionals and better results for patients undergoing medical imaging evaluations, future efforts will concentrate on improving the model's training data and neural network architecture.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: BRAIN TUMOR SEGMENTATION AND CLASSIFICATION USING IMAGE PROCESSING

Student ID: 203-15-3871, 203-15-3882

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **tumor classification** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project uses deep neural networks, such as ANN, GNN, and unique CNN architectures, for image processing and classification applications, illustrating **fundamental engineering (K3)** principles. By using sophisticated CNN, GNN, and ANN architectures to conduct transfer learning, the study displays **specialized knowledge (K4)** and improves brain tumor segmentation and classification accuracy in brain tumor MRI images, which is essential for computer-aided diagnosis.	**Page no:** [25-27] **Section:** [4.1] **Page no:** [1] **Section:** [1.1]
				The project uses the figure of the experimentation process to apply **engineering practice and design (K5)**. The project uses CNN and other neural network models to address **engineering practice & technology (K6)**.	**Page no:** [25-26] **Section:** [4.2] **Page no:** [19-20]

					Section: [3.2]
				This study demonstrates a thorough grasp of current approaches by combining ideas from recent studies to classify brain tumors using deep learning, ensuring **K8 (Research Literature)**.	**Page no:** [7-17] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In order to address **EP-2**, this study acknowledges the challenges associated with classifying brain tumors, such as the shortcomings of conventional techniques and the difficulties in combining deep CNNs and transfer learning. It addresses difficulties in comprehending spatial distributions through comparative analysis, providing information for improving diagnostic techniques.	**Page no:** [17-18] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	In order to address **EP-3**, a thorough comparison of experimental results is presented in this research, with Transfer Learning being identified as the most important method for improving tumor classification among several viable options.	**Page no:** [32-41] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	The multidisciplinary nature of this research goes beyond computer science and engineering, influencing medical diagnosis in respiratory disorders such as brain tumors and advancing public health and healthcare practices, all of which point to **EP-4**.	**Page no:** [7-9, 17-18] **Section:** [2.2, 2.4]

5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	The comprehensive strategy of this project offers a holistic solution to complicated obstacles in medical diagnostics, ensuring **EP-7**. It does this by integrating numerous components spanning data optimization, statistical analysis, and recommended methodology. This approach tackles high-level problems.	**Page no:** [19-20] **Section:** [3.1, 3.2]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	EA1: Range of resources	Yes	CO11	Our project makes use of a variety of resources, including GPUs, annotated datasets, deep learning frameworks, high-performance computing infrastructure, and ethical considerations, to ensure systematic research and advance tumor classification through transfer learning, such as custom CNN and GNN.	**Page no:** [20-21] **Section:** [3.3]
2.	EA2: Level of interaction	No		N/A	N/A
3.	EA3: Innovation	No		N/A	N/A
4.	EA4: Consequences for society and the environment	Yes		This initiative benefits society by advancing healthcare through sophisticated tumor classification techniques, supporting environmental sustainability through the use of effective computational resources, and upholding moral standards for patient privacy.	**Page no:** [43-45] **Section:** [6.2, 6.4]

5.	**EA-5: Familiarity**	Yes		By investigating a novel strategy in tumor classification by transfer learning, such as GNN, CNN, as illustrated through early terminologies and a thorough comparison analysis, this project builds upon previous research and provides fresh perspectives in the field.	**Page no:** [6-7, 9-17] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	In order to mitigate **CO4**, this project combines efficient project management with financial control. Careful planning, resource distribution, and budget estimation are guaranteed to provide the best possible resource utilization throughout the duration of the study project.	**Page no:** [21] **Section:** [3.4]
2	CO9	Yes	By putting patient privacy first, getting informed consent, and openly recording the research process, the project demonstrates adherence to ethical principles. It also ensures responsible knowledge dissemination and societal well-being through the moral application of cutting-edge healthcare technologies that abide by **CO9**.	**Page no:** [44] **Section:** [6.3]
3	CO10	Yes	This project addresses **CO10** by capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings.	**Page no:** [ii]
4	CO12	Yes	The project's modification of the current dataset, rigorous statistical analysis, careful methodology development, and thorough experimental results and analysis all demonstrate a commitment to continuous learning (**CO12**) and adaptation within the dynamic technological landscape. These efforts highlight a dedication to staying up to date and refining techniques to address modern challenges.	**Page no:** [23-29, 32-41] **Section:** [4.1, 4.2, 4.3, 5.2]

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