UNIVERSITY OF ENERGY AND NATURAL RESOURCES, SUNAYNI

SCHOOL OF SCIENCES

DEPARTMENT OF INFORMATION TECHNOLOGY AND DECISION SCIENCES

TOPIC:

BRAIN TUMOR IDENTIFICATION VIA CONVOLUTIONAL NEURAL NETWORK (CNN) APPROACH

A project presented to the Department of Information Technology and Decision Sciences,

At University of Energy and Natural Resources, Sunyani

Submitted to meet part of the requirements for the Bachelor of Science degree in Information Technology.

BY:

OPOKU CHRISTIAN	*UEB3202621*
SULEMAN ABDUL RASHID	*UEB3206621*
BOATENG JOSEPHINE AKOSUA (MS)	*UEB3202221*
NANGKU PORTIA (MS)	*UEB3218521*
ANTWI VERA ASANTEWAA (MS)	*UEB3278623*

September, 2025

ABSTRACT

Tumors of the brain develop from irregular cell multiplication within the brain tissue and represent the second primary contributor to cancer-related fatalities (Badran et al., 2010). Key categories include non-cancerous (benign), cancerous (malignant), hormone-related (pituitary), and support-cell-based (glioma) varieties (Choudhary et al., 2022). Non-cancerous growths consist of atypical cells that remain localized without spreading to adjacent areas or distant body parts. These typically expand at a gradual pace, feature distinct margins, and pose fewer risks compared to aggressive forms (Goyal et al., 2021). Pituitary growths form in the endocrine gland situated near the brain's foundation, which oversees hormonal balance. Although mostly non-spreading, they may trigger endocrine disruptions or exert force on nearby neural elements, resulting in symptoms such as migraines or sight disturbances. Management often involves operative removal, targeted radiation, or pharmacological interventions (Armstrong et al., 2004). Cancerous masses comprise aberrant cells capable of infiltrating surrounding structures and disseminating through circulatory or lymphatic pathways. Such formations tend to advance swiftly and may prove fatal without prompt care (Sharmila et al., 2022). Gliomas emerge from glial elements that assist and safeguard neural cells in the central nervous system, potentially exhibiting either non-aggressive or aggressive traits (Gupta et al., 2023). Aggressive brain growths carry elevated mortality risks owing to their position in a crucial bodily structure. Despite their scarcity comprising just 1.8% of worldwide cancer cases (Abdellatef et al., 2021) innovations in deep learning (DL) and machine learning (ML) have advanced the assessment of diagnostic scans (Rahman & Islam, 2021). Diverse scan enhancement strategies are applied in this domain. Computerized identification through magnetic resonance imaging (MRI) is vital, as it supplies details on irregular tissues essential for therapeutic strategies (Soundarya et al., 2023). With ongoing AI developments, healthcare providers increasingly rely on DL frameworks alongside MRI for identifying neural growths (Goyal et al., 2021). MRI employs intense magnetic forces and radiofrequency signals to generate comprehensive internal visualizations (Cho et al., 2020). Clinicians utilize these depictions to deliver effective care for affected individuals. Advanced DL architectures, such as convolutional neural networks (CNNs) a subset of neural networks are effective for recognizing neural malignancies (Brindha et al., 2023).

ACKNOWLEDGEMENT

We express gratitude to our advisor, Dr. Michael Opoku, for his insightful direction, knowledge, and continuous assistance during this endeavour. His constructive input and motivation played a pivotal role in guiding the project's progress and achievement. We also extend thanks to all contributors, whether directly or indirectly involved, such as classmates, advisors, and relatives, for their sustained inspiration and support.

DECLARATION

We OPOKU CHRISTIAN, SULEMAN ABDUL RASHID, BOATENG JOSEPHINE AKOSUA, NANGKU PORTIA, and ANTWI VERA ASANTEWAA hereby confirm that we have thoroughly reviewed the university guidelines concerning plagiarism and artificial intelligence and affirm that this report represents our independent effort in pursuit of a BSc Information Technology. It is our assurance that this report is entirely our original work, devoid of any uncredited content from external sources. Additionally, we acknowledge that we received supervision while preparing and submitting this report.

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CHAPTER ONE

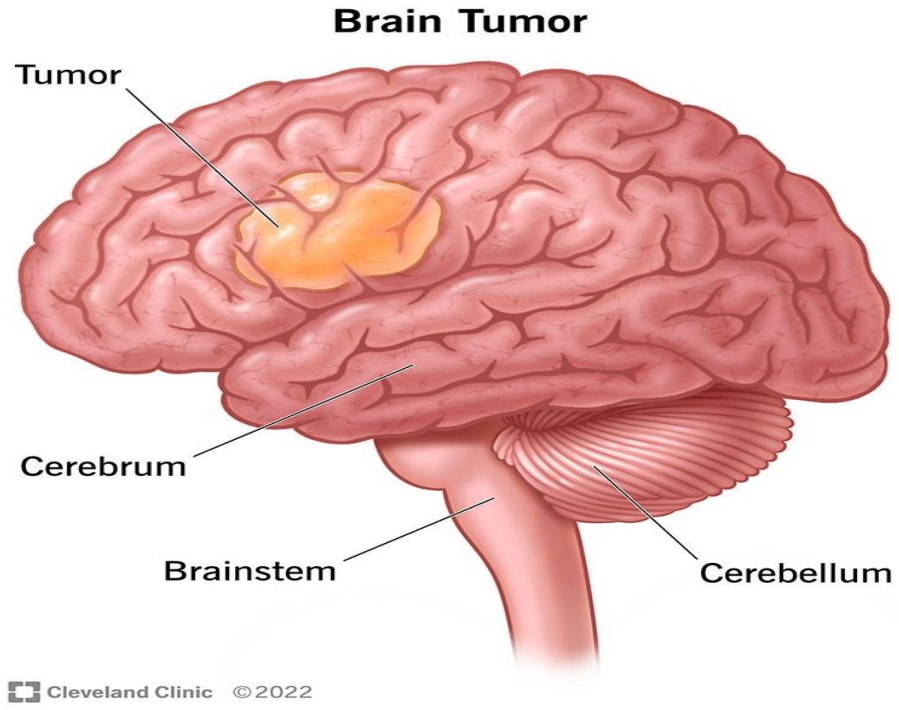
1.0 BACKGROUND OF THE STUDY

A person's system consists of numerous organs, with the brain being the most vital. A common cause within the nervous system dysfunction can be a cancer. A cancer occurs when cells grow excessively and uncontrollably. These tumor cells consume the vitamins and minerals intended to serve normal cellular structures and tissues, leading to the breakdown of neurones. A nervous system tumor remains a serious illness that can be fatal for many people. This project focuses on a framework that requires usage of computing device methods for recognising cancer areas then categorise the cancer's nature. It employs a formula for Artificial Neural Networks to analyse imaging from different people.

The system is expected to strengthen the present procedure for screening for cancer of the brain. It may also lower the demand for afterwards procedures, treatment expenditures. The establishment of differentiating brain cancers may prevalent within the fields of biomedical engineering and the information technology fields within biomedical engineering, where differentiating brain cancers constitutes a substantial topic. Aforementioned leading rationales about tumor growth models, computer-aided surgical blading, radiation therapy, tumor growth and treatment response evaluation has led to the establishment and true demonstration of computational aided diagnosis system in the area of medical diagnosis and treatment. This means clinical workload of physicians has lessened while obtaining a translated process that is accurate. This chapter describes the rationale of segmentation of medical imaging, the various segmentation methodologies, the several methods of MRI scanning, the occupancy of classifications of brain tumors, and elementary understandings. Research of the last 8 years, has dedicated itself towards machine learning of tumor detection and tumor prediction (Hemanth et al., 2019). As this mechanism, allow imaging and diagnostic purposes to run the rehearsal and guess estimations, while tasking. Nevertheless, advance research of the machine learning process remain viable for the study.

1.1 SUMMARY OF BRAIN STRUCTURE AND GROWTHS

The brain leads the nervous network, sheltered in the head. It directs body activities, allowing perception, adaptation, movements, ideas, and feelings. Growths fall into non-harmful, harmful, hormone, and glial types. Non-harmful growths are localized abnormal cell clusters that do not spread. Harmful ones are invasive and can metastasize. Hormone growths develop in the gland regulating secretions.



1.2. INSPIRATION

The ultimate purpose of brain cancer screening is to identify tumors and, when possible, evaluate what kind. The system works to determine if a tumor is present or not, returning a positive or negative result. The system is capable of reviewing medical images and returning more detailed results that describe the presence of a brain tumor, or otherwise. The task in hand involves building a framework that has a component that locates parts of the tumor through computer techniques and an algorithm that will determine the type of tumor.

1.3 REASONS FOR THE STUDY

The aim of growth identification is to find and assess growths. The framework checks for presence, giving positive or negative outcomes. It reviews scans and delivers detailed findings on growths. The research builds a system with location components using digital methods and an algorithm for typing.

1.4 INQUIRY POINTS

1. How effective is the layered model compared to standard methods for growth prediction?

2. How does performance change with various optimizers like adaptive gradient, adaptive moment, and gradient descent?

3. Can techniques like neuron dropout enhance the model's ability to generalize?

1.5 BOUNDARIES

The objective is to create a system that automates and improves the identification and classification of brain tumors. This system would serve neurosurgeons and healthcare professionals. This system will utilize image processing and computer vision technology to improve the accuracy, precision, and overall efficiency of the brain tumor screening.

1.6 REPORT STRUCTURE

The document is organized into chapters. The first introduces the topic and inquiry points. The second describes the approach, including data gathering, tools, and assessment. The third reviews prior work. The fourth details sections and visuals. The fifth concludes the project with findings, summary, future ideas, and sources.

1.7 CHALLENGE DESCRIPTION

Manual scan analysis for growths is exhausting and slow. Experts spend significant time on each image, delaying care. Human mistakes can occur due to complex structures and subtle signs, leading to overlooked early growths. These issues emphasize the need for a reliable and efficient system to detect brain tumors automatically. Such a system would help health professionals, like radiologists, improve diagnostic accuracy, shorten the time to diagnosis, and ultimately enhance patient outcomes. An automated system is needed to boost accuracy, reduce time, and improve results. This research uses scans to check for growth presence. This project emphasises the automatic identification of brain cancers. Typically, Magnetic Resonance Imaging images are employed to look at the brain's anatomy.

1.8 GOALS

1.8.1 MAIN GOAL

To build a system for automatic growth detection in scans, assisting radiologists in efficient and precise diagnosis.

1.8.2 SPECIFIC GOALS

1. Obtain and pre-process the brain-imaging data (MRI scans).

2. Assess the accuracy and speed of the developed model compared to the expert radiologists' diagnoses.

3. Refine the model to improve detection performance, especially for less common tumour types.

1.9 CONSTRAINTS

1. Needs large training sets.

2. Requires suitable frameworks.

3. Consumes time.

4. Can be repetitive.

5. Layered networks' success was limited by scale in the past.

CHAPTER TWO
2.0. APPROACH

This section outlines methods for constructing and assessing the growth detection system. It ensures model reliability through steps like data preparation, model building, training, app creation, and evaluation. Each step addresses challenges and improves real-world application (Pereira et al., 2016).

It illustrates the methodical approach we take to guarantee the validity and reliability of the model. Overall, this includes logical but distinct steps such as dataset preparation, model development, training, application development, and recommendations for evaluation. Each has its purpose and goal in simplifying the challenges and enhancing the real-world context.

Dataset Preparation

Data quality is crucial for automated learning projects.

Data Collection

The data was sourced from an open platform, Kaggle, with images from various medical centers for diversity in growths and conditions. This variety helps train robust models for accurate identification. The images were collected from different hospitals and research facilities to provide access to a large variety of tumors and imaging conditions

Optimization

An adaptive rate technique adjusts based on gradient history. A loss measure for multi-category tasks assesses predicted vs. actual labels, suiting grouping problems. This loss function is well suited for multi-class classification problems and is beneficial for the model's performance.

Application Development

The application development stage focused on providing an easy-to-use interface. The user interface will allow medical practitioners to submit scans and get fast, actionable diagnosis outcomes. The front-end user interface built using the popular cross-platform mobile application framework called Flutter. Flutter has various widgets and utilities that help design an intuitive and responsive interface for the user. Below are some features of the application

I. Upload - Users can upload an MRI scan image directly from their device.

II. Real-Time - The application processes the uploaded images in real time and provides immediate feedback.

2.1. ANTICIPATED RESULTS

The system is expected to:

1. Offer a dependable scan-based growth detection tool.

2. Shorten diagnosis time and boost early identification.

3. Increase precision for complex cases.

4. Provide expandable options for resource-limited clinics.

5. Aid professionals by minimizing errors for better care.

2.2. IMPORTANCE OF RESEARCH

1. Boost the diagnosis' accuracy. Better the speed of cancer detection

2. Reduce the time needed for diagnosis. For quick and accurate clinical decision-making, enhance the assessment of diagnostic data.

3. Grow the workforce of medical professionals. Give medical professionals working in radiology and neurology a tool to help them make decisions.

2.3. INITIAL TREATMENT AND IMPROVEMENT

Pre-processing and improvement methods can be implemented regarding enhancing identification concerning doubtful lobe areas in MRIs. This part provides MRI images, a gradient-based image optimisation technique that relies through local statistics and the initial component. This part incorporates two phases: initial treatment and improvement. During the beginning, we apply a tracking algorithm to remove film artefacts from the MRI, including labels and X-ray markers. In the second stage, we use a weighted median filtering method to address high-frequency components. Unlike spatial, adaptive, and median filters, this method provides high-resolution MRIs.

2.4. GROUPING AND DIVISION

For grouping, various feature methods tested by training networks and checking errors on test sets to select the best. Division is key for analysis, extracting info from images. Automated division applies to diagnosis, planning, and integrated surgery (Işın et al., 2016).

2.5. LAYERED NEURAL SYSTEM

A deep method processes input visuals, weighting elements. It needs less prep than others need and learns characteristics during training. Inspired by visual processing, it has receptive areas. Layers extract traits like boundaries, with deeper ones handling complex patterns, mimicking human perception (Liu & Guo, 2015). A Convolutional Neural Network (CNN) is a deep learning technique designed to process and analyse images by assigning significance to different elements or objects within them. Unlike traditional classification approaches, CNNs require minimal pre-processing, as they autonomously learn filters and features during training, eliminating the need for manually crafted filters [1]. This capability stems from their architecture, which draws inspiration from the human visual cortex, mimicking the interconnected neuron structure in the brain. In the visual cortex, individual neurons respond only to stimuli within a limited region of the visual field, termed the receptive field. These regions overlap to cover the entire visual space. Similarly, CNNs use convolution operations to extract high-level attributes, such as edges, from input images. A typical CNN consists of multiple convolutional layers, where the initial layer identifies basic features like edges, colours, and gradient orientations.

2.6. DETAILED SCANNING (MRI)

MRI is a tool for anatomical study, capturing visuals across spectra. Sensors and physics make it suited for specific uses. It uses fields 10,000 times Earth has to align protons in body fluids. Pulses disrupt, and realignment signals create images. Functional MRI assesses activation via oxygen levels in blood, non-invasively with high resolution (Preston, 2006). Magnetic Resonance Imaging (MRI) is a sophisticated diagnostic tool used to visualize the internal structures of the human body. It employs a powerful magnetic field approximately 10,000 to 60,000 times stronger than Earth's magnetic field, depending on whether the scanner operates at 1.5 or 3 Tesla (T) to generate detailed images [1]. Unlike ultrasound, MRI provides superior soft-tissue contrast and detailed anatomical maps, making it ideal for various medical applications. The technology captures images by detecting the magnetic resonance of hydrogen nuclei (protons) in water and fat molecules, producing 12-bit signal values that yield 4096 intensity levels per pixel. During an MRI scan, a patient is placed within a strong magnetic field, which aligns the protons in the body's water molecules either parallel or anti-parallel to the field. A radio frequency (RF) pulse is then applied, temporarily disrupting this alignment. As the protons return to their original state after the pulse ceases, they emit RF energy signals. An antenna within the scanner to construct detailed images [1] detects these signals, localized by rapidly switching magnetic gradients. Functional MRI (fMRI) is a specialized application that maps brain activity. Unlike positron emission tomography (PET), fMRI is non-invasive and offers high spatial resolution. It commonly employs blood oxygen level-dependent (BOLD) contrast, which exploits differences in blood oxygenation. In a resting state, deoxyhemoglobin, a paramagnetic substance, reduces the MRI signal in T2 or T2*- weighted images. During neural activity, increased oxygen demand elevates oxyhemoglobin levels, enhancing the signal. In a typical fMRI study, patients alternate between rest and task periods while images are acquired repeatedly. Signal variations are analysed pixel by pixel to identify regions with statistically. Significant correlations to the task pattern.

CHAPTER THREE
3.0 BACKGROUND ANALYSIS

Habib used layered networks on similar data for growth detection, achieving 88.7% accuracy, improved with a new structure of 2D layers and pooling (Habib, 2019). Lin and Chang used color division and clustering for tracking, uniquely applying clustering to grayscale-derived colors (Wu et al., 2007). Sharma and Komal used scan data for identification and traits, segmenting with effects methods that are more precise needed. Studies show deep learning is potential for diagnosis and outlook (Jafari et al., 2012; Hossain et al., 2019). Research is ongoing for optimal structures and data. Evidence is limited to specific types, needing broader evaluation. Calls for better prediction efficiency exist (Gill et al., 2022). Using a dataset of brain tumors similar to the one in this paper, Habib applied artificial convolutional neural networks (ANN) to detect tumors. During testing, he achieved an accuracy of 88.7%. He raised his accuracy by introducing a new neural network. A unique aspect of this paper is their use of the K-means algorithm to cluster colour-spaced images derived from greyscale. To identify brain cancers, the researchers used magnetic resonance imaging, or MRI. Because brain tumors can differ in size and shape, classifying MRI scans is challenging. Two supervised learning methods for spotting brain tumors are the Decision Tree classifier and MRI enhancement technique. This technique involves feeding images into the model from different viewpoints and angles. This approach allows the model to learn from a variety of new photos, leading to positive outcomes and scores. They implemented LinkNet architecture alongside a Convolutional Neural Network (CNN). Sharma and Komal proposed a method that uses MRI data to identify brain tumors and their features. They segmented the images and applied various effects. There is a need for more accurate and reliable methods to detect brain tumors. Many studies have explored deep learning's potential to enhance the diagnosis and prognosis of brain tumors (Jafari et al., 2012; Hossain et al., 2019; Rajeshwari et al., 2013; Daljit Singh et al., 2012; Magboo et al., 2022; Gill et al., 2022; Mahajani et al., 2013; Bidkar et al., 2023).

3.1. FRAMEWORK DESIGN (UML VISUALS)

3.1.1 Entity Relationship Diagram

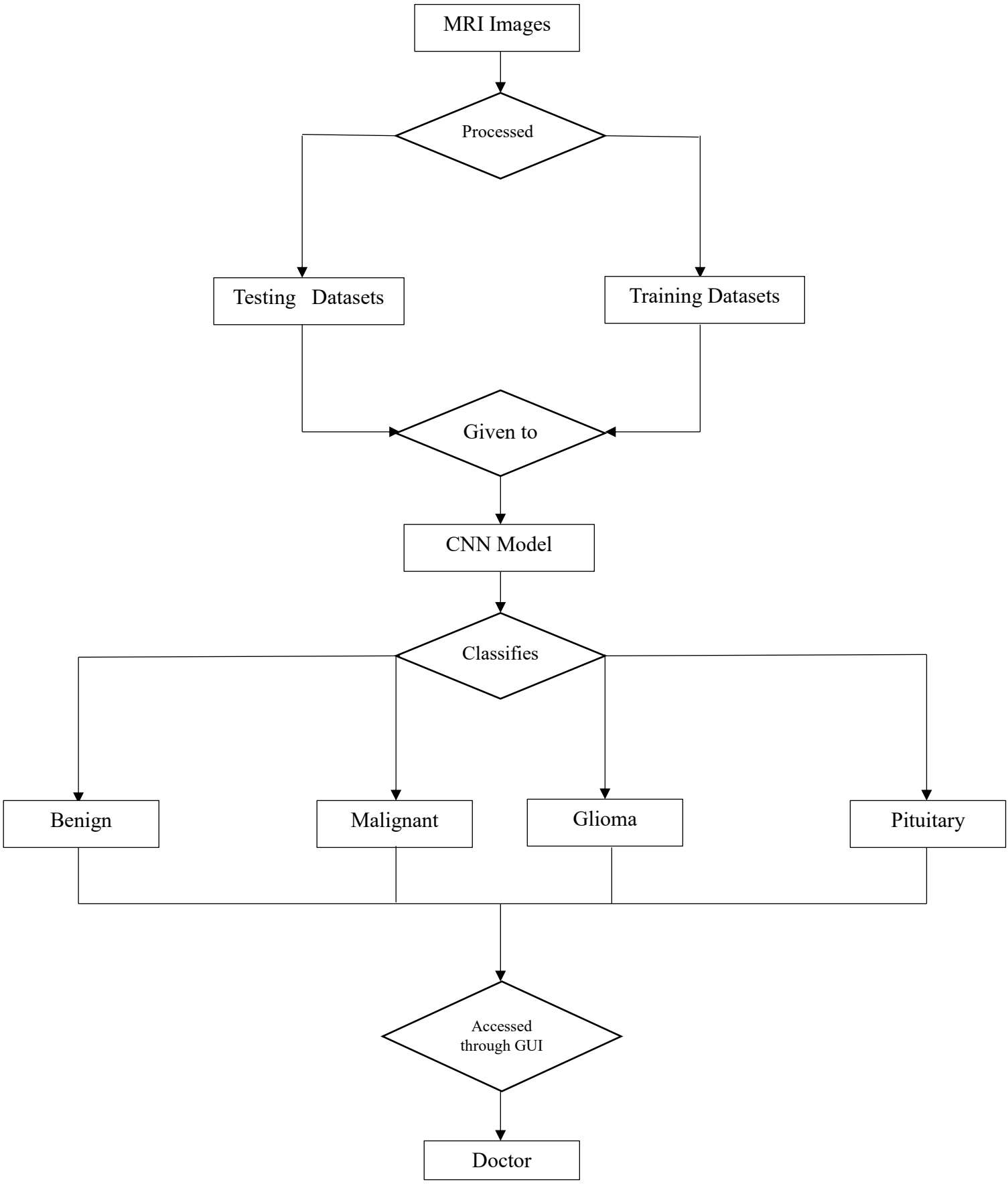


Figure 1. Entity Relationship Diagram

3.1.2 Use Case Visual

The diagram of a usage instance contains two actors that user and the system.

1. The User: The user provides an input image and views the final output.

2. The System: The system handles all clustering, feature extraction, classification, and training algorithms.

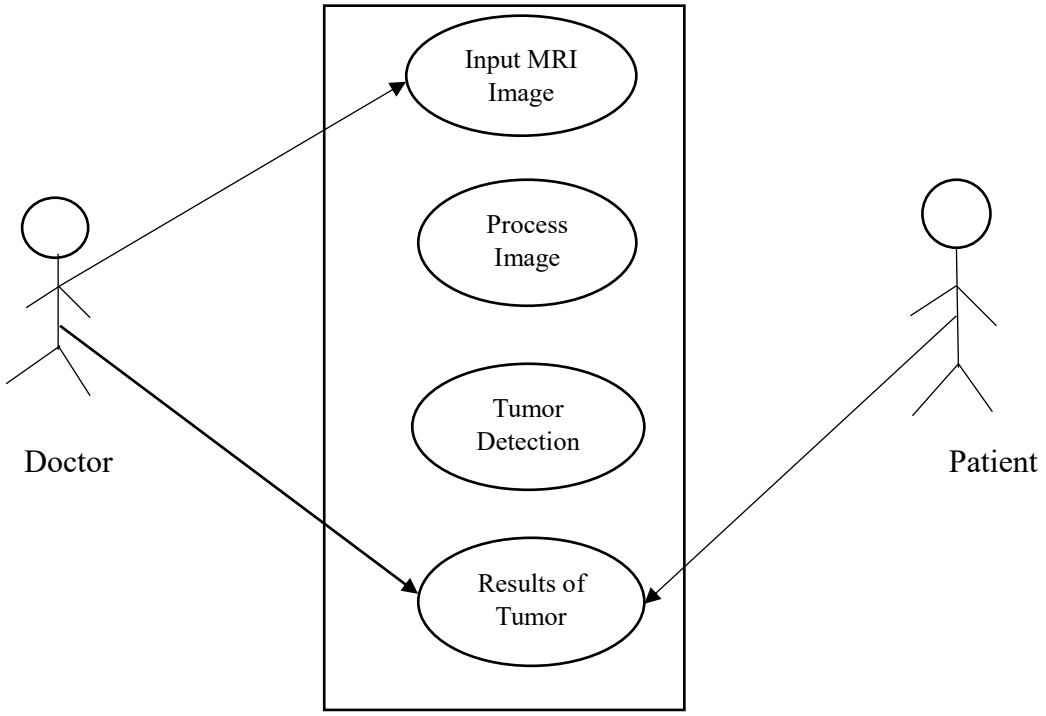


Figure 2. Use case visual

3.3. DEPLOYMENT DIAGRAM

This diagram relies on convolutional neural networks (CNNs), a type of artificial intelligence, to examine medical images for signs of tumors. The system operates on a server, processing images uploaded by users in real time. Results, including whether a tumor is present, its location, and its severity, are stored for doctors to review or for record-keeping purposes.

Key Component

Data Source: The system starts with a collection of MRI scans, kept in a database that contains thousands of labelled pictures (for instance, more than 3,000 scans from open sources like Kaggle). The convolutional neural network (CNN) is trained using the pictures that have been labelled with cancer types such as gliomas or malignant.

Automated Learning Framework: The CNN, a specific model trained to identify and label cancers, is the central component of the system. During training, it learns from the MRI data before deploy to a server for practical application.

User: Through an application or other user-friendly interface, users communicate with the system. Through a quick and effective connection, they upload an MRI scan, which is then sent to the server for processing. With this configuration, rapid, non-invasive tumour screening is possible without requiring invasive techniques like biopsies.

Server: The server manages new user scans and houses the trained CNN. It uses programs like TensorFlow or Keras to process the images, obtaining information like tumor locations or classifications. For instance, these outputs are stored in a database as a component of a patient's electronic health record or as a report for doctors.

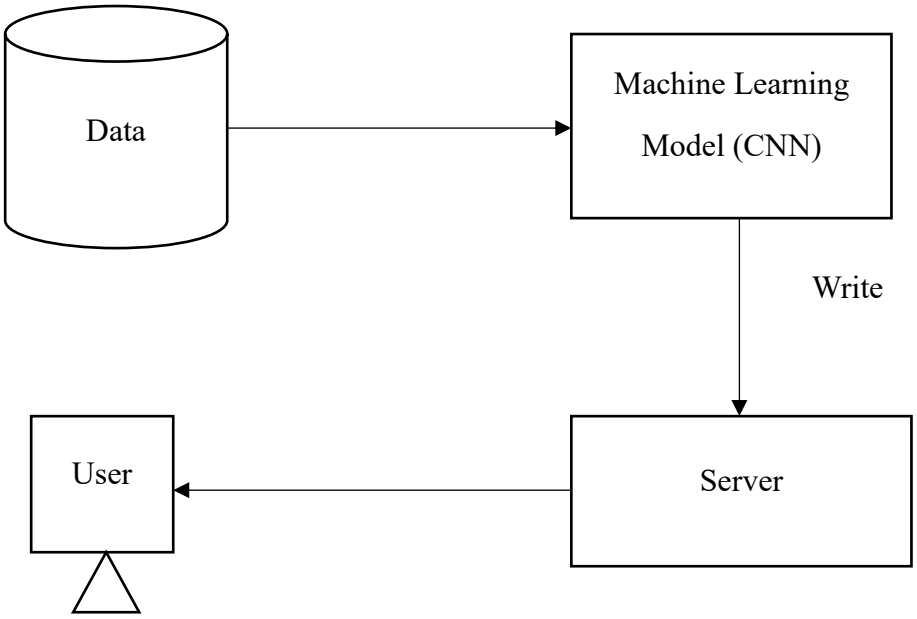


Figure 3. Deployment diagram

3.4 CURRENT FRAMEWORK

Existing systems explain how to automate cell segmentation. Current systems focus on automating cell segmentation. This method works with N-dimensional images for interactive multi-label classification. It breaks down the more complex areas into segments. This systematic process provides feedback to the user when calculating the section.

3.5 SUGGESTED FRAMEWORK

Five phases: data set, initial processing, division, model creation, training for epochs, and grouping. Select scans, encode, resize, split 80/20, build model, train, classify as present/type or absent.

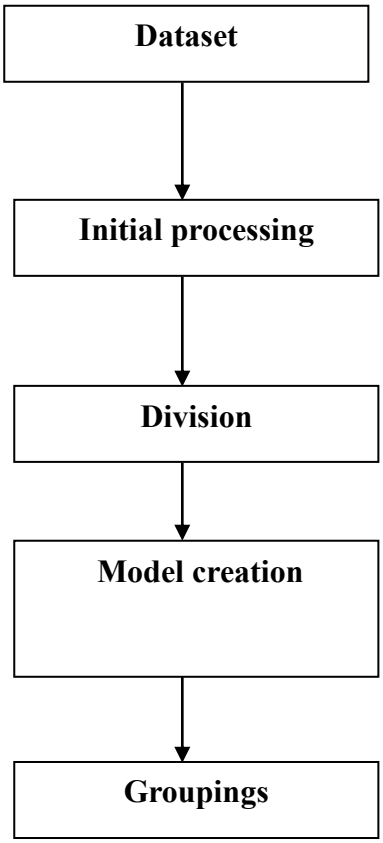


Figure 4 Suggested framework

3.6 VIABILITY EVALUATION

3.6.1 **Ecological Feasibility**

The system's impact on the environment is negligible. There are no negative effects on the environment.

3.6.2 **Operational Feasibility**

The system is simple to use and friendly for users. The system works well in most settings. Therefore, our system is operationally feasible.

3.6.3 **Schedule Feasibility**

The project was developed from start to finish in five to six months.

CHAPTER 4

4.1. OPERATIONAL AND NON-OPERATIONAL NEEDS

4.1 Operational needs

4.1.1 Picture Input and Loading

This framework receive information from ultrasound machines from MRI examinations in common formats, such as PNG and JPEG. Before processing, the system will check the input photos for compatibility, such as resolution and format. Users can upload one or more images through an API or user interface.

4 1.2. Image Pre-processing

The system will apply noise reduction filters, normalize pixel values, and resize photos to a standard resolution to improve their quality. To make the model more robust, the system must support data augmentation methods, such as flipping and rotation, for training datasets.

4.1.3. Tumor Detection and Segmentation

This framework will segment the tumor region and provide coordinates, such as a pixel-wise mask or bounding box, to pinpoint its location. The algorithm will classify identified tumors into classifications, including benign, malignant, or particular types like gliomas or malignant, with a confidence score. The system will employ a labelled dataset of images of brain MRIs to train the machine- learning model.

4.1.4 Model Management

System will allow for loaded and saved model weights for future use. The user will be able to set parameters for the model in the configuration interface (for example, set the learning rate, or epochs).

4.1.5. Result Visualization

The system will show the input image with tumor edges or segmented areas that show the detected areas. The system will show a summary of the detection including type of tumor, a confidence score, and location details.

4.1.6. Visual display

This application includes a user interface for the radiologist to upload scans, view the results, and generate a report.

4.2 Non-operational needs

4.2.1. Performance

The system shall process a single MRI image for the purposes of tumor detection on standard hardware comprising a GPU with 8GB RAM or equal hardware within 20 seconds. It will achieve a minimum detection accuracy of 95% on a validated test dataset for detecting tumors and 90% for classifying tumor types.

4.2.2. Scalability

The system will handle the processing of up to 1,000 images in a batch without losing performance. It will support scaling to multiple users, such as 10 concurrent users, accessing the GUI or API.

4.2.3. Reliability

The system will have 99.9% uptime for online deployment scenarios. It will manage invalid inputs, like corrupted images, gracefully with appropriate error messages.

4.2.4 Usability

The GUI will be easy to use, requiring no more than 5 minutes of training for radiologists to learn basic functions. The system will provide clear, simple error messages and tooltips to help users. 5. Maintainability The system will be modular, allowing updates to the machine-learning model or pre-processing pipeline without affecting other parts. It will include documentation for developers to extend or change functionality.

4.2.5 Compliance

The system will follow medical data regulations, such as HIPAA for the U.S. and GDPR for the EU, when handling patient data. It will keep an audit trail of all operations, such as image uploads and model predictions, for regulatory reasons.

4.3. ORDER VISUAL

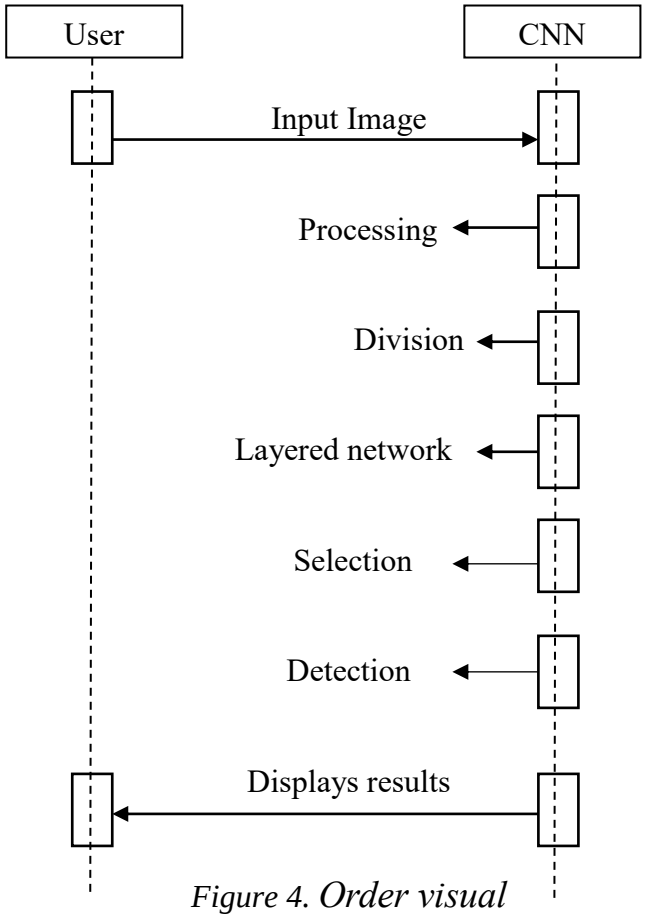


Figure 4. Order visual

The order visual illustrates how a user interacts with a Convolutional Neural Network (CNN) system to detect brain tumors using MRI or CT scans. Below is a clear, systematic explanation of the process:

4.3.1. Submitting the Scan

The process begins when a user, such as a doctor, uploads a brain scan (like an MRI or CT image) to the CNN system for analysis.

4.3.2. Image Preparation

The CNN system pre-processes the scan to ensure it is ready for analysis. This involves cleaning up the image scaling it to meet the needs of the system, setting up its format, and reducing noise.

4.3.3. Image Breakdown

The scan is divided into smaller patches or sections by the system. This enables the CNN to look carefully for clues of a tumor in particular brain regions.

4.3.4. Feature Extraction

The CNN's convolutional, gathering, and fully connected layers are among the layers that the segmented image goes through. Together, these layers reveal important characteristics in the scan, such as edges, textures, or complex patterns that might indicate a tumor.

4.3.5. Finding Important Features

After analysing the features that were extracted, the CNN chooses the most important ones that indicate whether a brain tumour is present or not.

4.3.6. Tumour Detection

The CNN examines the scan using the chosen features to identify any questionable regions that may contain a tumor.

4.3.7. Sharing Results

Lastly, the user receives the results from CNN. These findings could reveal whether a tumour is present, where it is, how big it is, and whether it seems benign or malignant.

4.4. SECTIONS

1. Collection of images

The first step is image collection. Once the photos have been collected, use a wide field of view to process them. Take the input images first. From the available source.

2. Image pre-processing

Before use, the collected photos go through pre-processing. Basic techniques include resizing images to create a clean easy to identify. Digital segmentation will divide the pre-processed photos into different pixels. This segmentation changes the image's representation so that it can be examined more clearly.

3. Image segmentation

The first step involves turning the processed brain magnetic resonance image into a binary image with a cut-off value of 128. Mapping pixel values over the thresholds creates different zones around the disease white for the affected areas and black for others. In the second stage, white pixels are

extracted using a morphological erosion method. The region with black pixels from the erosion is then used as a mask for the brain magnetic resonance image when the eroded area and the original image are split into two equal regions.

4. Convolutional neural network

A convolutional neural network algorithm is used to classify brain images. It achieves the best results for the images.

5. Tumor detection

Finally, analyse the image using filters and the convolutional neural network algorithm to detect either a tumor or a non-tumor.

4.5. CLASS DIAGRAM

In this system, a class diagram displays the classes, attributes, methods, and relationships inside the system to demonstrate its structure. It offers a software blueprint that shows how several parts work together to detect tumors, usually with the use of MRI scans and other medical imaging data.

Components of the Class Diagram

1. Classes and Their Roles: Classes represent the main entities in the system. In a brain tumor detection project, common classes might include:

Image: Represents the medical image (e.g., MRI scan).

Attributes: image ID, Patient name, etc.

Methods: Showresults ().

Model: Represents the machine-learning model (CNN for tumor detection).

Attributes: modelid, modellayers

Methods: train (), Classification ()

Tumor: Represents the detected tumor or region of interest.

Attributes: tumorID, tumor type (e.g., benign, malignant, glioma, and pituitary).

Methods: getLocation (), classifyTumor ().

Dataset: Manages the collection of images and labels for training/testing.

Attributes: dataset name, dataset id.

Methods: loadDataset (), splitTrainTest ().

2. Relationships: Relationships define how classes interact. Common relationships in this context include:

Association: A general connection between classes. For example, Model uses Image for prediction.

Dependency: A class temporarily depends on another. For example, Pre-processor depends on Image for processing but does not own it.

A class diagram.

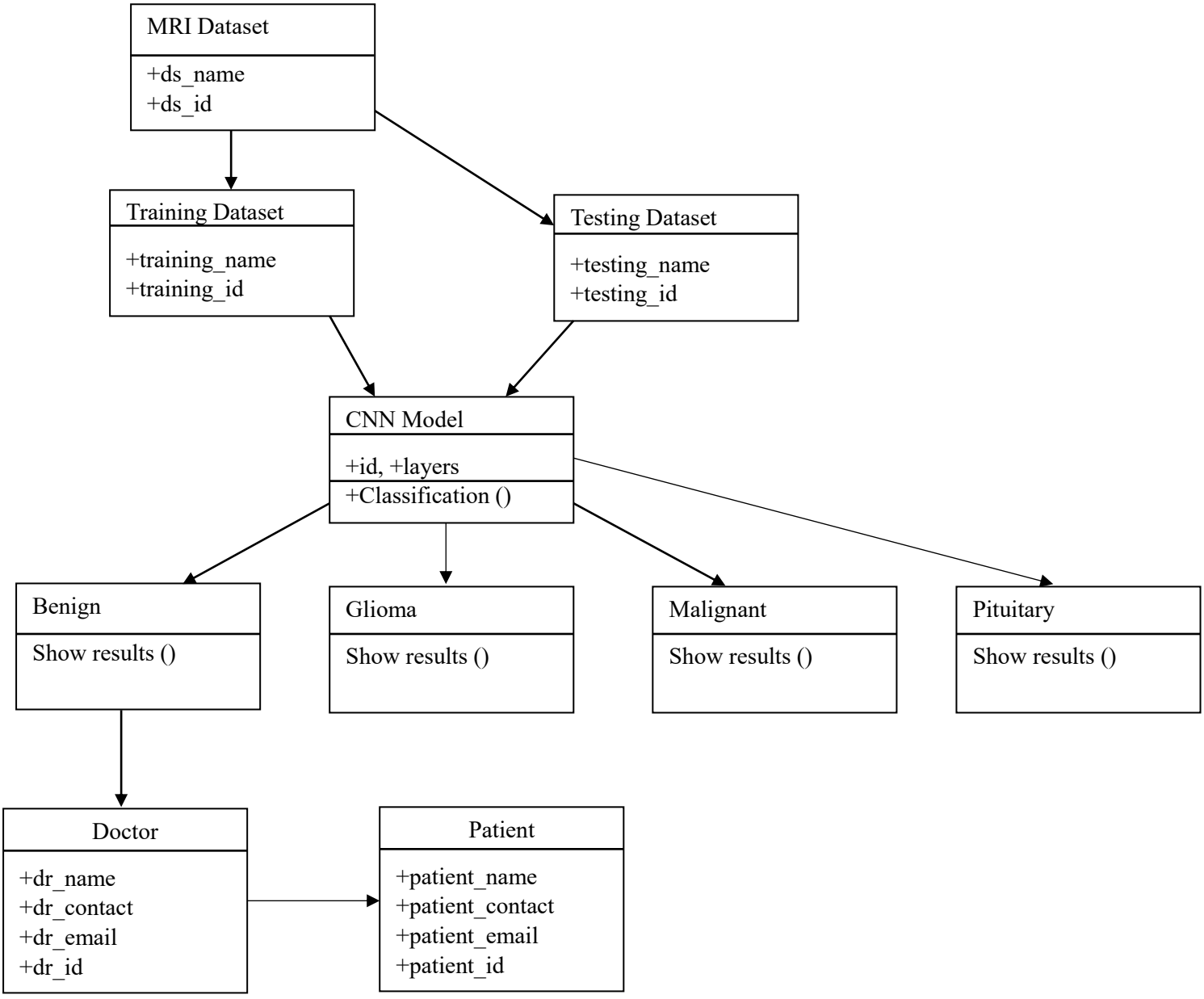


Figure 5 Class diagram

4.4 INFORMATION STRUCTURE

Table 1: MRI Dataset

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	Name	Varchar	Not null

Table 2: Training Dataset

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	Name	Varchar	Not null

Table 3: Testing Dataset

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	Name	Varchar	Not null

Table 4: CNN Model

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	trainingimgid	Varchar	Not null
3	testingimgid	Varchar	Not null

Table 5: Tumor

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	Tumor name	Varchar	Not null

Table 6: Doctor

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	Name	Varchar	Not null
3	Contact	int	Not null
4	Email	Varchar	Not null

Table7: Patient

Sr.no	Attribute	Datatype	Constraints
1	Id	int	Primary key
2	Name	Varchar	Not null
3	Email	Varchar	Not null

LIST OF FIGURES/ TABLES

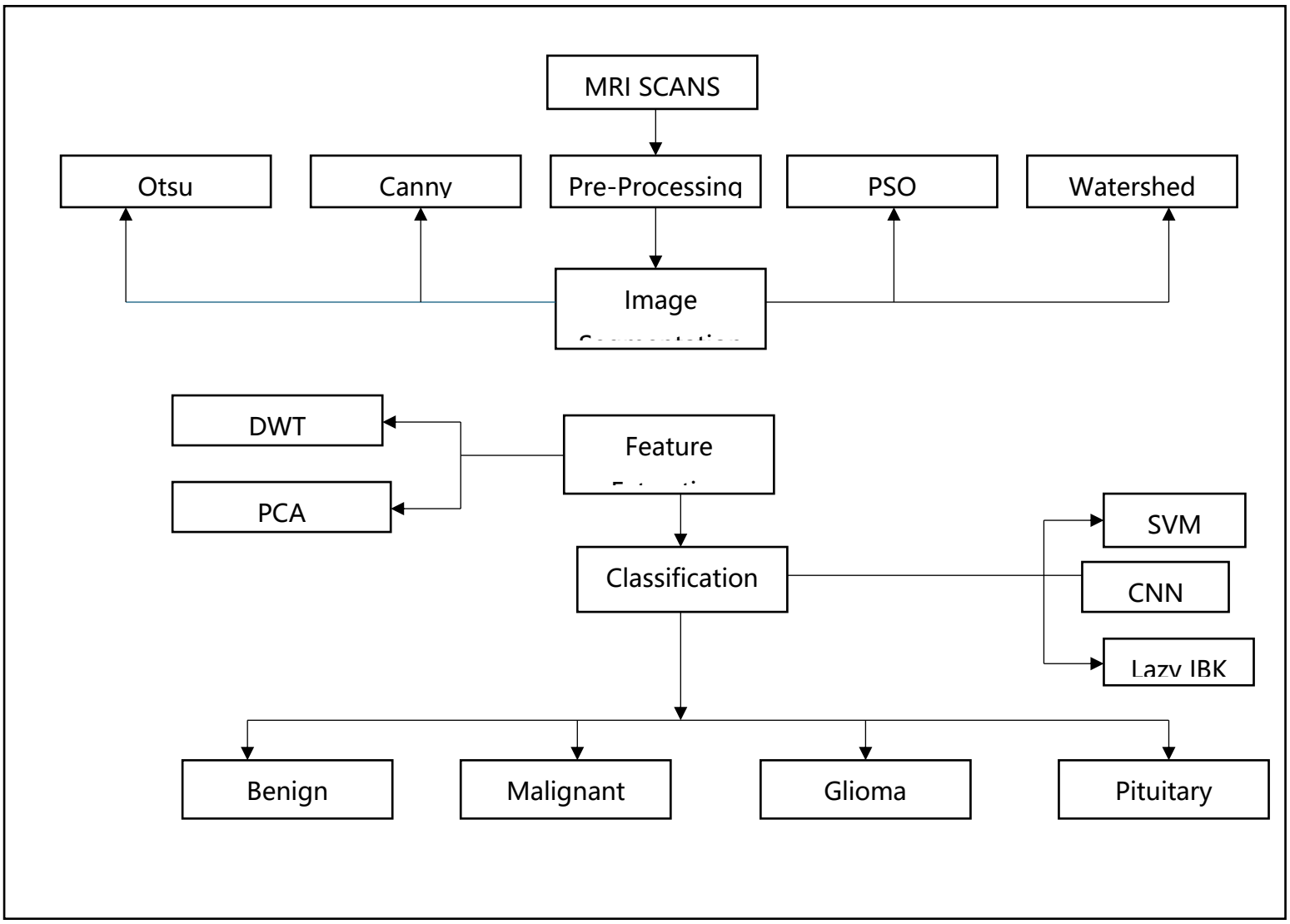


Figure 6. Software Architecture Diagram

Architectural Style and Justification

The diagram (Figure 10) shows the various stages in the development of our system. The diagram shows interaction between the various components of the application and their position in the development hierarchy. This style hence, is appropriate for the selected problem because all the modules in the selected problem function independently. The communication is strictly through message passing connectors. The flow of the system is from the top to the bottom.

10 37.0%	2 7.4%	83.3% I6.7%
10 37.0%	5 18.5%	33.7% 66.7%
50.0% 50.0%	71.4% 28.6%	55.6% 44.4%

Figure 7. Evaluation Grid for OTSU and SVM

Top-Left (Green, 10 cases, 37.0%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, 10 people with tumors were accurately identified as having them.

Top-Right (Red, 2 cases, 7.4%) – False Positives (FP)

These are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, two people without tumors were misclassified as having them.

Bottom-Left (Red, 10 cases, 37.0%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, 10 people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 5 cases, 18.5%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, five people without tumors were accurately classified as healthy.

19 36.5%	3 5.8%	86.4% I3.6%
4 7.7%	26 50.0%	86.7% 13.3%
82.6% 17.4%	89.7% 10.3%	86.5% 13.5%

Figure 8. Evaluation Grid for OTSU and Lazy IBK

Top-Left (Green, 19 cases, 36.5%) – True Positives (TP)

These are patients with brain tumors that the CNN correctly detects. For instance, nineteen (19) people with tumors were accurately identified as having them.

Top-Right (Red, 3 cases, 5.8%) – False Positives (FP)

These are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, three (3) people without tumors were misclassified as having them.

Bottom-Left (Red, 4 cases, 7.7%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, four (4) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 26 cases, 50%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, twenty-six (26) people without tumors were accurately classified as healthy.

19 36.5%	3 5.8%	86.4% I3.6%
4 7.7%	26 50.0%	86.7% 13.3%
82.6% 17.4%	89.7% 10.3%	86.5% 13.5%

Figure 9 Evaluation Grid for OTSU and CNN

Top-Left (Green, 19 cases, 36.5%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, nineteen (19) people with tumors were accurately identified as having them.

Top-Right (Red, 3 cases, 5.8%) – False Positives (FP)

these are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, three (3) people without tumors were misclassified as having them.

Bottom-Left (Red, 4 cases, 7.7%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, four (4) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 26 cases, 50%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, twenty-six (26) people without tumors were accurately classified as healthy.

11 40.1%	1 3.7%	91.7% 8.3%
7 25.9%	8 29.6%	53.3% 46.7%
61.1% 38.9%	88.9% 11.1%	70.4% 29.6%

Figure 10. Evaluation Grid for Canny and SVM

Top-Left (Green, 11 cases, 40.1%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, eleven (11) people with tumors were accurately identified as having them.

Top-Right (Red, 1 cases, 3.7%) – False Positives (FP)

these are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, one (1) people without tumors were misclassified as having them.

Bottom-Left (Red, 7 cases, 25.9%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, seven (7) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 8 cases, 29.6%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, eight (8) people without tumors were accurately classified as healthy.

12 44.4%	0 0.0%	100.0% 0.0%
15 55.6%	0 0.0%	0.0% 100.0%
44.4% 55.6%	NaN% NaN%	44.4% 55.6%

Figure 11. Evaluation Grid for Canny and Lazy IBK

Top-Left (Green, 12 cases, 44.4%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, twelve (12) people with tumors were accurately identified as having them.

Top-Right (Red, 0 cases, 0.0%) – False Positives (FP)

these are individuals tumor is difficult to detect, it might be a stage zero cancer or tumor.

Bottom-Left (Red, 15 cases, 55.6%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, four (4) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 0 cases, 50%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor.

17 32.7%	3 5.8%	85.0% 15.0%
6 11.5%	26 50.0%	81.3% 18.8%
73.9% 26.1%	89.7% 10.3%	70.4% 17.3%

Figure 12. Evaluation Grid for Canny and CNN

Top-Left (Green, 17 cases, 32.7%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, seventeen (17) people with tumors were accurately identified as having them.

Top-Right (Red, 3 cases, 5.8%) – False Positives (FP)

these are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, three (3) people without tumors were misclassified as having them.

Bottom-Left (Red, 6 cases, 11.5%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, six (6) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 26 cases, 50%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, twenty-eight (28) people without tumors were accurately classified as healthy.

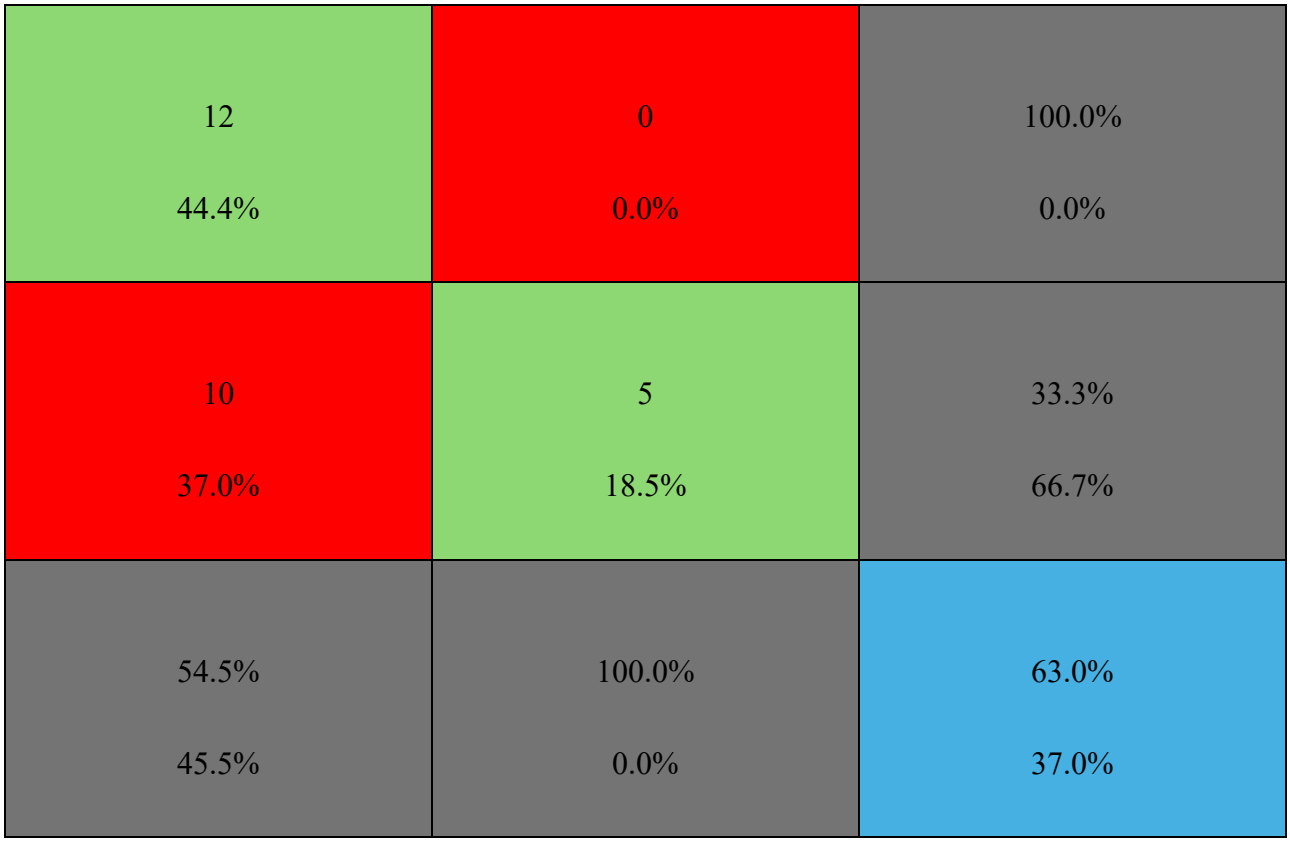


Figure 13 Evaluation Grid for Watershed and SVM

Top-Left (Green, 12 cases, 44.4%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, twelve (12) people with tumors were accurately identified as having them.

Bottom-Left (Red, 10 cases, 37.0%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, ten (10) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 5 cases, 18.5%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, five (5) people without tumors were accurately classified as healthy.

12 44.4%	0 0.0%	100.0% 0.0%
15 55.6%	0 0.0%	0.0% 100.0%
44.4% 55.6%	NaN NaN	44.4% 55.6%

Figure 14 Evaluation Grid for Watershed and Lazy IBK

Top-Left (Green, 12 cases, 44.4%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, twelve (12) people with tumors were accurately identified as having them.

Bottom-Left (Red, 15 cases, 55.6%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, fifteen (15) people with tumors were incorrectly identified as tumor-free.

15 28.8%	4 7.7%	78.9% 21.1%
8 15.4%	25 48.1%	75.8% 24.2%
65.2% 34.8%	86.2% 13.8%	76.9% 23.1%

Figure 15 Evaluation Grid for Watershed and CNN

Top-Left (Green, 15 cases, 28.8%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, fifteen (15) people with tumors were accurately identified as having them.

Top-Right (Red, 4 cases, 7.7%) – False Positives (FP)

these are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, four (4) people without tumors were misclassified as having them.

Bottom-Left (Red, 8 cases, 15.4%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, eight (8) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 25 cases, 48.1%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, twenty-five (25) people without tumors were accurately classified as healthy.

9 33.3%	3 11.1%	75.5% 25.5%
12 44.4%	3 11.1%	20.0% 80.0%
42.9% 57.1%	50.0% 50.0%	44.4% 55.6%

Figure 16 Evaluation Grid for PSO and SVM

Top-Left (Green, 9 cases, 33.3%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, nine (9) people with tumors were accurately identified as having them.

Top-Right (Red, 3 cases, 11.1%) – False Positives (FP)

these are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, three (3) people without tumors were misclassified as having them.

Bottom-Left (Red, 3 cases, 11.1%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, three (3) people with tumors were incorrectly identified as tumor-free.

Bottom-Right (Green, 26 cases, 50%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, twenty-eight (28) people without tumors were accurately classified as healthy.

12 44.4%	0 0.0%	100.0% 0.0%
15 55.6%	0 0.0%	0.0% 1.0.0%
44.4% 55.6%	NaN NaN	44.4% 55.6%

Figure17 Evaluation Grid for PSO and Lazy IBK

Top-Left (Green, 12 cases, 44.4%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, twelve (12) people with tumors were accurately identified as having them.

Bottom-Left (Red, 15 cases, 55.6%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, fifteen (15) people with tumors were incorrectly identified as tumor-free.

9 33.3%	3 11.1%	75.5% 25.5%
12 44.4%	3 11.1%	20.0% 80.0%
42.9% 57.1%	50.0% 50.0%	44.4% 55.6%

Figure 18 Evaluation Grid for PSO and CNN

Top-Left (Green, 9 cases, 33.3%) – True Positives (TP)

these are patients with brain tumors that the CNN correctly detects. For instance, three (3) people with tumors were accurately identified as having them.

Top-Right (Red, 3 cases, 11.1%) – False Positives (FP)

these are healthy individuals mistakenly flagged by the CNN as having a tumor. For example, three (3) people without tumors were misclassified as having them.

Bottom-Left (Red, 12 cases, 44.4%) – False Negatives (FN)

these are patients with tumors that the CNN misses, labelling them as healthy. For instance, twelve (12) people with tumors were incorrectly identified as tumor-free.

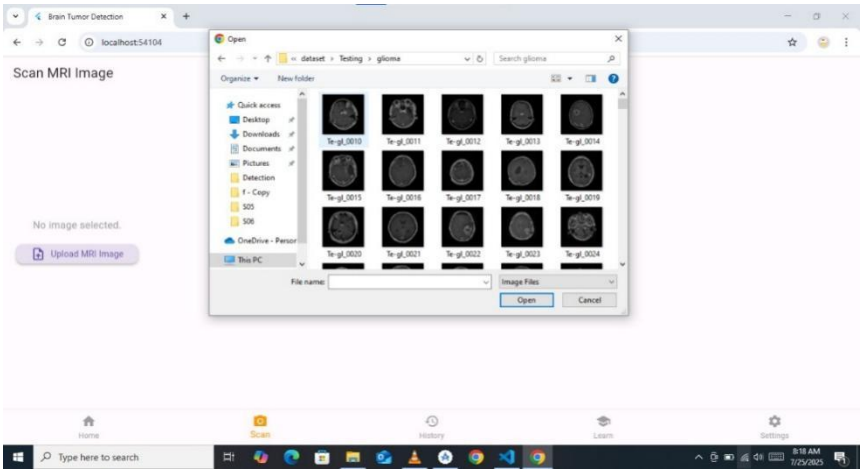
Bottom-Right (Green, 3 cases, 11.1%) – True Negatives (TN)

these are healthy individuals correctly identified by the CNN as not having a tumor. For example, three (3) people without tumors were accurately classified as healthy.

CHAPTER FIVE
5.0 OUTCOMES / INTERFACE DESIGNS

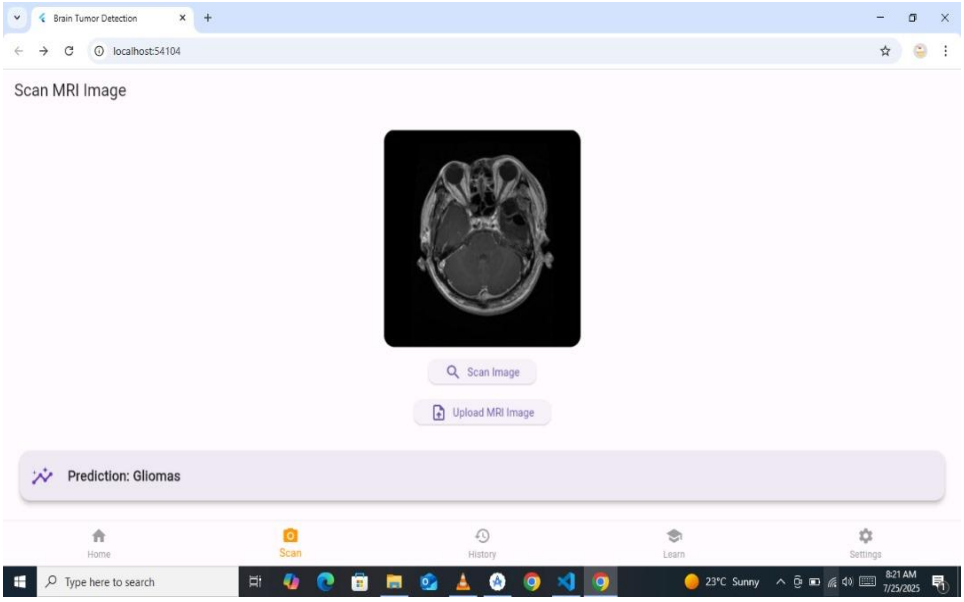
This interface (figure 5.0.1) is designed to help doctors or users upload MRI images and receive diagnostic assistance using machine learning or deep learning models.

Fig 5.0.1



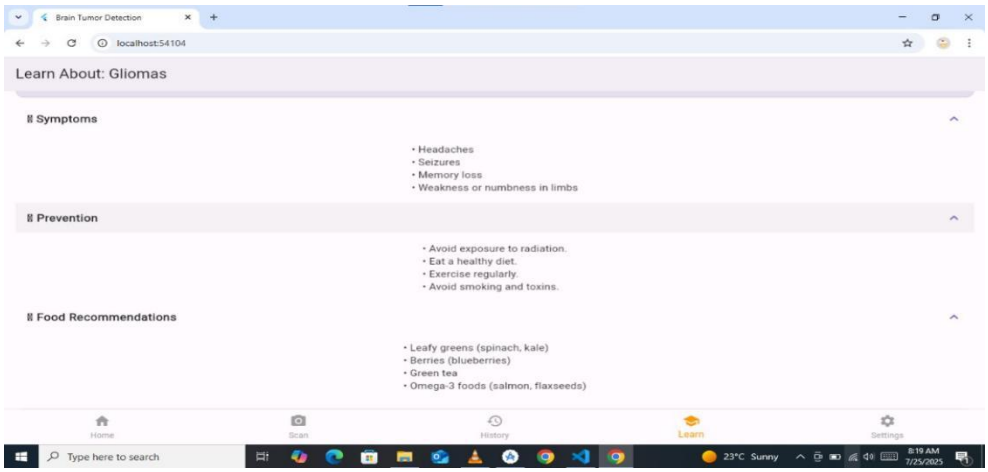
This screen (fig 5.0.2) represents the second step of our Brain Tumor Detection System, where the system has successfully analysed an uploaded MRI image and predicted that the tumor type is Glioma.

Fig 5.0.2



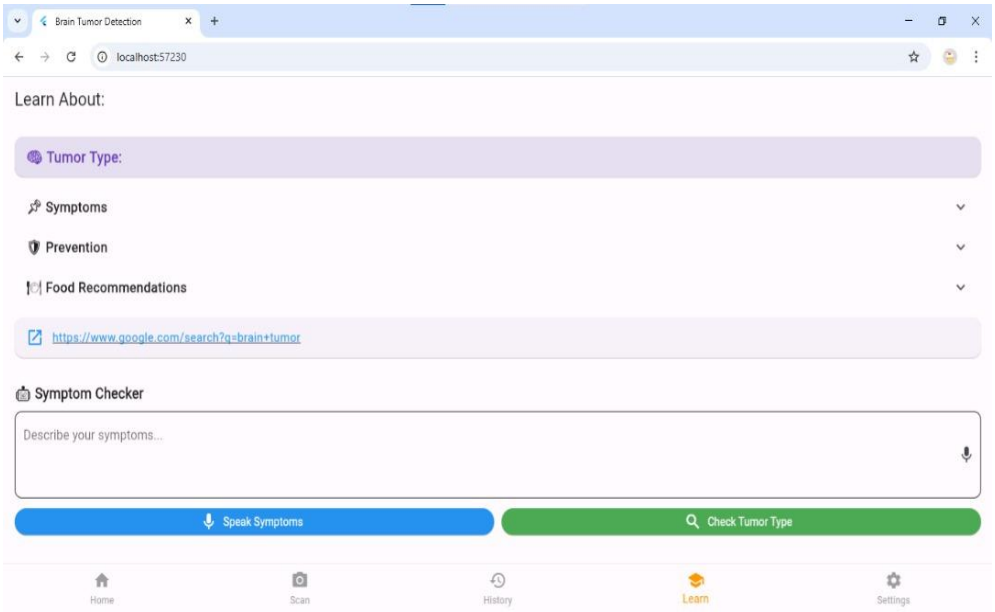
This screen (fig 5.0.3) provides information about symptoms, prevention, and food recommendation of the tumor detected.

Fig 5.0.3



This interface (fig 5.0.4) is designed with accessibility offering a user-friendly solution for individuals who may have difficulty in typing. The inclusion of a microphone feature allows users to verbally describe their symptoms, which are then processed by the system.

Fig 5.0.4



5.1 EVALUATION

The testing of the system is done through a process of different tests to ensure the correct working of the software and measure its capabilities and limitations. A brief explanation of the proposed type of tests to be conducted are given below

Unit Testing

It concentrates on the efforts required for verification on the minute units of software design, which namely, is the software module. We use the component level design description as a guide. Important control paths are tested to uncover errors within the boundary of the module. The unit test is white box oriented, and the steps can be conducted in parallel for multiple modules.

Integration Testing

Interfacing of various modules can be problematic. Data loss can occur across an interface, one module may affect the other, and individually acceptable imprecision may be magnified when combined. Integration testing is thus used to construct the program structure and to conduct tests to unfold errors related to the interface.

Performance Testing

Performance testing is conducted through all the steps in the testing process to test runtime performance of software within the context of an integrated system.

Security Testing

This system manages sensitive information related to patients. There may be causes and actions that can harm these individuals thus becoming a target for improper or illegal penetration.

Recovery Testing

Numerous computer-based systems are designed to recover from errors and resume operations within a designated timeframe. In certain instances, systems must be fault-tolerant, meaning that processing errors should not lead to a complete halt in system functionality. In other cases, a system failure must be rectified within a specific period to prevent significant financial losses. The testing methodology employed in the project started at an initial stage and progressively expanded to encompass the integration of the entire system. The testing process served as a comprehensive activity throughout the system's development. Each module was individually evaluated upon completion before moving on to the subsequent component. After choosing a specific dataset for a kidney tumor and identifying potentially effective network configurations, these were evaluated, and the results were compared against the expected outcomes. Following the creation of the graphical user interface (GUI), the network's integration with the GUI was tested. The testing strategy incorporated various methods, including unit testing and integration testing.

5.2 UPCOMING DIRECTIONS

Future research should focus on enhancing the neural network capabilities of deep learning models for brain tumor prediction by investigating regularization techniques beyond dropout. Exploring alternative methods could further improve model generalization and robustness, leading to more reliable predictions in clinical settings. Investigating the impact of various neural network architectures and hyperactive parameters on model performance is essential. By systematically analysing these factors, researchers can identify critical training components that enhance both accuracy and computational efficiency, optimizing the model for practical applications. Research should prioritize the development of accessible and intuitive interfaces for deploying complex deep learning models in medical environments. Understanding the specific needs of healthcare professionals will be crucial in designing user-centric interfaces. These interfaces would enable seamless integration of predictive models into clinical workflows, empowering medical practitioners to utilize advanced tools effectively. Encouraged by the current findings, future efforts should aim to refine classification outcomes and boost overall model accuracy. Expanding the dataset size and diversity could allow for an increase in the number of output classes, enhancing the model's ability to distinguish between various tumor types or characteristics. Incorporating additional hidden layers into the neural network architecture could improve classification performance. By increasing the number of layers, the model can better adjust its weights, leading to more precise predictions and improved handling of complex data patterns. Applying fine-tuning and transfer learning techniques can further optimize the model by building on pre-existing training knowledge. These approaches allow for more efficient refinement of the model, improving its performance on specific datasets and tasks related to brain tumor prediction.

5.3 SUMMARY

The study evaluated the performance of a deep learning model, specifically EfficientNetV2B3, in predicting brain tumors, comparing it to conventional techniques. The findings indicate that this deep learning approach outperformed traditional methods in detecting brain tumors. This is significant due to the complexity and difficulty in treating brain tumors, which are among the most challenging cancers. The model demonstrated superior accuracy and consistency in its predictions compared to established methods, suggesting potential advancements in the diagnosis and treatment of brain tumors through advanced technology. The performance of the deep learning model was assessed using different optimizers Adagrad, Adam, and SGD to determine their influence on predictive accuracy. The results showed variations in final accuracy across the three optimizers. The Adam optimizer achieved the highest accuracy among the tested options, indicating that the choice of optimizer significantly affects the model's effectiveness. The combination of the EfficientNetV2B3 model and the selected dataset, when paired with the Adam optimizer, proved to be the most effective configuration. To enhance the neural network’s ability to generalize and avoid overfitting, regularization techniques such as dropout were employed. Dropout improves model generalization by randomly deactivating a subset of neurons during training, which helps the model learn broader patterns rather than overfitting to specific data. This technique reduces neuron co-dependency by selectively ignoring certain neurons, fostering the development of robust features. As a result, dropout enhances the model’s ability to accurately predict outcomes for new, unseen data samples.

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