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ROBERT GORDON UNIVERSITY ABERDEEN

Multimodal Brain Tumor Detection System

Group 21 Project Proposal Document by

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Submitted in partial fulfilment of the requirements for the BSc (Hons) in Artificial Intelligence and Data Science degree at the Robert Gordon University.

October 2025

Declaration

We hereby certify that this project proposal and all the artifacts associated with it is our own work and it has not been submitted before nor is currently being submitted for any degree program.

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Content

1 Introduction

Among the most burdensome medical problems, brain cancer is the deadliest form of cancer today. Currently, medical professionals mainly rely on neuroimaging techniques with computer tomography (CT) and Magnetic Resonance Imaging (MRI). This approach adopts a multimodal approach, which has a major impact on enhancing the reliability of brain tumor detection and classification. The proposed method mainly focuses on extracting complementary features from both MRI and CT scans, each of providing unique features but less accurate and incomplete diagnostic information when used alone. MRI images represent soft-tissue contrast features and CT images represent brain high density structure, by combining both features to interpret complete diagnostic information including fused image. As a result, providing richer features, machine learning and deep learning models perform more accurately to detect brain tumor. However, this proposed system successfully aims to overcome the limitations of single-modality analysis.

2 Problem Domain

There are several brain tumor types originating from their tumor locations and whether they are cancerous and non-cancerous. Major types are Gliomas Tumors, Meningiomas Tumors, Pituitary Tumors, Gliosarcoma Tumors. etc. The global incidence of brain and central nervous system cancer has increased from $2, 843, 075$ in 1992 to $3, 420, 786$ in 2021, and the death count has risen by 80.62% (Li, Y. and Zhao, K., 2025). In 2022, $322, 000$ new cases of brain and CSN tumors were estimated globally (Filho, A. *et al.*, 2025).

The major tumor types of Gliomas originate in the glial cells of the brain. It comprises about 30% of all brain and central nervous system tumors and 80% of all malignant brain tumors. Commonly there are 3 different types of gliomas. They are astrocytoma, glioblastoma, oligodendrogliomas (Wikipedia, 2025), Meningiomas is typically a slow-growing tumor and starts in the tissue layers covering the brain and spinal cord. That specific kind of tissue is identified as meninges. Most meningiomas are not cancerous. In many cases meningiomas never show symptoms (Wikipedia, 2025), Pituitary starts in the pituitary gland. Most Pituitary Adenoma tumors are not cancerous. While pituitary tumors are common, affecting approximately 1 in 6 members of our general population (Wikipedia, 2025), Gliosarcoma is a rare type of fast-growing cancer of the brain that comes from brain cells. That typically grows in the brain but can also develop in the spinal cord.

Over the past two decades, AI has revolutionized medical image analysis and diagnose detection, segmentation and classification tasks. Machine learning and deep learning techniques have a major impact on processing medical data and reduce human errors.

A computerized tomography scan (CT) and magnetic resonance imaging (MRI) are required to identify these tumors. To avoid these difficulties, we have come up with a realistic solution. By analyzing the brain tumor MRI scan images and CT scan images we identified similarity between tumor tissue and other brain tissues. In this study, we have filled this gap by proposing a multimodal brain tumor detection system. The proposed method, combining MRI images with CT scans and creating fused image, examines to improve brain tumor diagnosis. Then after the obtained fused image we use that image for final prediction. In comparison with other approaches, the proposed method has represented clinically usable, accurate and information-rich results.

3 Problem Definition

In the past studies most of the methods tumor classification has not been extended to include CT and MRI sequence together. Most of the classification has been limited to MRI or CT scan images and performed using a single imaging modality. As a result, single-modality imaging fails to capture all clinically relevant information (Song, J., 2025). CT images provide excellent description and visualization about high density structures, such as bones with actual geometrical (Salahshour, F. *et al.*, 2020). Overall compared with the MRI image CT may be less sensitive to subtle soft-tissue contrast.

On the other hand, MRI offers reachable soft-tissue contrast and makes it more suitable for tumor classification (Ghafourian, E. *et al.*, 2023). However, that can reveal tumor surrounding abnormalities more effectively than CT images, but MRI lacks information on tissue density and bone structure. As a result, relying on a single imaging modality can only lead to incomplete and less accurate feature interpretation.

In conclusion there's a major need for an optimized solution to minimize this problem. By implementing MRI and CT multimodal concepts, this could reach rich medical information included image (Xu, L. and Bai, J., 2023). The fused approach can enhance tumor location interpretation, classification performance, segmentation accuracy and overall comprehensive brain tumor identification.

4 Problem Statement

Inability of single-modality imaging using either MRI or CT scan alone fails to provide a complete representation of brain tumor characteristics that can be minimized through the integration of both modalities.

5 Research Motivation

Brain tumor detection requires accurate imaging to guide diagnosis and treatment. However, single imaging modalities such as MRI or CT alone provide limited information. Instead, the combination of the soft tissue clarity from MRI and the bone and dense structures from CT images can increase the reliability of diagnostic insights. Therefore, a system that utilizes all available information to generate the final result can greatly enhance diagnostic accuracy in the medical field.

6 Existing work

Citation	Model	Dataset	Strengths	Limitations

Kattamanchi, H. *et al.*	Explainable AI with Grad-CAM and attention weights	BraTS 2018, TCIA	Builds clinician trust	Computational costs, data availability and thorough clinical validation
S, G. *et al.*	VGG16	High resolution MRI images	Scalable to hospitals	Computational cost and limited explainability
Ashtagi, R. *et al.*	Wavelet decomposition + VGG-19 deep learning, transfer learning, watershed segmentation	Meningioma and Sarcoma brain tumor images., Kaggle Brain MRI Dataset	Early brain tumor detection and an innovative approach	Computational overhead and limited explainability
Ramprasad, M., Rahman, Md. and Bayleyegn, M.	BTFSC-Net	Public datasets of MRI and CT images	Advanced feature extraction techniques	High complexity and computational cost

7 Contribution to the Body of Knowledge

7.1 Technological contribution

This project contributes technologically by developing an integrated multimodal hybrid deep learning framework that combines four key components - CT feature extraction, MRI feature extraction, multimodal image fusion, and optimized classification. The proposed system uses CNN-based and hybrid feature extractors for both CT and MRI modalities (He, K. *et al.*, 2016; Tan, M. and Le, Q., 2021; Kar, S. and Singh, P., 2025), integrates an efficient fusion mechanism to preserve spatial and textural details (Usha, M., Kannan, G. and Ramamoorthy, M., 2024; Zhang, Y. *et al.*, 2022; Ashtagi, R. *et al.*, 2025), and employs a hybrid deep-learning classifier for precise tumor categorization (Adamu, M. *et al.*, 2024; Ghasemi, R. *et al.*, 2025; Ramprasad, M., Rahman, Md. and Bayleyegn, M., 2022). This architecture enhances feature representation, reduces computational overhead, and improves generalization compared to existing single-modality and isolated models (Wong, Y. *et al.*, 2025; Byeon, H., 2024). Furthermore, the incorporation of explainable AI elements will enhance model interpretability, offering a more robust and scalable foundation for future real-world brain tumor diagnosis.

7.2 Domain contribution

This project contributes to the medical imaging and healthcare domain by demonstrating how the integration of multimodal data (MRI and CT) can enhance the accuracy, reliability, and interpretability of brain tumor diagnosis (Kar, S. and Singh, P., 2025; Zhang, Y. *et al.*, 2022). The developed framework supports radiologists, clinicians and patients in early and automated detection, reducing diagnostic time and potential human error (Wong, Y. *et al.*, 2025; Byeon, H., 2024). By addressing current limitations in dataset diversity, clinical validation, and interpretability, this study bridges the gap between AI-based research and practical healthcare application (Usha, M., Kannan, G. and Ramamoorthy, M., 2024; Ghasemi, R. *et al.*, 2025;), offering a more robust, trustworthy, and accessible diagnostic support tool for hospitals and research institutions (Selvaraju, R. *et al.* 2017; Ashtagi, R. *et al.* 2025).

8 Research Challenges

1. Data Availability and Annotation
   - There are very limited number of publicly available paired MRI and CT datasets containing properly labeled brain tumor images. Most existing datasets focus on single modalities such as CT or MRI only. To overcome this limitation, the research team will need to combine multiple datasets, and collaborate with healthcare institutions for anonymized patient scans.
2. Image Quality and Noise Variability
   - MRI images often suffer from magnetic field distortion, and CT images can include noise from radiation exposure and beam hardening. These inconsistencies make it difficult to fuse the CT and MRI images. The researches will use, preprocessing steps such as denoising, histogram equalization, and contrast enhancement will be needed to improve quality before fusion.
3. Data Privacy and Ethical Considerations
   - This project uses medical data of patients collected from web sources and hospitals, which are highly sensitive information. Therefore, the project will ensure compliance with data protection regulations, apply anonymization methods, and use secure data handling practices when working with hospital datasets.
4. Fusion Method Selection and Optimization
   - Selecting the most effective fusion approach remains a significant challenge, as each technique offers different strengths in terms of efficiency and image quality. Instead of implementing multiple methods experimentally, the researchers will conduct a review of existing image fusion studies to identify the approaches that have demonstrated the best performance in previous research.
5. Evaluation and Validation of Results
   - Assessing the effectiveness of the fusion is difficult since there is no universal quantitative standard for evaluating fused medical images. Metrics such as PSNR, SSIM, and mutual information will be used to validate the quality of the fused images.

9 Research Aim

The aim of this research is to design, develop and evaluate data-based solution that fuses CT and MRI scans to create a more accurate system for brain tumor detection and diagnosis, helping healthcare professionals to make faster, and more reliable clinical decisions.

10 Research Objective

Research Objectives	Explanation	Learning Outcome
Problem Identification	Current brain tumor detection methods using a single imaging modality (either CT or MRI) which fails to provide complete diagnostic information. Whereas a multimodal brain tumor detection method that combines both CT and MRI scans improve accuracy and detail in tumor detection.	LO1
Literature Review	RO1. To validate and extract features from MRI Image to obtain relevant structural and textural features of brain tissue. RO2. To validate and extract features from CT image validation and feature extraction to capture complementary density-based features essential for tumor localization. RO3. To fuse the validated and extracted features from CT and MRI modalities for enhanced multimodal brain imaging. RO4. To implement a tumor identification model to detect tumor using the fused multimodal data for accurate brain tumor detection.	LO1
Data Gathering and Analysis	MRI and CT image datasets will be gathered from the Kaggle and local hospital reports of brain tumor patients. Data will be preprocessed by resizing and preparing multimodal image pairs for fusion and analysis.	LO2, LO3
Research Design	This follows a quantitative research design , aiming to evaluate the effectiveness of multimodal brain tumor detection using CT and MRI.	LO3,LO4

Implementation	• Implementation of CNN based image validation and extraction of CT images. • Implementation of CNN based image validation and extraction of MRI images. • Implementation of image fusion model using VGG19 model. • Building of a Tumor detection and classification model using the fused images.	LO2, LO3, LO4
Testing and Evaluation	Metrics such as different accuracies , sensitivity and specificity were used to evaluate the overall model performance, and the results will be compared against single-modality models to evaluate the effectiveness of the fusion approach.	LO2, LO4

11 Project Scope

11.1 In-scope

No	Description
1	Use global datasets
2	Focusing on Brain tumor types
3	Components work independently
4	Creation of a MRI and CT fused images

11.2 Out-scope

No	Description
1	Real-time clinical deployment
2	Data collection from hospitals
3	Treatment planing
4	Multi-disease analysis

12 Feature Prototype

12.1 CT Feature Extractor

- Upload CT scan - The user inputs CT scan images in standard and preferred formats. (.png, .jpg, .tiff, most commonly - .dcm).
- Procedure - Utilize standardization in format, adapt every image into a stable format, normalize intensity to guarantee consistent analysis, and reduce noise to enhance feature quality.
- Multi-feature extraction - To extract a complete set of features and transmit the result to the fusion model, the images are passed by the system step-by-step through a predetermined pipeline.
- Analyze Feature Insights - The dashboard is where the system displays the outcome.

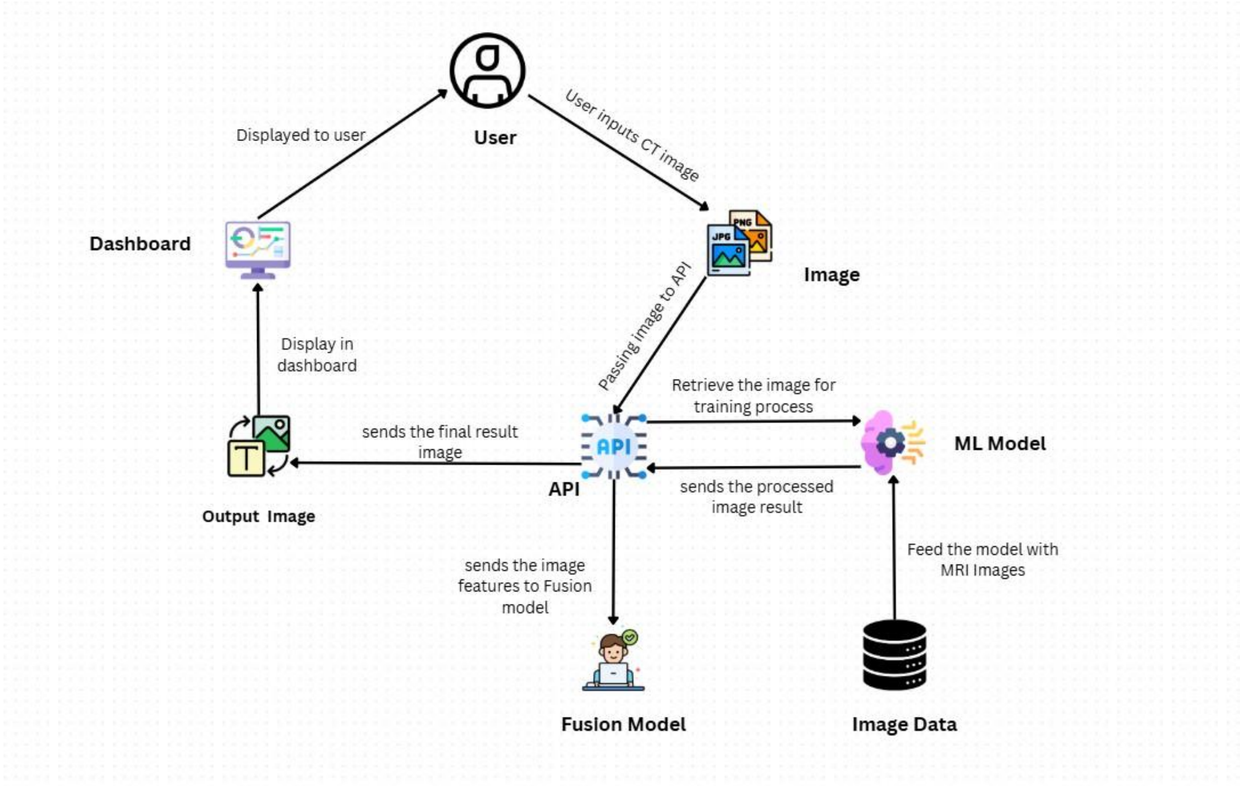


Figure 1: Diagram of the CT Feature Extractor

12.2 MRI Feature Extractor

- Upload MRI Scan - The user uploads the MRI scan image in standard and supported formats(PNG, JPEG, DICOM, etc.)
- System Processing - apply format standardization convert all the images into consistent format, noise reduction to clean the image for improved feature quality, intensity normalization to ensure consistent analysis.
- Multi feature extraction - The system sequentially passes the image step by step in a fixed pipeline to extract a comprehensive set of features and result pass to the fusion model.
- Analyze Feature Insights - The system shows the result through the dashboard.

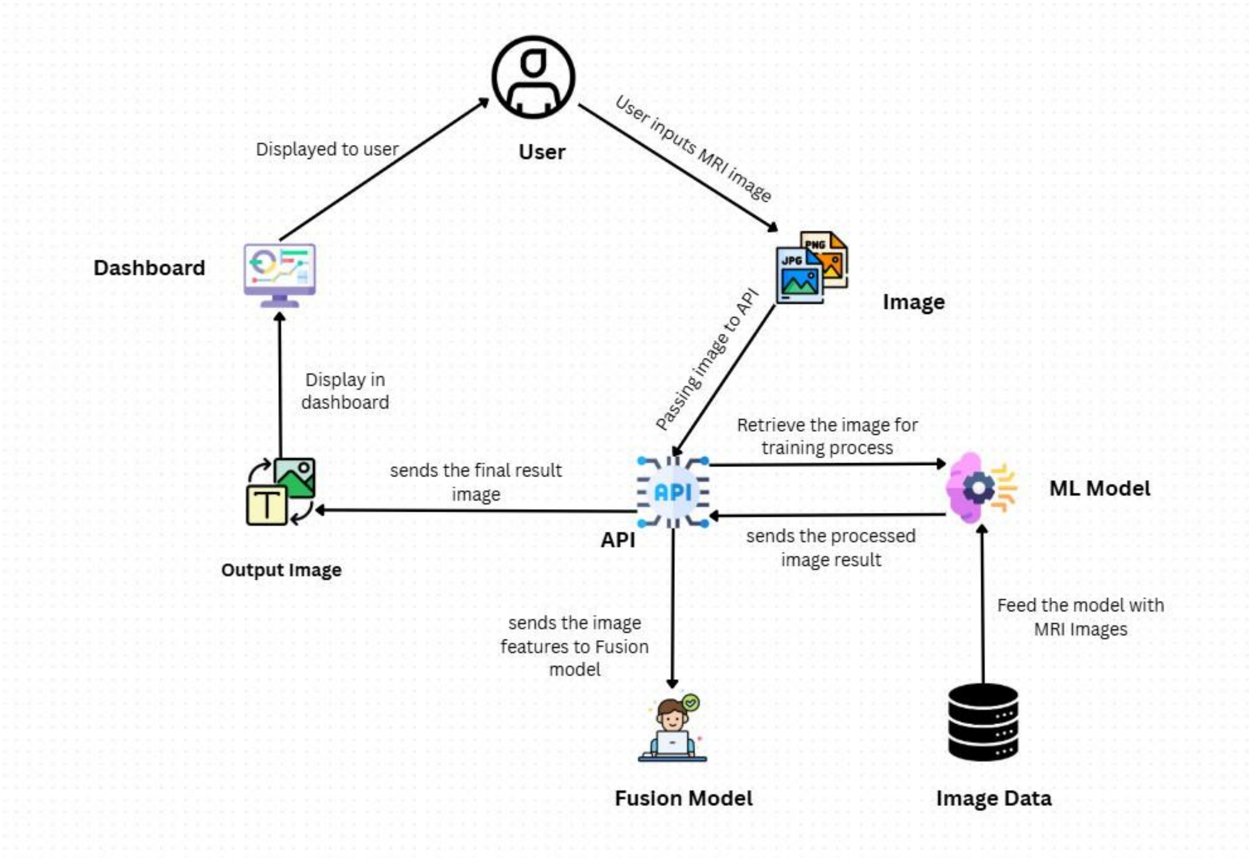


Figure 2: Diagram of the MRI Feature Extractor

12.3 Fusion Engineer

- Upload MRI and CT Features - The data extracted from the MRI and CT scan images are uploaded.
- Image Fusion - The extracted features are fused together to make a final image using VGG19.
- Image Output - The fused image is forwarded to the Brain tumor detection system and the result is displayed in the dashboard.

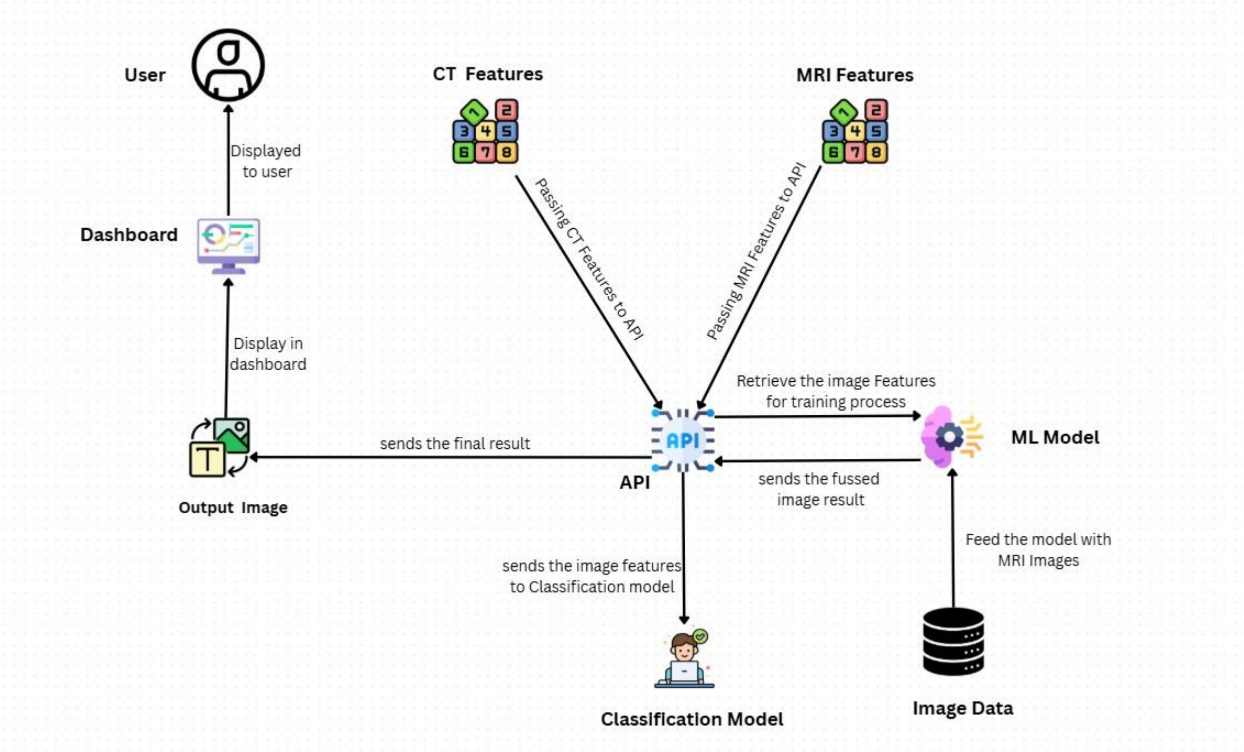


Figure 3: Diagram of the Fusion Engineer

12.4 Classification Engineer

- Image Input - A fused image (pixel-aligned MRI and CT fused image/s) per patient, in order to classify into different tumour types, using a CNN and a MLP classifier. This image now contains both soft-tissue detail from MRI and bone/structural detail from CT, giving the model richer information than a single modality.
- Preprocessing - Resize the image, normalization and carry out data augmentation for better model optimization, robustness and generalization and to reduce overfitting.
- Feature Extraction - The fused image goes through a CNN, to detect and identify patterns for a specific tumor.
- Classification - Then it is passed through a SVM / MLP to performs the classification and according to their probability scores the specific tumor is outputted.

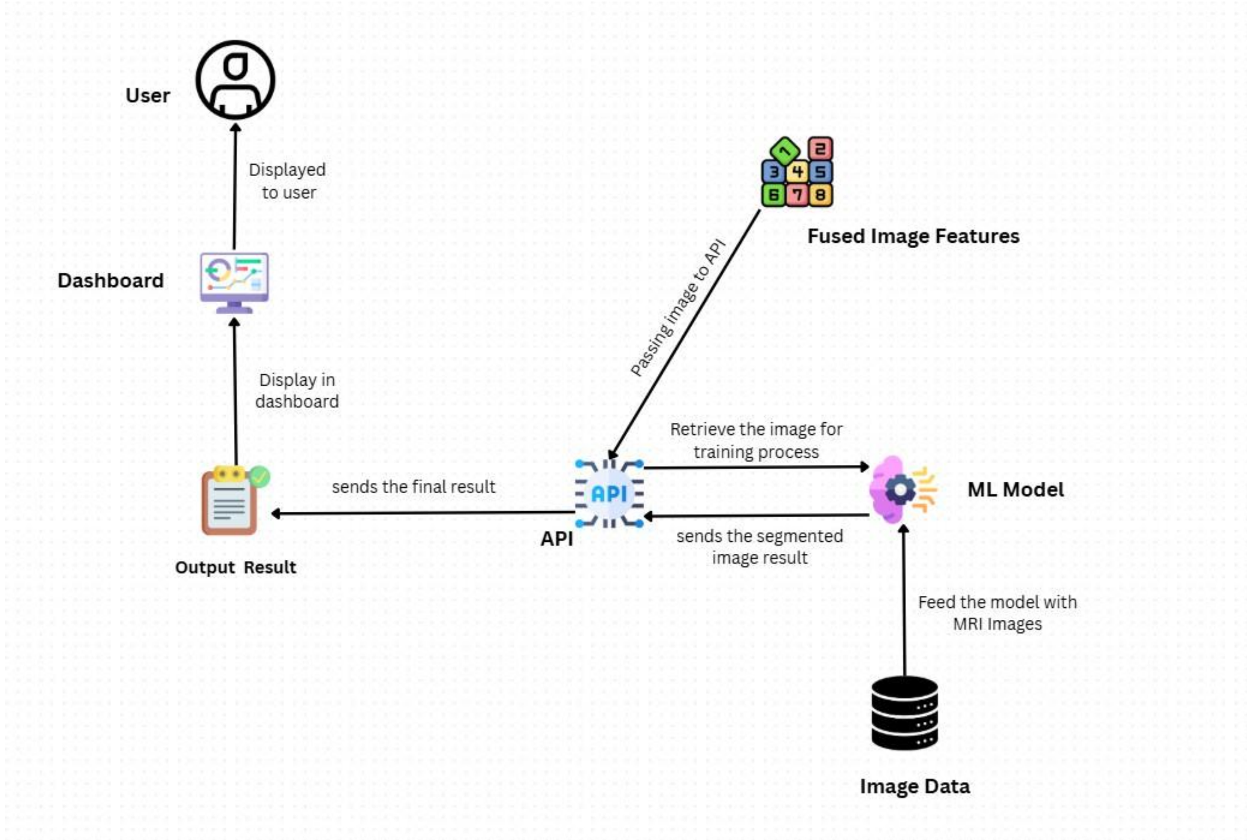


Figure 4: Diagram of the Classification Model

13 Methodology

13.1 Research Methodology

Research Philosophy	We will adapt a positivism methodology since this project focuses on quantitative and statistical data.
Research Approach	A deductive approach will be employed to develop an accurate diagnostic model for tumor classification using patterns since the study tests existing theories found via a deep learning model.
Research Strategy	Our work utilizes an experimental strategy, using fusion methods, datasets, and architecture to evaluate their impact on tumor detection accuracy.
Research Choice	A mono-method quantitative choice is adopted, as the study relies on numerical data (images, accuracy, and F1-score) and statistical methods, producing quantifiable and verifiable performance metrics.

Time zone	We employ a cross-sectional time horizon with the collected medical scan dataset; each data point will represent a single diagnostic snapshot using existing MRI and CT scan datasets.

13.2 Development methodology

13.2.1 Lifecycle Model

We are following the Agile life cycle model due to its iterative nature, which encourages continuous feedback, improvements, and refinement. This model allows us to break down development into short sprints for CNN design, data fusion, tuning, and retraining, and allows fast adaptation to results.

13.2.2 Design methodology

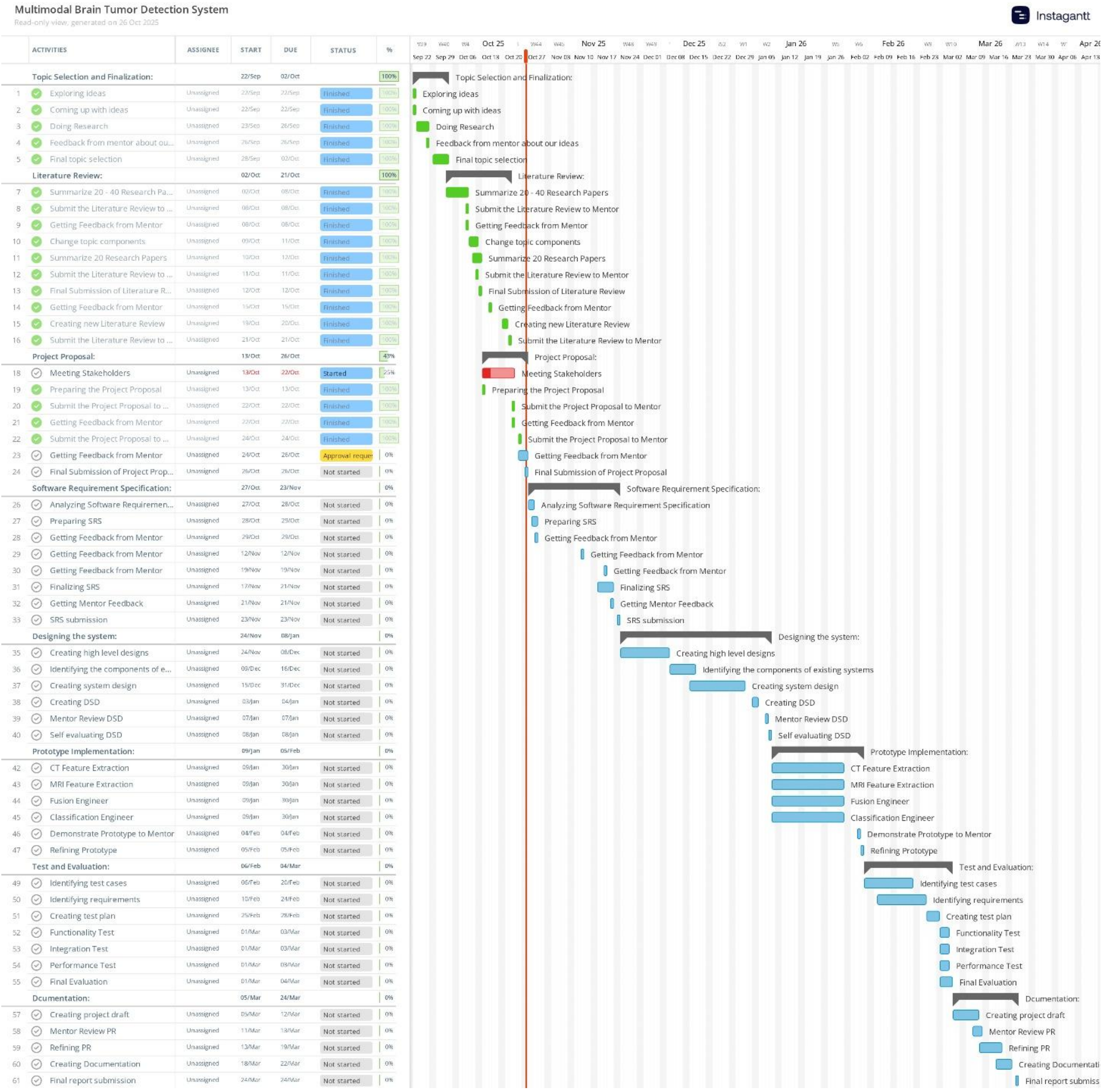
Proposed approach uses an Object-Oriented Analysis and Design (OOAD). This method enables modularity, reusability, and clear representation of real-world entities through UML diagrams since our system involves multiple interacting modules such as MRI and CT image processing, feature fusion, and classification that are ideal for complex AI-based systems like brain tumor detection.

13.2.3 Evaluation methodology

Our system performance will be calculated using Accuracy, Precision, Recall, F1 score, and Area Under the Curve (AUC). The F1-score is particularly major in medicine for addressing class imbalance. Benchmarking will compare the multimodal CNNs with unimodal CNNs and issue modern results to validate the image fusion approach.

13.3 Project Management methodology

13.3.1 Gantt Chart



13.3.2 Deliverables

Deliverable	**Date**
Semester 01	
Literature review submit	Week 03
Project Proposal submit to the supervisor	Week 04
Final Project Proposal submit	Week 05

SRS submit to the supervisor	Week 08
Final SRS submit	Week 09
Semester 02	
Implementation of Prototype	Week 14
Testing and Evaluation	Week 19
Submission of documentation and final report	Week 23

13.3.3 Resource Requirements

Hardware requirements

- High-Performance CPU (intel core i7 13th gen/ intel(R) processor of higher) - To do computer-based activities and get high performance.
- 16GB RAM or higher - To process large datasets, to run algorithms and train machine learning models.
- At least 1TB SSD - to store a lot of data.
- NVIDIA GeForce RTX 3080/ High-end GPU - if model running locally/ testing.

Software requirements

- Python – Python was used to develop this proposed system because it able to simplifies error handling and provide light weight supportive libraries.
- Pycharm/ VS Code - used in the management of the files and creating commercial and private applications.
- Jupyter Notebook and Google Colab – Use for model development , test performance and model evaluation.
- Streamlit library - To build the dashboard.
- MS Word, Notion and Latex - To create project reports, proposals and other documents.
- TensorFlow and PyTorch - To develop and train machine learning models to get predictions.
- Windows OS – To handle large volumes of data and manage computationally intensive tasks.

Skill requirements

- Data gathering and extraction
- Writing Reports

- Strategic Plans and time allocation
- Computer Vision Skills
- Programming skills
- Medical Imaging Knowledge
- Machine Learning Knowledge

Data Requirements

- Sufficient number of paired MRI and CT images of patients with brain tumor.

13.3.4 Risk Management

Risk Item	**Severity**	**Frequency**	**Mitigation Plan**
Data Privacy and Ethical Compliance	5	3	Anonymize all patient data, follow regulations and implement secure storage and access controls.
Unsuccessful Fusion (Poor Performance)	5	3	Define clear performance metrics and plan for fallback options, such as using a different multi-modal fusion methods that has been researched on.
CT/MRI Image Alignment Error	4	5	Prioritize and enforce strict pre-processing steps for aligning CT and MRI scans using established medical imaging libraries.
Lack of perfectly paired CT and MRI scans	5	4	Focus on securing datasets from specialized clinical trials that explicitly collect co-registered (paired) data for research.

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