TITLE : Medical Image Enhancement and Segmentation based on conventional and deep learning Algorithms

Report submitted to GITAM (Deemed to be University) as a partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in (write your respective branch)



DEPARTMENT OF ELECTRICAL, ELECTRONICS AND COMMUNICATION ENGINEERING

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**DECLARATION**

I/We declare that the project work contained in this report is original and it has been done by me under the guidance of my project guide.

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Date: Signature of the Student

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**CERTIFICATE**

This is to certify that (Student Name) bearing (Regd. No.:) has satisfactorily completed Mini Project Entitled in partial fulfillment of the requirements as prescribed by University for VIIth semester, Bachelor of Technology in “Electrical, Electronics and Communication Engineering” and submitted this report during the academic year 2025-2026.

[Signature of the Guide] [Signature of HOD]

**Table of contents**

**Chapter 1: Introduction 1**

* 1. Overview of the problem statement 1
  2. Objectives and goals 1

**Chapter 2 : Literature Review 2**

**Chapter 3 : Strategic Analysis and Problem Definition 3**

* 1. SWOT Analysis 3
  2. Project Plan - GANTT Chart 3
  3. Refinement of problem statement 3

**Chapter 4 : Methodology 4**

* 1. Description of the approach 4
  2. Tools and techniques utilized 4
  3. Design considerations 4

**Chapter 5 : Implementation5**

* 1. Description of how the project was executed 5
  2. Challenges faced and solutions implemented 5

**Chapter 6: Results 6**

* 1. outcome 6
  2. Interpretation of results 6
  3. Comparison with existing technologies 6

**Chapter 7: Conclusion 7**

**Chapter 8 : Future Work 8**

**References 9**

**Chapter 1: Introduction**

**1.1 Overview of the Problem Statement**

Medical images often suffer from **low contrast, noise, and artifacts**, which reduce clarity and make diagnosis difficult. Accurate **segmentation of anatomical structures and tumors** is critical but challenging with conventional methods, as they lack robustness in complex or noisy data. Deep learning techniques such as **U-Net** offer improved accuracy and reliability, motivating the need for a framework that combines **image enhancement** with **deep learning–based segmentation**.

**1.2 Objectives and Goals**

The objective of this project is to develop a framework for **enhancing medical images** and achieving **accurate segmentation**.

**Goals:**

* Enhance images using techniques like **CLAHE, filtering, and denoising**.
* Develop and train **deep learning models (U-Net)** for segmentation.
* Compare **conventional vs. deep learning approaches**.
* Evaluate performance using **Dice, IoU, Precision, and Recall**.
* Visualize segmentation results and compile a **final report**.

**Chapter 2 : Literature Review**

Medical image analysis has been an active research area, focusing on improving image quality and achieving accurate segmentation of anatomical and pathological regions. This section reviews conventional image enhancement techniques, classical segmentation approaches, and recent deep learning–based methods.

**2.1 Conventional Image Enhancement**

Traditional methods such as Histogram Equalization, Contrast Stretching, CLAHE (Contrast Limited Adaptive Histogram Equalization), Gaussian filtering, and median filtering are widely used to improve visibility and reduce noise. While effective for basic preprocessing, these methods often fail in preserving fine details in complex medical images.

**2.2 Classical Segmentation Approaches**

Techniques like Otsu Thresholding, Region Growing, and Watershed Segmentation have been applied to medical imaging. These approaches rely on pixel intensity and edge information but are highly sensitive to noise and intensity inhomogeneity, leading to limited accuracy in tumor detection.

**2.3 Deep Learning for Medical Image Segmentation**

The emergence of Convolutional Neural Networks (CNNs) has revolutionized image analysis. Models such as U-Net, SegNet, and Fully Convolutional Networks (FCNs) provide end-to-end learning, enabling precise segmentation even in noisy or low-contrast images. U-Net, in particular, has become the benchmark for medical image segmentation due to its encoder–decoder structure and skip connections that preserve spatial details.

**2.4 Comparative Studies**

Recent studies show that deep learning methods significantly outperform traditional approaches in terms of Dice coefficient, IoU, and robustness. Hybrid approaches, where image enhancement is combined with deep learning, have also been explored to further boost performance, especially in challenging datasets like BRATS for brain tumor segmentation.

**Chapter 3: Strategic Analysis and Problem Definition**

**3.1 SWOT Analysis**

| **Strengths** | **Weaknesses** |
| --- | --- |
| - Use of both conventional enhancement and deep learning methods.  - U-Net ensures high segmentation accuracy.  - Availability of benchmark datasets (e.g., BRATS). | - Deep learning models require high computational resources (GPU/TPU).  - Dependence on large, labeled datasets.  - Training time is relatively long. |

| **Opportunities** | **Threats** |
| --- | --- |
| - Can be extended to multiple medical imaging modalities (CT, MRI, X-ray).  - Potential for clinical decision support systems.  - Research contribution towards AI in healthcare. | - Risk of overfitting due to limited labeled data.  - Ethical and privacy concerns with medical datasets.  - Rapid advancements may lead to obsolescence of methods. |

**3.2 Project Plan – Gantt Chart**

| **Phase** | **Tasks** | **Duration** |
| --- | --- | --- |
| **Phase 1: Data Handling** | Collect and load BRATS dataset, preprocess images and masks. | Week 1–2 |
| **Phase 2: Image Enhancement** | Apply histogram equalization, CLAHE, noise filtering, artifact removal. | Week 3–4 |
| **Phase 3: Segmentation** | Implement Otsu, Watershed, and U-Net models for tumor segmentation. | Week 5–8 |
| **Phase 4: Evaluation** | Compute Dice, IoU, Precision, Recall, compare methods. | Week 9–10 |
| **Phase 5: Visualization** | Overlay masks, generate plots, compare results. | Week 11 |
| **Phase 6: Documentation** | Compile results, prepare final report and presentation. | Week 12 |

**3.3 Problem Statement**

Medical images often suffer from low contrast, noise, and artifacts, which limit the visibility of critical structures. Conventional segmentation techniques such as Otsu and Watershed provide baseline results but are not reliable for complex cases. The key challenge is to achieve accurate and robust segmentation of pathological regions (e.g., brain tumours) in MRI scans, especially when images are noisy or of low quality.

This project addresses the problem by developing a comprehensive framework that:

1. Enhances medical images using conventional preprocessing methods.
2. Segments tumours using both classical and deep learning approaches (U-Net).
3. Compares the performance of these methods using standard metrics (Dice, IoU, Precision, Recall).
4. Provides visual and quantitative validation for future medical image analysis research.

**Chapter 4: Methodology**

**4.1 Description of the Approach**

The proposed framework follows a hybrid approach combining conventional image enhancement techniques with deep learning–based segmentation to improve medical image quality and ensure accurate detection of pathological regions. The methodology consists of the following key steps:

1. **Data Loading & Preprocessing**
   * Load the BRATS dataset (.h5 format).
   * Normalize intensity values, resize images, and prepare ground-truth masks.
2. **Image Enhancement**
   * Apply Histogram Equalization, CLAHE, filtering, and denoising to improve visibility and reduce artifacts.
3. **Segmentation**
   * Implement classical methods such as Otsu thresholding and Watershed segmentation.
   * Develop and train deep learning models (U-Net) for tumor segmentation.
4. **Evaluation**
   * Assess segmentation performance using Dice coefficient, IoU, Precision, and Recall.
   * Compare conventional and deep learning approaches.
5. **Visualization and Reporting**
   * Overlay segmentation masks on original images.
   * Generate plots and compile results into a comprehensive report.

**4.2 Tools and Techniques Utilized**

* **Programming Languages**: Python
* **Libraries & Frameworks**:
  + *Image Processing*: OpenCV, scikit-image
  + *Numerical Computation*: NumPy, SciPy
  + *Deep Learning*: TensorFlow / Keras, PyTorch (for U-Net implementation)
  + *Visualization*: Matplotlib, Seaborn
* **Dataset**: BRATS dataset (Brain Tumor Segmentation Challenge)
* **Evaluation Metrics**: Dice Coefficient, Intersection over Union (IoU), Precision, Recall
* **Hardware/Software Requirements**:
  + GPU-enabled system for deep learning training
  + Python 3.x environment with required dependencies

**4.3 Design Considerations**

1. **Data Quality and Preprocessing**
   * Medical images often contain noise and low contrast. Preprocessing is critical to ensure reliable segmentation.
2. **Model Architecture**
   * U-Net was chosen due to its proven effectiveness in medical image segmentation, particularly for tasks requiring pixel-level precision.
3. **Performance vs. Complexity**
   * Conventional methods (Otsu, Watershed) are computationally lightweight but less accurate.
   * Deep learning methods are more accurate but require greater computational resources.
4. **Evaluation Criteria**
   * Selection of **Dice, IoU, Precision, Recall** ensures fair comparison between methods.
5. **Scalability and Extensibility**
   * The framework is designed to support other imaging modalities (CT, X-ray) and different segmentation tasks in the future.

**Chapter 5: Implementation**

**5.1 Description of How the Project Was Executed**

The project was executed in a step-by-step pipeline, combining both conventional image enhancement and deep learning–based segmentation methods. The execution involved the following stages:

1. **Dataset Loading and Preprocessing**
   * The BRATS dataset was loaded in .h5 format.
   * Images were normalized to ensure uniform intensity distribution.
   * Resizing operations were performed for consistency across samples.
   * Ground-truth masks were extracted for supervised training and evaluation.
2. **Image Enhancement**
   * Conventional techniques such as Histogram Equalization, CLAHE, Gaussian Filtering, and Median Filtering were applied.
   * These methods improved contrast and reduced noise, making tumor boundaries more visible.
3. **Segmentation Approaches**
   * **Classical Methods**: Otsu Thresholding and Watershed segmentation were implemented to provide baseline performance.
   * **Deep Learning Method**: A U-Net architecture was designed and trained on the BRATS dataset.
     + Encoder-decoder structure captured both global context and fine details.
     + Training was performed using Dice loss and cross-entropy loss for improved accuracy.
4. **Performance Evaluation**
   * Models were evaluated using Dice coefficient, IoU, Precision, and Recall.
   * Comparison showed that U-Net significantly outperformed conventional methods in terms of segmentation accuracy and robustness.
5. **Visualization and Reporting**
   * Results were visualized by overlaying predicted masks on original MRI images.
   * Comparative plots were generated to illustrate performance differences.
   * Final outcomes were documented in a comprehensive report.
   1. **Challenges Faced and Solutions Implemented**

| **Challenge** | **Description** | **Solution Implemented** |
| --- | --- | --- |
| **Data Size and Variability** | Large dataset with varying resolutions and contrast levels. | Standardized preprocessing steps: resizing, normalization, and intensity scaling. |
| **Noise and Artifacts in Images** | MRI scans contained distortions that affected segmentation accuracy. | Applied **CLAHE, denoising filters, and artifact removal** before segmentation. |
| **Training Deep Models** | U-Net training required high computational power and was prone to overfitting. | Used GPU acceleration, data augmentation, and early stopping to prevent overfitting. |
| **Classical Methods’ Limitations** | Otsu and Watershed failed in complex tumor regions. | Used them as baseline comparisons, while focusing on **deep learning methods** for accuracy. |
| **Evaluation Consistency** | Needed fair comparison between conventional and deep learning methods. | Adopted standard metrics: **Dice, IoU, Precision, Recall**. |

**Chapter 6: Results**

**6.1 Outcomes**

The project successfully developed and tested a framework for medical image enhancement and tumor segmentation. Key outcomes include:

* **Enhanced Medical Images**
  + CLAHE and filtering improved contrast and reduced noise, making tumor boundaries clearer.
* **Segmentation Performance**
  + **Classical Methods**: Otsu thresholding and Watershed provided basic segmentation but failed in cases of low contrast or irregular tumor shapes.
  + **Deep Learning (U-Net)**: Achieved high-precision segmentation with improved boundary detection and robustness across different MRI scans.
* **Evaluation Metrics**
  + U-Net consistently achieved higher Dice coefficient and IoU scores, indicating superior overlap with ground-truth masks.
  + Precision and Recall values confirmed reduced false positives and false negatives.
* **Visualization**
  + Overlays of predicted masks on original MRIs showed accurate tumor localization and shape preservation.

**6.2 Interpretation of Results**

* **Conventional methods** (Otsu, Watershed) are useful for quick and low-computation segmentation but lack accuracy in real clinical settings.
* **U-Net outperformed classical techniques** due to its ability to learn hierarchical features, preserve fine details, and handle image variability.
* **Hybrid approach** (enhancement + deep learning) further boosted performance, showing that preprocessing improves deep model outcomes.
* The results confirm that deep learning–based segmentation is more reliable and clinically viable compared to traditional image processing methods.

**6.3 Comparison with Existing Literature or Technologies**

* Previous studies using classical segmentation reported limited accuracy, especially on complex datasets like BRATS. The outcomes here align with those findings, showing their inadequacy in challenging scenarios.
* Literature on U-Net and CNN-based segmentation highlights their dominance in medical imaging tasks. This project’s results support those claims, demonstrating high Dice scores comparable to reported benchmarks.
* **Hybrid techniques** combining preprocessing with deep learning are emerging in current research. The project’s framework resonates with these advancements, confirming that enhancement prior to segmentation improves overall accuracy.
* Compared to existing technologies, the implemented framework offers a balanced pipeline: conventional methods for benchmarking and deep learning for high-precision segmentation.

**Chapter 7: Conclusion**

The project successfully developed a framework for medical image enhancement and segmentation by integrating both conventional image processing methods and deep learning approaches. Image enhancement techniques such as CLAHE and filtering improved the visibility of anatomical details, while segmentation using U-Net outperformed classical methods like Otsu and Watershed. Evaluation metrics (Dice, IoU, Precision, Recall) confirmed that deep learning–based methods are significantly more accurate and robust for tumor segmentation in medical images.

**Suggestions for Further Research or Development**

1. **Multi-Modal Data Integration**
   * Extend the framework to handle multi-modal medical imaging (CT, PET, and ultrasound) in addition to MRI, allowing for more comprehensive diagnostic tools.
2. **3D Segmentation Models**
   * Develop 3D U-Net or Transformer-based architectures that can capture volumetric features and spatial context better than 2D approaches.
3. **Transfer Learning and Pretrained Models**
   * Apply transfer learning with pretrained medical imaging models to reduce training time and improve performance with limited labeled data.
4. **Clinical Validation**
   * Collaborate with healthcare institutions to test the system on real-world datasets and validate its clinical applicability.

**Potential Improvements or Extensions**

1. **Hybrid Approaches**
   * Combine classical enhancement with advanced deep learning methods (e.g., U-Net++, Attention U-Net, Vision Transformers) to further improve accuracy.
2. **Real-Time Segmentation**
   * Optimize the framework for real-time processing, enabling faster tumor detection during medical examinations.
3. **Explainability and Interpretability**
   * Integrate explainable AI (XAI) techniques to help clinicians understand model decisions, increasing trust in automated systems.
4. **Automated Reporting System**
   * Extend the project to automatically generate structured medical reports with segmented images, performance metrics, and diagnostic insights.
5. **Cloud/Edge Deployment**
   * Implement cloud-based or edge-based deployment for scalable access in hospitals and diagnostic centers.

**Chapter 8: Future Work**

This project has demonstrated the effectiveness of combining conventional image enhancement techniques with deep learning–based segmentation models for improved medical image analysis. However, there are several directions for further research and development that can enhance the system’s accuracy, scalability, and clinical applicability.

**8.1 Suggestions for Further Research or Development**

1. **Incorporation of Multi-Modal Data**
   * Extend the framework to integrate different imaging modalities such as CT, PET, and ultrasound, providing more comprehensive diagnostic support.
2. **3D and Sequential Modeling**
   * Develop 3D deep learning models (e.g., 3D U-Net, V-Net) that can process volumetric scans and exploit spatial continuity for more precise segmentation.
3. **Transfer Learning and Foundation Models**
   * Leverage pretrained medical imaging models and foundation models to handle limited labeled datasets while improving performance.
4. **Clinical Trials and Real-World Validation**
   * Collaborate with healthcare professionals to validate the framework on diverse patient datasets and assess clinical usability.

**8.2 Potential Improvements or Extensions**

1. **Hybrid Segmentation Frameworks**
   * Combine classical segmentation (e.g., Otsu, Watershed) with advanced deep learning models to improve performance in low-quality images.
2. **Real-Time Implementation**
   * Optimize models for deployment on GPUs or edge devices to enable real-time tumor detection in clinical settings.
3. **Explainable AI (XAI)**
   * Incorporate interpretability methods to explain segmentation decisions, thereby improving trust and adoption among clinicians.
4. **Automated Reporting and Visualization**
   * Extend the system to automatically generate diagnostic reports with visual overlays and performance metrics.
5. **Cloud and Distributed Deployment**
   * Implement cloud-based frameworks to support large-scale data processing and make the system accessible to multiple hospitals and research labs.

**References IEEE Papers:**

**1)A Review Paper about Deep Learning for Medical Image Processing**

Summary: Reviews the application of current state-of-the-art deep learning approaches in medical image processing, highlighting their effectiveness and challenges.

**2)Medical Image Segmentation: A Comprehensive Review of Deep Learning Methods**

Summary: Categorizes and summarizes current representative methods and research status in the field of medical image segmentation, focusing on deep learning techniques.

**3)Advances in Medical Image Segmentation**

Summary: Explores the transformative impact of deep learning on medical image segmentation, discussing architectures like CNNs, U-Net, and GANs.

**4)A Survey on Deep Learning in Medical Image Analysis**

Summary: Provides an extensive review of deep learning techniques applied in medical image analysis, including segmentation, classification, and detection tasks**.**

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