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|  | **Hope Foundation's**  **International Institute of Information Technology, Pune-57**  **DEPARTMENT OF COMPUTER ENGINEERING** |

**Project Synopsis**

**Academic Year: 2024-2025 Semester: I Year: B.E Date:11/11/2024**

**Project Title:**

**“Bain Tumor Detection and Level Prediction System”**

**Project Domain:**

Deep Learning , Machine Learning, Medical & Healthcare.

**Team Members:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
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**Sponsorship if any: No**

**Name of External Guide (if any): NA**

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12. Ashish chandekar
13. Aayush Bhalavi Prof. Pallavi Yevale

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# Project Details

## Project Title:

“**Bain Tumor Detection and Level Prediction System**”

## Group Members:

* + 1. Aranav Mahalpure
    2. Rohan khatode
    3. Ashish chandhekar
    4. Aayush bhalavi

## Internal Guide:

Prof. Pallavi Yevale

## Sponsorship and External Guide:

NA

## Problem Statement:

"Developing an accurate and efficient system for detecting, classifying, and segmenting brain tumors in MRI scans."

# Technical Keywords

* + 1. Brain Tumor Detection
    2. Segmentation
    3. Convolutional Neural Networks(CNN)
    4. Tumor Classification
    5. BRATS Dataset
    6. Deep Learning
    7. Tumor Grade Prediction
    8. Pixel-Wise Segmentation
    9. Medical Image Analysis
    10. Data Augmentation
    11. Tumor Boundary Detection.

# Abstract

Brain tumors are important medical issues and must be detected quickly and accurately to give the right treatment. Checking the MRI scans manually can be slow and can have many human errors, so to make it easy and error-free, we use automated solutions, which are very important in the medical field. In our research, we found that there are many models that help us to find the brain tumors and the type of brain tumor. We reviewed the mostly used model known as Convolutional Neural Networks (CNN), which uses the BRATS dataset to create a better system for classifying and segmenting brain tumors. The aim is to improve both segmentation precision and classification accuracy, solving the problems while detecting the types and levels of brain tumor detection. The research used several deep learning methods. Techniques like ResNet and VGGNet, along with hybrid models such as CapsNet and VGGNet were applied. While these have helped find tumors better, gaps still exist in the research. A major issue is that there are not enough types of brain tumors classified thoroughly. Many models struggle to tell apart different tumors, and older methods often made mistakes in outlining the tumor areas on MRI scans. The approach of using deep learning boosts pixel-wise segmentation and enables accurate classification into different tumor types. It helps in clearly defining the tumor borders. This results in both tumor classification and segmentation, which can achieve high accuracy across various tumor types and levels.

# Project Objectives

The main aim is to build an automated system that detects, classifies, and segments brain tumors using deep learning techniques. It would be very resourceful to detect early and accurate brain tumors since it eliminates the errors that are made during manual processes and also enhances the accuracy with which tumors are classified, and the boundaries of tumors are segmented from MRI scans. Methods such as data augmentation, regularization, and the application of datasets like BRATS would make it clear that the model is performing efficiently in medical use, which makes the health professionals achieve further decision-making abilities for much better treatments of patients.

# Technical Details

* + 1. **User Interface**

The user interface of the Brain Tumor Detection System is meticulously designed for effortless interaction, ensuring a seamless experience for both users and medical professionals.

For radiologists, the interface features an intuitive dashboard displaying real-time scan data and comprehensive analytics. A user-friendly classification panel allows radiologists to swiftly verify whether scans show tumors.

Users have access to an easy-to-navigate panel where they can filter and view classified scans based on their preferences.

Users can provide feedback on scan classifications to flag cases that require additional review.

* + 1. **Hardware Interface**

The hardware interface requirements for the brain tumor detection system using deep learning are critical for efficient model development and training. These requirements are primarily centered around the hardware components needed to execute deep learning tasks effectively.

The system integrates with various external hardware, such as GPU/TPU, high-speed internet connections, distributed computing, external devices, and cooling systems, as the system consumes significant power.

* + 1. **GPU or TPU**

Deep learning models, especially those used for medical imaging, can be computationally intensive. A Graphics Processing Unit (GPU) or Tensor Processing Unit (TPU) significantly accelerates training times.

* + 1. **Internet Connection**

A stable and high-speed internet connection is essential for downloading datasets, libraries, and pre-trained models, as well as collaborating with cloud-based services and remote teams.

# Relevant Mathematical Models Associated with the Project

* + 1. **Dice Coefficient (Dice Similarity Coefficient, DSC)**

The Dice Coefficient is a measure of overlap between two sets. It is commonly used to evaluate the performance of image segmentation models.  
  
Formula:  
Dice Coefficient = (2 \* |A ∩ B|) / (|A| + |B|)  
Where:  
- A is the set of predicted pixels (from the model),  
- B is the set of ground truth pixels.  
  
This ranges from 0 (no overlap) to 1 (perfect overlap).

2. **Accuracy**

Accuracy is a basic metric, calculating the proportion of correctly classified pixels.  
  
Formula:  
Accuracy = (True Positives + True Negatives) / Total Pixels

3. **Precision**

Precision measures the proportion of correctly predicted positive pixels out of all predicted positive pixels.  
  
Formula:  
Precision = True Positives / (True Positives + False Positives)

4. **Recall (Sensitivity)**

Recall measures the proportion of correctly predicted positive pixels out of all actual positive pixels.  
  
Formula:  
Recall = True Positives / (True Positives + False Negatives)

**5. F1-Score**

The F1-Score is the harmonic mean of precision and recall. It is a balanced measure between precision and recall, providing a single score to evaluate the model’s performance.  
  
Formula:  
F1-Score = 2 \* (Precision \* Recall) / (Precision + Recall)

6. **Confusion Matrix**

A confusion matrix is a table used to describe the performance of a classification model, including true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). For segmentation, it is applied pixel-wise to compare the predicted segmentation with the ground truth.  
  
Example:

|  |  |  |
| --- | --- | --- |
|  | Predicted background | Predicted Object |
| Actual Background | TN | FP |
| Actual Object | FN | TP |

7. **Mean Absolute Error (MAE)**

MAE measures the average of the absolute differences between the predicted and ground truth pixel values, useful for continuous value prediction tasks.  
  
Formula:  
MAE = (1/N) \* ∑|y\_i - p\_i|  
Where y\_i is the ground truth pixel value, and p\_i is the predicted pixel value.

8. **Intersection over Union (IoU)**

IoU is another popular metric for segmentation tasks, measuring the overlap between the predicted and ground truth regions.  
  
Formula:  
IoU = |A ∩ B| / |A ∪ B|  
Where:  
- A is the set of predicted pixels,  
- B is the set of ground truth pixels.  
  
IoU gives a ratio of the intersection to the union of the predicted and ground truth sets, providing insight into how well the predicted segmentation matches the ground truth.

# Names of Conferences/ Journals where Papers can be Published

1. Institute of Electrical and Electronics Engineers (IEEE).
2. Artificial Intelligence Review (Springer)
3. Journal of Artificial Intelligence Research (JAIR)
4. Emerging Technologies for Intelligent Systems
5. International Conference on Intelligent Systems and Computational Networks
6. International Conference on Artificial Intelligence, Communication Technologies & Smart Cities (ICACS 2025)
7. International Conference on Power, Control, and Computing Technologies (ICPC2T)

# List of Conferences/Journals Papers Supporting Project Idea

1. N Noreen, Sellappan Palaniappan, Abdul Qayyum, Iftikhar Ahmad, Muhammad Imran, and Muhammad Shoaib, “A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor,” IEEE March 2020.
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11. Sunita Roy, Rikan Saha, Suvarthi Sarkar, Ranjan Mehera, Rajat Kumar Pal, (Member, IEEE), and Samir Kumar Bandyopadhyay, (Senior Member, IEEE), "Brain Tumor Segmentation Using S-Net and SA-Net" IEEE March 2023.
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13. Abdullah A. Asiri, Ahmad Shaf, Tariq Ali, Maryam Zafar, Muhammad Ahmad Pasha, Muhammad Irfan, Saeed Alqahtani, Ahmad Joman Alghamdi, Ali H. Alghamdi, Abdullah Fahad A. Alshamrani, Maqbool Aleylyani, and Sultan Alamri, "Enhancing Brain Tumor Diagnosis: Transitioning from Convolutional Neural Network to Involutional Neural Network" IEEE October 2023.
14. Ji-Hyeon Lee, Jung-Woo Chae, and Hyun-Chong Cho, "Improved Classification of Different Brain Tumors in MRI Scans Using Patterned-GridMask" IEEE March 2024.
15. Sohaib Asif, Wenhui Yi, Qurrat Ul Ain, Jin Hou, Tao Yi, and Jinhai Si, "Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors from MR Images" IEEE February 2022.
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18. Abdullah A. Asiri, Toufique Ahmed Soomro, (Senior Member, IEEE), Ahmed Ali Shah, (Senior Member, IEEE), Ganna Pogrebna, Muhammad Irfan, and Saeed Alqahtani, "Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification," IEEE March 2024.
19. Sedat Metlek and Halit Çetiner, "ResUNet+: A New Convolutional and Attention Block-Based Approach for Brain Tumor Segmentation," IEEE July 2023.
20. Ruqsar Zaitoon and Hussain Syed, "RU-Net2+: A Deep Learning Algorithm for Accurate Brain Tumor Segmentation and Survival Rate Prediction" IEEE October 2023.
21. **Plan of Project Execution**

**Phase 1: Problem Definition and Literature Review (1-2 weeks):**

Identify key goals, like classifying and segmenting brain tumors in MRI scans.

Review recent research on segmentation and classification techniques (e.g., U-Net, CNNs) and common metrics (e.g., Dice score, accuracy).

**Phase 2: Data Collection and Exploration (1-2 weeks):**

Collect MRI scans and segmentation labels (e.g., BraTS dataset with T1, T1CE, T2, FLAIR).

Explore data distribution and any preprocessing requirements.

**Phase 3: Data Preprocessing (2-3 weeks):**

Standardize images (normalize, resize) and apply augmentations (rotation, flipping) for model robustness.

Split the dataset into training, validation, and test sets, ensuring no patient data leakage.

**Phase 4: Model Development (3-4 weeks):**

Implement and train a U-Net (or variant) for segmentation, identifying tumor regions.

Develop a CNN-based model for classifying tumor types or combine both in a multi-task learning model.

**Phase 5: Model Evaluation (2-3 weeks):**

Measure segmentation performance (e.g., Dice coefficient, Jaccard index) and classification metrics (accuracy, F1 score).

Compare against baseline models and literature to assess the results.

**Phase 6: Model Optimization (1-2 weeks):**

Optimize hyperparameters (learning rate, batch size) and apply advanced techniques like attention mechanisms for improved accuracy.

Perform model fine-tuning based on validation performance.

**Phase 7: Integration and System Testing (2 weeks):**

Build an integrated system that outputs segmented regions and classification predictions for input MRI scans.

Test the pipeline end-to-end on unseen data to ensure reliability.

**Phase 8: Finalization and Documentation (1 week):**

Compile results and write the final report and documentation.