BRAIN TUMOR DETECTION USING MACHINE LEARNING

Suchetha N V

**Abstract**

Brain tumors can significantly impact a patient's well-being, necessitating prompt and accurate diagnosis for effective treatment. This work aims to develop an automated approach for brain tumor detection and identification using magnetic resonance imaging (MRI) grayscale images. The proposed system addresses the limitations of manual analysis, which is time-consuming and prone to errors. The automated approach incorporates a series of pre-processing and post-processing steps to enhance and analyze MRI grayscale images. In the pre-processing stage, techniques such as enhancement, filtering, and segmentation are applied to isolate the tumor region from healthy brain tissue. This work ensures a clearer representation of the tumor boundaries for subsequent analysis. The automated system serves as a valuable assistant, assisting in the early detection and precise identification of brain tumors.

## Chapter 1

**Introduction**

## Project Introduction

A brain tumour is brought on by the unchecked enlargement of brain or central spinal tissue, which can impair normal brain function. While secondary (metastatic) brain tumours start in another region of the body before spreading to the brain, primary brain tumours come from cells within the brain. Malignant (cancerous) or benign (non-cancerous) brain tumours are both possible. Based on the nature and location of the tumour cells, the WHO has designated approximately 120 classifications for brain tumours. They are ranked from I to IV according to the cells from which they emerge. Tumours of grades III and IV are thought to be of greater grade than those of grades I and II. A patient needs an accurate diagnosis and the necessary therapy because brain tumours can be fatal. Microscopic investigation, such as biopsy, is used in the pathology lab to analyse tumour tissue. Electronic modalities including CT, MRI, and ultrasonography, etc. Magnetic Resonance Imaging (MRI) is one of the most common and widely utilised electronic techniques for diagnosing brain tumours. It produces three-dimensional assessments of the lesion by taking high-resolution, high-contrast pictures of the brain in the axial, coronal, and sagittal orientations. An automated method for detecting brain tumours using MRI gray-scale pictures has been proposed in this research study. Medical image processing methods like pre-processing and post-processing were applied to input images of brain tumours in order to detect the tumour region only. Enhancement, filter operation, and segmentation are all part of the pre-processing, and feature extraction and identification are part of the post-processing.

## Problem Description

This project aims to automate the detection and identification of brain tumors using MRI grayscale images. Current manual analysis of these images by medical professionals is time-consuming and prone to errors. The proposed solution involves pre-processing steps such as enhancement, filtering, and segmentation to isolate the tumor region. Post- processing involves extracting relevant features and using classification algorithms to identify the tumor. The automated approach seeks to provide a reliable and objective method for detecting brain tumors, improving the efficiency and accuracy of diagnosis. It can assist medical professionals in making more accurate treatment decisions and potentially enhance patient outcomes. It is important to note that the system is designed as a supportive tool and not a replacement for medical professionals. The final diagnosis and treatment decisions should still be made by experts who validate and interpret the results. Overall, it aims to develop an automated system that can efficiently detect and identify brain tumors from MRI images, providing valuable assistance to medical professionals in the diagnosis and treatment of brain tumors.

## Chapter 2

**Literature Review**

## Literature Survey

Paper titled “VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection” by MS Majib, MM Rahman & Samrat Kumar Dey [1]. They created and thoroughly examined a variety of conventional and hybrid ML models to classify the images of brain tumours without the aid of humans. In the end, a stacked classifier was introduced, surpassing all previously established models, and it was constructed using a combination of state-of-the-art technologies. The precision, recall, and F1 scores for this innovative model, known as VGG-SCNet (VGG Stacked Classifier Network), were measured at 99.2%, 99.1%, and 99.2%, respectively. The paper is named “A Novel Framework for Brain Tumor Detection Based on Convolutional Variational Generative Models” by Wessam M. Salama & A. Shokry[2]. They proposed a two-model system to detect Brain tumors. The first model is a generative model to capture the distribution of the important features in a set of small class-unbalanced brain MRI images. The second model is the classifier that is trained using the large balanced dataset to detect brain tumors in MRI images. The proposed framework acquires an overall detection accuracy of 96.88%. Paper titled “A Systematic Approach for MRI Brain Tumor Localization and Segmentation using Deep Learning” by Shanaka Ramesh, HNTK Kaldera-2021[3]. They suggested a three-fold architecture for tumour extraction that involves accurately annotating and segmenting tumour boundaries. Both the first and second region-based CNNs are used to implement the classifiers. The concentrated Tumour Boundary is counted using the chan-Vesesegmentation algorithm in the third step. The proposed architecture's accuracy as a whole performed at 92%. Paper titled “Development of automated Brain Tumor Identification using MRI images” by TM Shahriar Sazzad, Misbah UI Hoque-2020 [4]. They suggested an automated method that uses initial enhancement to reduce colour fluctuations in grey scale and filter operations to eliminate undesired noises. Instead of colour segmentation, a threshold-based OTSU segmentation was employed. The proposed architecture's accuracy as a whole performed at 95%. Paper titled “Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks” by Guotai Wang, Wenqi li-2021 [5]. To separate multi-modal magnetic resonance pictures of brain tumors into the backdrop and three hierarchical regions—the complete tumor, the tumor core, and the background—they developed a cascade of fully convolutional neural networks improving tumor core, and. The tumor must first be divided into segments before the tumor core may be divided. 90% of architectural performance predictions were accurate.

## Comparative Analysis of the Related Work

Table 2.1 discusses the comparative analysis of the current systems in light of the suggested proposal.

**Table 2.1 Comparative Analysis**

|  |  |  |  |
| --- | --- | --- | --- |
| **Sl.****No.** | **Author(s)** | **Algorithms/Techniques** | **Performance Measures** |
| **1.** | MS Majib, MM Rahman & Samrat Kumar Dey | Deep learning, stacked classifier (VGG-SCNet) | Accuracy |
| **2.** | Wessam M. Salama & A. Shokry | Generative models, classification | Accuracy |
| **3.** | Shanaka Ramesh, HNTK Kaldera | Deep learning, CNN, region- based CNN, Chan-Vesesegmentation | Accuracy |
| **4.** | TM Shahriar Sazzad, Misbah UI Hoque | Image enhancement, filteroperations, threshold-based segmentation | Accuracy |
| **5.** | Guotai Wang, Wenqi Li | Cascaded convolutionalneural networks | Accuracy |

## Summary

The literature review explores various techniques for brain tumor detection. Deep learning approaches, generative models, CNNs, and segmentation algorithms have shown promise in accurately identifying brain tumors. These methods enable automated and precise detection, improving clinical practices. The studies emphasize the potential of advanced techniques for reliable and efficient brain tumor diagnosis.

## Chapter 3

**Problem Formulation**

## Problem Statement

In the medical field, doctors detect Tumors by referring to MRI images, which are very time- consuming. Therefore, an alternative way to overcome this problem is to design a system that will automatically identify the presence of Tumors in MRI images using machine learning techniques and provide faster and more accurate solutions.

## Objectives of the Present Study

The objectives of the proposed project are as follows:

1. To train the data set using the ML Classification algorithms, namely Logistic Regression, Naïve Bayes, K-Nearest Neighbor, and Support Vector Machine Algorithm.
2. To calculate and compare the accuracy of each model.
3. To find out the best model for early detection of Brain Tumor.
4. To create a web interactive page for doctors for the detection of tumor.
5. To perform real-time analysis.

## Summary

The best solution for early detection of breast cancer is using machine learning techniques. The classification algorithms are more accurate when compared to traditional imaging techniques. Developing an early cancer detection system can be useful for many doctors as well as patients by helping them be alert and take the required medications to prevent the spread of cancer.

## Chapter 4

**Requirements and Methodology**

## 4.1 Requirements

The proposed project consists of the following requirements:

* 1. Hardware requirements
	2. Software requirements

## Hardware Requirements

The hardware requirements for the proposed project are depicted in Table 4.1.

**Table 4.1: Hardware requirements**

|  |  |  |
| --- | --- | --- |
| **Sl. No.** | **Hardware/Equipment** | **Specification** |
| 1. | Graphics Card | Intel 621 Graphics card or 2GB |
| 2. | RAM | 4GB or above |

## Software Requirements

The software requirements for the proposed project are depicted in Table 4.2.

**Table 4.2: Software requirements**

|  |  |  |
| --- | --- | --- |
| **Sl. No.** | **Software** | **Specification** |
| 1. | Jupiter Notebook | Jupiter 64 bit |
| 2. | Python | Python 3 and above |
| 3. | Framework | Flask |

## Methodology Used

The proposed brain tumor detection system is implemented using the following steps:

1. The working of the system starts with the collection of MRI images.
2. Then the images are preprocessed and sent to the image segmentation.
3. The algorithms are put into action, and the model is trained using the training dataset.
4. The system's accuracy is determined by evaluating its performance with testing data.

The following ML algorithms are being used:

##### Logistic Regression (LR) Algorithm

One of the most often used Machine Learning algorithms is logistic regression. It forecasts a categorical dependent variable's result. As a result, the result must be a discrete or categorical value. The cost function is generally limited to the range of 0 and 1 according to the logistic regression hypothesis.

##### Support Vector Machine (SVM) Algorithm

SVM is one of the most well-liked algorithms for supervised learning, and it may be applied to both classification and regression issues. To efficiently classify future data points, the SVM algorithm seeks to identify the optimal line or decision boundary capable of segregating an n-dimensional space into distinct classes. This optimal decision boundary is referred to as a hyperplane.

##### Convolutional Neural Networks (CNNs)

CNNs are a type of deep learning algorithm commonly used in image recognition and computer vision tasks. They are designed to automatically learn and extract relevant features from input images.

We have used ResNet-50 a deep-learning architecture commonly used for brain tumor detection. With 50 layers, including convolutional and fully connected layers, ResNet-50 is capable of extracting intricate patterns and features from brain MRI images. By training the model on a large dataset of labeled brain tumor images, it can learn to differentiate between normal brain tissue and tumor regions.

During training, ResNet-50 adjusts its weights using backpropagation and gradient descent to optimize its performance in classifying brain tumor images. Its skip connections help address the vanishing gradient problem and improve learning in deeper architectures. Once trained, ResNet-50 can accurately predict the presence of tumors in new, unseen brain MRI images.

## Chapter 5

**System Design**

## Architecture of the Proposed System

Figure 5.1 shows the architecture of the proposed system.



**Figure 5.1: Architecture of the proposed system**

Enhancement and filter procedures are used during the preprocessing step to enhance the quality and eliminate unwanted noise from the images.

To separate the tumor region from the remainder of the brain, segmentation is then carried out. Medical image processing methods are used to retrieve pertinent information from the tumor region following segmentation.

The brain tumor is then identified and classified using the retrieved features using a classification algorithm or stacked classifier.

## System Flowchart

A system flowchart is a way of depicting how data flows in a system and how decisions are made to control events. Figure 5.2 depicts the system flowchart.



**Figure 5.2: System Flowchart**

The raw dataset must be loaded, cleaned, and preprocessed. The data frame is created with the selected features. The prediction model is created using CNN. This model classifies the data into Giloma, meningioma, pituitary, and no tumor.

## Chapter 6

**System Testing, Results, and Discussion**

## System Testing

**Table 6.1: Unit test cases**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Test case number** | **Input** | **Stage** | **Expected behavior** | **Observed behavior** | **Status P=Pass F=Fail** |
| 1 | Login credentials | Login page | If the details matched, the input page is shown | As expected | P |
| 2 | Upload the MRI image | Input page | The result should appear as one of the types of tumor | As expected | P |

## Result Analysis

The main aim of the project was to classify the patient’s tumor as benign or malignant using machine learning algorithms. Table 6.2 shows the analysis that was performed on the four algorithms with different training and testing sizes. It was found that CNN was the most accurate in all the cases.

**Table 6.2: Analysis of the three algorithms**

|  |  |  |
| --- | --- | --- |
| **Training Size** | **Testing Size** | **Accuracy (%)** |
| **CNN** | **LR** | **SVM** |
| 80% | 20% | 97.85 | 94.73 | 92.98 |

Figure 6.1 shows the bar graph for the accuracy of the three algorithms, where the train set size was 80%, and test set size was 20%.

**Chart Title**

99

98

97

96

95

94

93

92

91

90

97.85

94.73

92.98

CNN LR SVM

**Figure 6.1: Graph analysis of classifiers**

Figure 6.2 is the Home page for the user.



**Figure 6.2: Home Page**

Figure 6.3 is the login page for the user



**Figure 6.3: Login Page**

Figure 6.4 is the input page where an image can be selected.



**Figure 6.4: Input Page**

Figure 6.5 is the page where the result is obtained as glioma.



**Figure 6.5: Result value as glioma**

Figure 6.6 is the page where the result is obtained as pituitary.



**Figure 6.6: Result value as pituitary**

Figure 6.7 is the page where the result is obtained as meningioma.



**Figure 6.7: Result value as meningioma**

Figure 6.8 is the page where the result is obtained as no tumor.



**Figure 6.8: Result value as no tumor**

## Summary

Overall, brain tumor detection using machine learning holds great promise in improving the accuracy and efficiency of brain tumor diagnosis. By leveraging the power of artificial intelligence and analyzing large amounts of imaging data, this approach has the potential to assist medical professionals in making more accurate and timely diagnoses, leading to better patient outcomes.

## Chapter 7

**Conclusion and Scope for Future Work**

## Conclusion

In conclusion, the project focused on the development and evaluation of an automated approach for brain tumor detection using MRI images. The findings from the literature review highlighted the effectiveness of deep learning techniques, particularly Convolutional Neural Networks (CNNs), in achieving high accuracy in brain tumor detection, with reported accuracies ranging from 90% to 99.2%. This underscores the potential of automated approaches in improving the accuracy and efficiency of brain tumor diagnosis.

## Scope for Future Work

The future scope of the brain tumor detection project offers several potential areas for further development and advancement. Firstly, expanding the dataset used for training and evaluation can enhance the effectiveness and generalizability of the model. Collecting a larger and more diverse set of labeled brain tumor images, including various tumor types and subtypes, would contribute to a more accurate and reliable detection system. Secondly, incorporating advanced techniques into the project can lead to improved performance. Exploring methodologies such as transfer learning, and ensemble methods, or designing novel deep learning architectures specifically tailored for brain tumor detection could result in more precise and robust outcomes. Leveraging pre-trained models on large-scale image datasets and adapting them to the specific task at hand may yield significant improvements.

**References**

1. "VGG-SCNet: A VGG Net-Based Deep Learning Framework for Brain Tumor Detection" by MS Majib, MM Rahman & Samrat Kumar Dey.
2. "A Novel Framework for Brain Tumor Detection Based on Convolutional Variational Generative Models" by Wessam M. Salama & A. Shokry.
3. "A Systematic Approach for MRI Brain Tumor Localization and Segmentation using Deep Learning" by Shanaka Ramesh, HNTK Kaldera-2021.
4. "Development of automated Brain Tumor Identification using MRI images" by TM Shahriar Sazzad, Misbah UI Hoque-2020.
5. "Automatic Brain Tumor Segmentation using Cascaded Anisotropic Convolutional Neural Networks" by Guotai Wang, Wenqi Li-2021.
6. F. Islami, C. E. Guerra, A. Minihan, K. R. Yabroff, S. A. Fedewa, K. Sloan, T. L. Wiedt, B. Thomson, R. L. Siegel, N. Nargis, R. A. Winn, L. Lacasse, L. Makaroff, E.

C. Daniels, A. V. Patel, W. G. Cance, and A. Jemal, ‘‘American Cancer Society’s report on the status of cancer disparities in the United States, 2021,’’ CA, Cancer J. Clinicians, vol. 72, no. 2, pp. 112–143, Mar. 2022.

1. Q. T. Ostrom, G. Cioffi, H. Gittleman, N. Patil, K. Waite, C. Kruchko, and J. S. Barnholtz-Sloan,‘‘CBTRUS statistical report: Primary brain and other central nervous system tumors diagnosed in the United States in 2012–2016,’’ Neuro-Oncol., vol. 21, no. 5, pp. v1–v100, Nov. 2019.
2. World Health Organisation. (2021). Cancer. Accessed: Jan. 23, 2022. [Online]. Available: https:/[/www.who.int](http://www.who.int/).
3. G. Raut, A. Raut, J. Bhagade, J. Bhagade, and S. Gavhane, ‘‘Deep learning approach for brain tumor detection and segmentation,’’ in Proc. Int. Conf. Converg. Digit. World Quo Vadis (ICCDW), Feb. 2020, pp. 1–5.
4. T. C. Hollon, B. Pandian, A. R. Adapa, E. Urias, A. V. Save, S. S. S. Khalsa, D. G. Eichberg, R. S. D’Amico, Z. U. Farooq, S. Lewis, and P. D. Petridis, ‘‘Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks,’’ Nature Med., vol. 26, no. 1, pp. 52–58, Jan. 2020.