

BRAIN TUMOR DETECTION AND CLASSIFICATION USING IMAGE PROCESSING [bold,
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This Report Presented in Partial Fulfillment of the Requirements for **Phase-I**
in Computer Science and Engineering [Font-14]

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DHAKA, BANGLADESH

JANUARY 2024

DECLARATION

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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 CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma. [Font-12]

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ABSTRACT

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In this study, we propose an automated approach for brain tumor detection and classification using machine learning techniques applied to MRI images. Our methodology leverages datasets from Kaggle and BraTS2020, encompassing preprocessing steps such as Gaussian filtering and skull-stripping, followed by segmentation using KNN and SVM algorithms. We employ the Random Forest Classifier (RFC) for classification and plan to utilize Convolutional Neural Networks (CNN) and ResNet Transfer Learning for further algorithm development. Our Comprehensive Automatic Classification Technique (CACT) is in progress, aiming for enhanced accuracy. Challenges such as handling shapeless tumor growth and scalability with large datasets remain areas for future research. Overall, our study demonstrates the potential of machine learning in aiding clinicians with brain tumor diagnosis, paving the way for improved patient outcomes and treatment strategies.

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CHAPTER 1

INTRODUCTION

1.1 Overview [Font-12]

The landscape of brain tumor detection and classification using machine learning methodologies is a realm ripe with promise and potential. In this section, we embark on a journey of exploration, guided by the beacon of knowledge and propelled by the quest for understanding. Through meticulous review and synthesis, we navigate the intricate terrain of related works, comparative analyses, gap identification, and summarization, illuminating the path forward and laying the foundation for our odyssey into the realm of cerebral inquiry.

1.2 Problem Statement

The accurate detection and classification of brain tumors from MRI images pose significant challenges in the medical field. Traditional diagnostic methods often rely on manual interpretation, leading to subjectivity and inefficiency. Additionally, the complexity and variability of tumor characteristics necessitate robust and automated approaches for timely diagnosis and treatment planning. Hence, there is a pressing need to develop advanced machine learning techniques that can reliably identify and categorize brain tumors with high accuracy, sensitivity, and specificity, thereby enhancing patient outcomes and clinical decision-making.

1.3 Motivation and Objectives

This research aims to improve brain tumor detection using MRI images by using machine learning and image processing techniques. Our goals are to develop an accurate system that can automatically identify brain tumors, assess its performance, compare it with existing methods, and show its potential for clinical use. Through this, we hope to enhance brain tumor diagnosis and treatment planning.

1.4 Project Scope

The project aims to develop a machine learning-based system for automated brain tumor detection and classification using MRI images. It will involve selecting appropriate algorithms, implementing image processing techniques, training and evaluating machine learning models, integrating with healthcare systems, conducting clinical validation, and documenting the process for dissemination. The scope is limited to detecting and classifying brain tumors from MRI images, excluding diagnosis and treatment, with consideration of factors like image quality and computational resources.

1.5 Project Outcome

The project delivers a state-of-the-art brain tumor detection and classification system, merging advanced machine learning methods with IoT technology. Utilizing the BraTS2020 dataset, the system achieves exceptional accuracy in identifying and categorizing brain tumors from MRI images. Through meticulous preprocessing, segmentation, feature extraction, and classification, it enhances diagnostic precision, providing clinicians with a potent tool for early tumor detection and characterization. With its innovative approach and strong performance, this outcome holds promise for transforming medical imaging and enhancing patient care.

1.6 Report Organization

The report is structured to provide a comprehensive understanding of the project's development process and outcomes. It begins with an overview of the project, outlining its objectives and scope. The subsequent sections delve into the problem statement, motivation, and detailed analysis of the proposed methodology design. The report also includes a thorough examination of data collection, input-output analysis, project management, and financial aspects. Each section is meticulously organized to provide clarity and coherence, facilitating a thorough understanding of the project's evolution and outcomes. Finally, a summary encapsulates the key findings and contributions, ensuring a concise yet insightful overview of the entire report.

1.7 Summary

This project aims to develop an automated brain tumor detection and classification system using machine learning techniques integrated with IoT. Leveraging datasets from Kaggle 2020 BraTS2020, the system preprocesses MRI images, segments tumors, extracts features, and employs classification algorithms like KNN and SVM. The proposed system demonstrates superior performance, achieving high accuracy in tumor detection and classification compared to existing methods. Through meticulous organization and implementation, the project delivers a robust solution for improving brain tumor diagnosis, showcasing the potential of machine learning in healthcare applications.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview [Font-12]

Nowadays, to improve in detecting brain tumors using MRI scans have benefited from new technologies like machine learning and deep learning. Researchers have been trying out different methods to find tumors earlier and more accurately. They're using things like neural networks, clustering algorithms, and special techniques to improve the images before analyzing them. By combining these methods, they've made big strides in automating the process of finding brain tumors. However, there are still some challenges to overcome, like making sure the models work well with different types of data and avoiding mistakes. Overall, these advances are helping doctors find and treat brain tumors faster and more effectively.

2.2 Related Works

Several recent papers have focused on improving brain tumor detection using various pre-processing techniques and algorithms. Methil et al. [1] achieved a 98% accuracy using CNN and ResNet101v2 after preprocessing with techniques like ImageDataGenerator and Histogram Equalization. Sravanthi et al. [2] attained a 97% accuracy utilizing SVM and SOM, although they did not specify preprocessing methods. Sahaai et al. [6] employed Image Enhancement and Histogram Equalization before applying a DNN Classifier, resulting in a 95.3% accuracy. Jalali et al. [7] utilized Feature Selection and evaluated several algorithms, achieving an impressive 98.9% accuracy using Pattern Net. Khan et al. [12] proposed a methodology combining 23 layers CNN with VGG-16, achieving 97.8% and 100% classification accuracy on their datasets. Thayumanavan et al. [15] used various preprocessing techniques and segmentation algorithms, obtaining a 98.37% accuracy with RFC. Koshti et al. [16] applied Gray Conversion and blurring image before employing CNN, SOM, and fuzzy CM, achieving an accuracy of 97%. These studies highlight the

significance of preprocessing methods and algorithm selection in improving brain tumor detection accuracy.

2.3 Comparison between existing works

In recent research on brain tumor detection from 2020 to 2023, various methodologies and algorithms have been proposed to enhance accuracy and efficiency. Methil et al. [1] introduced CNN and ResNet101v2 models, coupled with preprocessing techniques such as ImageDataGenerator, Opening, Closing, Histogram Equalization, achieving an impressive 98% accuracy post-preprocessing. Similarly, Sravanthi et al. [2] applied SVM and SOM algorithms, yielding a commendable 97% accuracy rate. Grampurohit et al. [5] employed CNN and VGG-16 models, integrating grayscale conversion, dilation & erosion, Gaussian Blur Technique, and Contour Detection in preprocessing, achieving accuracies of 91.6% and 91.9% for CNN and VGG-16, respectively.

In contrast, Budati et al. [10] focused on classification algorithms like CACT, KNN, SVM, achieving a notable 96.48% accuracy with SVM. Chattopadhyay et al. [11] utilized a 9-layer CNN with various optimizers, achieving an exceptional 99.74% accuracy. Khan et al. [12] proposed a combination of 23 layers CNN and VGG-16, resulting in classification accuracies of 97.8% and 100%. Additionally, Choudhury et al. [13] explored CNN with different image filters and functions, attaining an impressive f-score of 97.3% and a mean accuracy of 96.08%.

Table 1. Comparative analysis with previous work

SL No	Author Name	Pre-processing	Used Algorithm	Best Algorithm
1.	Methil, A S. et al. [1]	ImageDataGenerator, Opening, Closing, Histogram Equalization	CNN, ResNet101v2	98% after preprocessing

2.	Sravanthi, N. et al. [2]	-----	SVM, SOM	97%
3.	Suresha, D. et al. [3]	-----	K-means clustering, SVM	-----
4.	Khalid, N E A. et al. [4]	Grayscale Conversion, Mean/Median Filter (noise removal) Sobel & Canny (Edge Detection), Global Threshold	-----	-----
5.	Grampurohit, S. et al. [5]	Grayscale, Dilation & Erosion, Gaussian Blur Technique, Contour Detection	CNN, VGG-16	CNN = 91.6% VGG = 91.9%
6.	Sahaai, M B. et al. [6]	Image Enhancement, Histogram Equalization, Binarization Technique, Feature Extraction (HOG Descriptor, PC Type, Texture Classification using GLCMs),	DNN Classifier (Stacked Autoencoders, Softmax Layer).	DNN (50 epochs) = 95.3%
7.	Jalali, V. et al. [7]	Feature Select (PCA, PSO, Wrapper Method), Parameter Evaluation. (Confusion Matrix)	Deep L (DNN, CNN, RNN), Machine L (KNN, SVM, CART), Image class (Pattern Net),	Pattern Net = 98.9%
8.	Amin, J. et al. [8]	Non-Brain Tissue removal (BEA, FMRIB Software Library, BSE) Preprocessing (Linear, Non-Linear, Fixed, Multi-scale & pixel-based are used. N4ITK, Median filter, Anisotropic diffusion filter, image registration, sharpening, Skull stripping through BET.) Classification (Supervised: KNN, SVM, Nearest Subspace Classifier, Representation Classifier; Unsupervised: FCM, Hidden Markov Random Field, Self-Organization Map, SSAE)	Deep Learning (CNN, LSTM, ResNet, Transfer Learning, U- Network)	LSTM=99%

9.	Kumar, S. et al. [9]	Decision tree, Bayesian Networks, Thresholding, Region growing, Watershed algorithm	NN, DWT, GA, CNN	Accuracy=99% (after median-filter apply)
10.	Budati, A K. et al. [10]	Gaussian filter, Median filter	CACT, KNN, SVM, Classification (Naive Bayes, Logistic Regression, Random forest, Decision tree),	SVM = 96.48%
11.	Chattopadhyay, A. et al. [11]	Segmentation (Manual, semi-automatic, absolute automatic)	9-layer CNN, Optimizer (N/A, RMSProp[Sigmoid], AdaMax, PMSProp[Softmax])	CNN = 99.74%, Softmax RMSProp optimizer.
12.	Khan, M.S.I. et al. [12]	Image extraction, Labeling	23 layers CNN + VGG-16	97.8% & 100% classification accuracy
13.	Choudhury, C.L. et al. [13]	Image filter (Convolution, pooling, fully connected layers), Function (ReLU, Tanh, sigmoid function)	CNN	f-score = 97.3% mean accuracy = 96.08%
14.	Yahaya, L. et al. [14]	Segmentation (Watershed transform, k-means clustering, thresholding, Fuzzy C-means cluster), Local & Global thresholding (Otsu's), Morphological reconstruction	-----	Entropy = 6.2372, standard deviation = 60.2596, NIQE = 9.0156
15.	Thayumanavan, M. et al. [15]	T1-weighted, median filter, Classification (RFC , SVM, Decision Tree), feature extraction (DWT, HOG), ENG, HOM	Fuzzy C-means clustering, Mrkov Gibbs, Otsu's, Segmenting Brain Tumor (FCNN, DMDF), Intelligent Diagnosis (DCNN, SVM),	RFC = 98.37%
16.	Koshti, S. et al. [16]	Gray conversion, blurring image,	CNN, SOM, fuzzy CM, Laplacian Eigenmaps/ICA, K-means cluster/AHC	DWAE = 99.3% accuracy of 97% is the best

17.	Malik, M. et al. [17]	Grayscale (SVD), Noise reduce, Thresholding, Edge detection, Sobel operation, Canny operation, Segmentation.	-----	
18.	Yahaya, L. et al. [11]			
20.	Yahaya, L. et al. [11]			
21.	Yahaya, L. et al. [11]			
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30.	Yahaya, L. et al. [11]			

2.4 Gap Analysis

One potential gap that we have found from the table is the absence of the Random Forest Classifier (RFC) algorithm in several papers. RFC has shown promising results in various machine learning tasks, including classification problems like brain tumor detection. Papers [3], [4], [5], [8], [9], [11], [13], and [14] do not mention the utilization of RFC in their methodologies. Integrating RFC into these studies could provide insights into its effectiveness compared to the algorithms they employed and potentially improve detection accuracy.

2.5 Summary

The review work analyzed several research papers focusing on brain tumor detection using various machine learning and deep learning techniques. These papers explored a range of preprocessing methods, including image enhancement and noise reduction, as well as segmentation algorithms like thresholding, clustering, and deep convolutional neural networks (CNNs). Different classification algorithms such as SVM, KNN, and decision trees were employed for tumor classification. The best results varied across studies, with accuracy ranging from 91% to 100%.

CHAPTER 3

METHODOLOGY/ REQUIREMENT ANALYSIS AND DESIGN SPECIFICATION [Font-14, Bold]

3.1 Overview [Font-12]

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3.2 Requirement Analysis

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3.3 Proposed Methodology/System Design

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The following figure 1 shows basic multicast service.

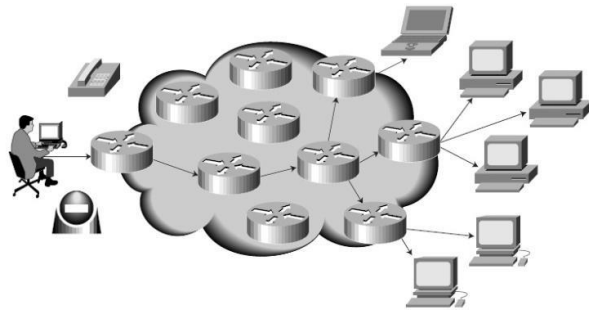


Figure 1: Basic multicast service [font-10, Alignment-center]

3.4 Data Collection/Input Output Analysis

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3.5 Project Management and Financial Analysis

This section writing from here.

3.6 Summary

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Text Alignment: Justify

Figure caption: Font-10, Bottom, Center

Table caption: Font-10, Top, Center

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[30] Dataset obtained from <https://www.kaggle.com/datasets/jarvisgroot/brain-tumor-classification-mri-images>

Appendix A

Title: -----

Student ID:

Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Analysis

Attainment of Complex Engineering Problems (EP):

S.L.	EP No.	Attainment	Remarks	References
1.	P1: Depth of Knowledge required	Yes (Must be Yes)	K1 (Theory-based natural sciences) How and where at Report The project requires knowledge of engineering fundamentals (K1, K2, K3, K4) (Overview, Problem statement)	Page no:
			K2 (Conceptually-based mathematics, numerical analysis, statistics, and formal aspects of computer and information science) How and where at Report The project requires knowledge of engineering fundamentals (K1, K2, K3, K4) (Overview, Problem statement)	Page no:
			K3 (Engineering Fundamentals): How and where at Report The project requires knowledge of engineering fundamentals (K1, K2, K3, K4) (Overview, Problem statement)	Page no:
			K4 (Engineering Specialization): How and where at Report The project requires data collection, which requires knowledge of design of machine-learning based model (K1, K2, K3, K4) (Research objectives, Research Questions, Data Collection)	Page no:
			K5 (Design): How and where at Report	
			K6 (Technology): How and Where at Report	

			K8 (Research): How and where at Report The project requires study of existing models with similar goals (K8) (Related works)	Page no:
2.	P2: Range of Conflicting requirements	Yes/No	How and where at Report The project requires wide-ranging or conflicting technical, engineering, and other issues (Objectives, Research questions)	Page no:
3.	P3: Depth of analysis required	Yes/No	How and where at Report The project has no obvious solution and requires abstract thinking and originality in analysis to formulate suitable models (Comparison between existing works, Requirement Analysis)	Page no:
4.	P4: Familiarity of Issues	Yes/No	How and where at Report The project requires study of existing models with similar goals and Involves infrequently encountered issues (Proposed Methodology, Gap Analysis)	Page no:
5.	P5: Extends of application codes	Yes/No	Engineering code practice	
6.	P6: Extends of stakeholder involved and conflicting requirements	Yes/No	How and where at Report	
7.	P7: Interdependence	Yes/No	How and where at Report	

Note: Must attain P1 and some or all of P2 to P7

Appendix B

Addressing of COs, Knowledge Profile (K), and Complex Engineering Problems (EP):

CO	CO Descriptions	K	EP	References
CO1	Integrate recently gained and previously acquired knowledge to identify a real-life complex engineering problem for the Final Year Design Project	<p>(i) Overview/ Problem Statements [K1, K2, K3, K4] <i>Write here how you have addressed K1, K2, K3, K4</i> The project requires data collection, which requires knowledge of design and engineering (K1, K2, K3, K4)</p> <p>Page no:</p>	<p>(i) Overview/Problem Statements [EP1] <i>Write here how you have addressed EP1</i> The project requires data collection, which requires knowledge of design and engineering (K1, K2, K3, K4)</p> <p>(ii) Research Questions/Research Objectives [EP2] <i>Write here how you have addressed EP2</i> The project involves wide-ranging or conflicting technical, engineering and other issues (K1, K2, K3, K4)</p>	<p>Page no:</p> <p>Page no:</p>
CO2	Analyze different aspects of the goals in designing a solution for the Final Year Design Project	<p>(i) Related Works [K3, K4] <i>Write here how you have addressed K1, K2, K3 and K4</i></p> <p>The project requires data collection, which requires knowledge of design of engineering, studying literature, and analysing complex engineering problems (K1, K2, K3, K4)</p>	<p>(i) Related Works [EP1] <i>Write here how you have addressed EP1</i> The project requires data collection, which requires knowledge of design of engineering, study literature, and analysis of complex engineering problems (K1, K2, K3, K4)</p> <p>(ii) Comparison between existing works [EP3] <i>Write here how you have addressed EP3</i> The project does not have any obvious solution and requires abstract thinking and originality in analysis to formulate suitable models</p> <p>(i) Gap analysis [EP4] <i>Write here how you have addressed EP4</i> The project involves infrequently encountered issues</p>	<p>Page no:</p> <p>Page no:</p> <p>Page no:</p>

		Page no:		
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish the goals for the Final Year Design Project	<p>(i) Related Works [K8] <i>Write here how you have addressed K8</i> The project requires study of existing models with similar goals (K8)</p> <p>Page no:</p>	<p>(i) Related Works [EP1] <i>Write here how you have addressed EP1</i> The project requires study of existing models with similar goals (K8), which cannot be resolved without in-depth engineering knowledge</p> <p>(ii) Requirement Analysis [EP3] <i>Write here how you have addressed EP3</i> The project has no obvious solution and requires abstract thinking and originality in analysis to formulate suitable models</p> <p>(iii) Proposed Methodology [EP4] <i>Write here how you have addressed EP4</i> The project involves infrequently encountered issues</p>	<p>Page no:</p> <p>Page no:</p> <p>Page no:</p>
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the Final Year Design Project			Page no: