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# DEEP LEARNING-BASED BRAIN TUMOR CLASSIFICATION USING MRI SCANS: A NETWORK APPROACH

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**ABSTRACT**

CapsNet based on deep learning provides some solutions to the problems of early diagnosis and accurate diagnosis of brain tumors in patients. The paper presents an automated brain tumor classification rule from MRI scans. The images ' noise removal and quality improvement are achieved through pre-processing the MRI scans with Gaussian filtering and roughness feature extraction. Important textural features are extracted from MRI images using LBP and subsequently passed to the CapsNet model, which is capable of mapping the spatial relationship of the tumor with the surrounding tissues for classification. Grad-CAM-LIME is the embedded Explainable AI technique unique to the present work that contributes to offering higher transparency to the model regarding making clinicians understand the reasoning behind the predictions. The model aims for an efficient, effective, and interpretable aid in reducing dependence on manual analysis and realizing as best as possible an accuracy of 85.71% for classifying MRI scans as tumor or no tumor images.

**Keywords:** Brain Tumor Classification, Capsule Networks, MRI Scans, Local Binary Pattern, Explainable AI (Grad-CAM-LIME)

## 1. INTRODUCTION

Brain tumors are among the most critical and challenging health problems confronting the world, where their successful treatment and the survival of the patient rely on early detection and accurate diagnosis [1]. They are characterized as abnormal growths of cells within the brain and may be classified as either benign or malignant; their classification bears heavily on the prognosis of the patient [2]. MRI (Magnetic Resonance Imaging) is now being deemed to be one of the utmost helpful and non-invasive diagnostic approaches for the identification and characterization of brain tumors [3]. Because of the intricacies involved and the variations in tumor appearances on MRI scans, any sort of effective classification and segmentation of the scans can aid doctors in achieving diagnosis and designing treatment plans [4]. The recent development in deep learning methods has changed the way the medical field has acted towards the detection and classification of brain tumors, which in turn has brought more accuracy and automaticity to them [5]. Brain tumor causes are permissive to many etiological agents: genetic aberrations, environmental factors, and radiation exposure [6]. Simply put, primary tumors arise from brain tissues, and secondary, or metastatic, tumors arise from other sites in the body and metastasize to the brain [7]. Age, genetic disposition, and family history are predisposing risk factors cumulatively leading to the development of a brain tumor [8]. Symptoms of brain tumors vary so much from tumor type and location that headaches, vision abnormalities, seizures, and cognitive deficits, among others, cannot be ignored [9]. Some of these symptoms also overlap with several other neurological pathologies, and thus, having accurate and reliable diagnostic modalities is very important [10]. MRI is an excellent tool for the visualization of brain tissues, but the interpretation of its findings requires a skillful evaluator due to the vast amount of data

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generated and the heterogeneous nature of tumor characteristics [11].In the last 10 years, diagnostic methods have seen quite a lot of evolution. Somewhere between the works of diagnosis, the radiologists would have been using interpretational bias based on fatigue or some subjective elements [12]. Texture analysis along with region-based segmentation have been seen in action for at least some decades as contrasting to tumor appearances from MR images [13]. Manual methods have been cruelly manual: The most popular types of automation for feature extraction are morphology features, edge detection, and texture analysis, all of which help but still require heavy feature handcrafting with serious domain knowledge [14]. But, the deep learning methods, in particular convolutional networks, are coming out on top in this case as they are least interventive in other words they learn hierarchically feature representations from raw data [15]. Furthermore, this became another load entirely for a medical expert in a clinical deployment due especially to the classifiers built for aiding clinician decisions [16]. Taking into consideration the shortcomings of already-existing technologies, a gene-drivenness approach is probing into some advanced neural networks for brain tumor classification from the MRI. For the model development, a CNN and a CapsNets have been formulated for automating a truly efficient feature extraction and classification task [17]. In the proposed model, between transfer-learning applications, fine-tunes some pre-trained networks for a broad generalization of the model that is less dependent on large labeled datasets [18]. However, explanations about the predictions of the models, complemented by areas on the MRI scans that made the decision changes, would be visual due to the integration of Explainable AI (XAI) approaches such as Grad-CAM and LIME [19]. Therefore, there would be more accurate classification as well as transparency and, thus, trust in the model for it to be applicable in a clinical situation [20]. Thus, making this adaptive model much more robust, scalable, and interpretable concerning brain tumor classification than previous approaches was the priority concern.

- Brain Tumor Classification Automation: It proposed a deep learning model to automate the classification of brain tumors from MRI scans so that less reliance would be granted to manual analysis and profoundly enhanced diagnostic aid would be presented to clinicians.
- Capsule Networks (CapsNets) were used: The intention of employing CapsNets in this study is to strengthen the model's capability of representing complex spatial relationships among features in MRI images and to overcome one inherent disadvantage of standard CNNs in handling orientation variation of tumors.
- Incorporating Explainable AI: Grad-CAM, LIME, as well as other XAI techniques have been integrated into frameworks that would facilitate visual explanations of how the model has been built and add transparency and trust to the clinical decision-making process.

## 2. LITERATURE REVIEW

Brain tumors are the major reason for increasing death rates and hence, are often diagnosed and treated. There is a new technique developed, which is based upon the hybrid architecture of CNN that classifies MRI brain tumors into three types **[21]**. The hybrid system involved an integrated Service Neural Network model that is weighted and uses Google-Net pretrained for feature extraction into SVM for pattern classification, with a finely tuned Google-Net model soft-max classifier [22]. The fine-tuned Google-Net performed on 1426 gliomas, 708 meningiomas, 930 pituitary tumors, and 396 MRI normal brain image datasets and got an accuracy of 93.1%, while fused Google-Net feature extraction by SVM classifiers achieved recognition accuracy improved up to 98.1% **[23]**. In modern medicine, brain tumors are classified among those pathologies with rapid acceleration, claiming thousands of lives each year [24]. Hence, any intimation of early diagnosis and treatment gives hope for a variety of treatment avenues [25]. Most classical machine-learning and deep-learning approaches rely on manual feature extraction, while the deep-learning paradigm implicitly relies on learning representation features [26]. Thus, the authors propose a hybridization approach called DeepTumorNet, based primarily on a CNN architecture for the detection and classification of brain tumor **[27]**. The proposed model achieved 99.67% classification accuracy, 99.6% precision, and an F1 score of 99.66%, which exceeded any performance levels from the existing numerical models for the classification of BT from MRI images [28]. This research work centers around the classification of brain tumors based on three-dimensional resonant images acquired from 159 patients using ResNet architecture As per the results, it achieved accuracy values of 87.21%, 90.35%, and 93.86% on original images, Gaussian-filtered images, and median-filtered images, respectively **[29]**. Thus, this study hints further necessity to explore more image-processing techniques on deep learning networks [30]. The automatic tumor detection system proposed will assist radiologists and physicians in detecting tumors in the brain [31]. The method consists of three major parts: pre-processing, tumor classification using ELM-LRF, and image processing **[32]**. This method makes use of cranial magnetic resonance images for classification and

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segmentation [33]. The study achieves a classification accuracy of 97.18%, exceeding that of previous studies in the literature and demonstrating that the process is effectively applied in computer-aided brain tumor detection [34]. The research is based on developing an automated resilient intelligent hybrid system for the early diagnosis and classification of brain tumors [35]. The Auto Contrast Enhancer, Tumor Detector, and Classifier aim to enhance the contrast of low-quality MRI images [36]. The methodology is two-phase: one phase increases image contrast while refined diagnosis occurs using deep transfer learning. The average maximum accuracy achieved was 98.89 % on a public dataset of MRI images under different contrast and brightness environments [37]. The authors argue that concerns have to be aligned with the goals of the system so that the harmful side effects may be avoided.

### 3. PROBLEM STATEMENT

This problem specifies the development of an automated system that will help classify brain tumors in MRI scans using Capsule Networks [38]. Magnetic resonance imaging is a major tool for diagnosing the presence of a tumor, but their appearances can be too complex or have variability to make interpretation difficult [39]. It requires manual, time-consuming, and inaccurate work and also requires high expertise levels to interpret these images [40]. Therefore, they are intended to be automated to allow faster and more accurate classification of MRI scans in the diagnostics, thereby improving detection and diagnosis of brain tumors with clinicians' treatment planning [41]. The primary challenge of this is how to pre-process MRI images to enhance their quality for accurate feature extraction [42]. Gaussian filtering smoothens the images to reduce noise while maintaining the major characteristics of the image such as important edges and textures [43]. Additionally, roughness feature extraction techniques help in identifying slight deviations in the images which are useful in differentiating affected brain tissues from healthy ones [44]. Once the images are cleaned and improved upon, the next stage is Feature Extraction in which LBP will be used [45]. LBP is an effective texture-based method that captures the local texture and structural patterns present in MRI scans [46]. It compares the intensity of each pixel with that of its neighbors and generates a binary code that represents the local textures [47]. With LBP, important feature contours in the MRI images created include edges and corners, which are essential for determining if there is a tumor presence [48]. CapsNet accepts the extracted features, which have been specifically created to keep the spatial relationships intact [49]. CapsNet beats some limitations of traditional CNN in the sense of orientation variation of tumors in MRI images [50]. In this way, CapsNet learns the spatial hierarchies of the features, making it very accurate in classifying MRI scans as either tumor or non-tumor images. This automates the tumor classification process and enhances the reliability of the model by focusing on the spatial context of the tumor, thus making it favorable for clinical applications.

### 4. PREPOSED METHODOLOGY

The methodology that is followed for brain tumor classification in MRI scans is through Capsule Networks (CapsNets). A brain tumor MRI dataset is inputted, which is later subjected to data pre-processing like Gaussian filter and roughness feature extraction for cleaning and enhancing the quality. The pre-processing is done to extract the necessary features from MRI scans using Local Binary Pattern (LBP) which is a method of feature extraction that extracts textural and structural patterns. The new features extracted are then forwarded to the CapsNet classification model for tumor classification, which distinguishes between tumor and non-tumor images. The output of the model predicts whether these images are tumor or not tumor MRI images based upon the learned spatial relationships and properties of the features.

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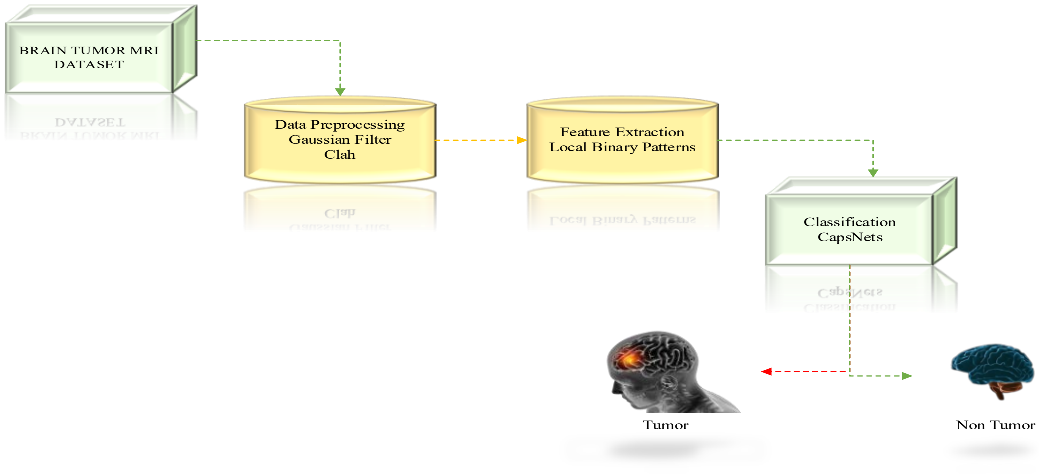


**Figure 1** Architectural Diagram of Proposed Methodology

## 4.1 DATA PREPROCESSING

The pre-processing data consists of two main techniques, Gaussian filtering, and Clah. The Gaussian filter smoothens the MRI images and thus reduces the noise in them and consequently helps in bettering the quality of the input data, which in turn would favor better identification of the salient features. It does so by averaging the pixel values around a given window while preserving the edges and minimizing high-frequency noise. Clah, which may be a misspelling or abbreviation for some feature extraction or enhancement method, may also serve the dual purpose of cleaning and enhancing the dataset. However, whatever the function may be, it is not clear from the image. The ultimate goal of these two methods is to ensure noise cleaning and a level of readiness of the MRI images necessary for feature extraction and classification.

### *4.1.1 Gaussian filtering*

Skin cancer images were noise suppressed and pre-processed with Gaussian filtering techniques to preserve details of structure. This is the linear smoothing convolution filter, which convolutes images with the Gaussian function, assigning more weight to the closest pixel than to a more distant one. The filter is said to be able to blur out unwanted details and retain information on some prominent features, such as edges or textures useful for good classification. It creates high-frequency noise attenuation thus saving the deep-learning models from certain artifact disturbances that could potentially influence their output. This is the improvement through which visibility is enhanced for the diagnostic purposes of medical imaging but without artifacts that may mislead the classification model. Thereafter, contrasts of images would be enhanced with CLAHE to visibility when it comes to lesions that are contrast-critical. This pre-processing combined with the already mentioned treatments indeed facilitates deep learning's most important feature extraction and classification.

Gaussian filtering refers to the process, in which convolution is executed using the Gaussian kernel,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

According to the notation defined, G(x,y) is interpreted as being an application of the Gaussian function; a change in standard deviations indicates the amount of smoothing concerning coordinates x and y of pixels. The greater sigma produces a more severe shimmering effect and a smaller maintains more detail. The kernel size is selected according to the nature of the dataset for the effect that optimally reduces noise without excessive blurring.

### *4.1.2 Contrast-limited adaptive histogram equalization*

CLAHE is a perfect contrast enhancement tool whose application is more directed toward medical realms, especially in skin cancer detection. Its process works on a local enhancement where pixel adjustments are done in small regions known as tiles with compensatory histogram equalization for the separate small regions and the local enhancement assistance leads to a noise reduction mechanism in the CLAHE method as it provides colimit to the Gray value redistribution limits imposed by the histogram as represented in the philosophy of local and global histogram equalization.

$$I'(x,y) = \frac{CDF(I(x,y)) - CDF_{min}}{M - CDF_{min}} \times (L-1) \quad (2)$$

Where I^' (x,y) is the enhanced intensity of the pixel at (x,y), I(x,y)Is the original intensity of the pixel at

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(x,y), CDF(I(x,y)) is the cumulative distribution function (CDF)of the intensity value, CDF_min is the minimum non-zero value of the CDF, M is the total number of pixels, and L is the maximum intensity.

**4.2 FEATURE EXTRACTION**

The prominent aim of feature extraction is to extract relevant patterns from MRI scans, which can then be used effectively in tumor identification. An important methodology used for this purpose is LBP, which is texture-based and extracts spatial information from an image by comparing the intensity value of the target pixel with that of the surrounding neighboring pixels. This generates some binary codes characterizing the local texture of the image by emphasizing the important features of edges, corners, and areas of interest related to brain tissue. The real strength of LBP lies in delineating subtle texture differences that hold significance in distinguishing the tumor from a non-tumor area. Feature extraction of such LBP-based descriptors would, in turn, assist the model in recognizing and classifying different types of brain tissues and help provide an efficient and strong way to enhance the accuracy of the deep-learning model in MRI-based brain tumor classification.

***4.2.1 Local Binary Patterns***

The LBP are quite common texture descriptors in image processing that are used for feature extraction for various purposes especially in the medical domain, for example, brain tumor classification. LBP compares every pixel in the image with its neighborhood and represents this relationship as a binary number. The binary number is produced by thresholding surrounding pixels, assigned as '1' if the neighboring pixel intensity is greater than that of the center, and vice versa for '0'. Compilation of local binary patterns around each pixel provides a binary pattern describing the local texture, which could then be aggregated to retain the overall texture information of the image. When studied concerning MRI images for brain tumor classification, LBP captures the texture of a tumor and that of the encircling brain tissues aiding in differentiating between healthy and abnormal tissue based on their characteristic varying textures.

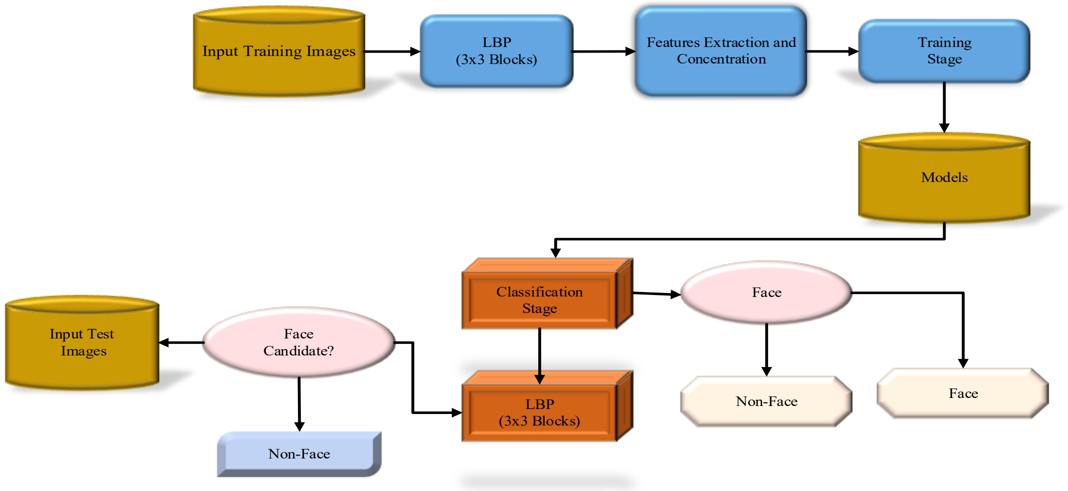


**Figure 2** Local Binary Patterns

The LBP of a particular pixel is defined by comparing the surrounding pixels to the main pixel in question and assigning them a value as either '1' or '0' depending on whether they are greater than or less than the center pixel. The LBP can mathematically be represented as:

$$LBP = \sum_{p=0}^{P-1} s(I_p - I_c) \cdot 2^p \tag{3}$$

Where, $P$Is the number of neighboring pixels (usually 8 for a $3 \times 3$ neighborhood), $I_p$Is the intensity of the $p$-th neighbor, $I_c$Is the intensity of the center pixel, $s(x)$Is a thresholding function defined as:

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{4}$$

$Also\ Where,$ $2^p$Is a weight assigned to each neighboring pixel (the least significant bit for the first neighbor and the most significant for the last).

**4.3 CLASSIFICATION**

Deep learning models involve features related to image classification like CapsNet. CapsNet also offers a kind of new architecture that is neural to address the limitations of classical CNNs by the introduction of capsules, neurons that signify certain features and their spatial relationships. More at the level of regional detection of such features from within an image, CNNs have that mentioned quality, while upholding their spatial hierarchy. Thus, CapsNet becomes much more robust toward variations in orientation as well as viewpoint. This is mainly important for medical imaging wherein there recur many variations of positioning and angling because of the nature of MRI scans in front of radiologists concentrating on perfecting the detection of tumor within the human brain. Therefore, CapsNet helps with classification accuracy by learning about that which contextually relates to the position of the tumor itself while linking it to predictions more robust and reliable in diagnosing brain tumors.

### *4.3.1 CABINETS*

Deep learning models such as CapsNet in the class of Capsule Networks are of great importance in this sector since they have demonstrated promising results in image classification tasks. Caps Net is an architecture of neural networks that overcomes some limitations of the existing CNNs by implementing capsules, which are groups of neurons representing specific features along with their spatial relationships. While CNNs detect features within localized regions of the image, CapsNet can preserve the spatial hierarchy of the features and hence be less sensitive to changes in orientation and viewpoint. This property is of paramount importance in medical imaging, where accurate detection of a tumor in an MRI scan is critical irrespective of variations in position and angle. With the unique property of CapsNet to identify the spatial context of tumor presence, it achieves high classification accuracy in brain tumor diagnoses through reliable prediction.

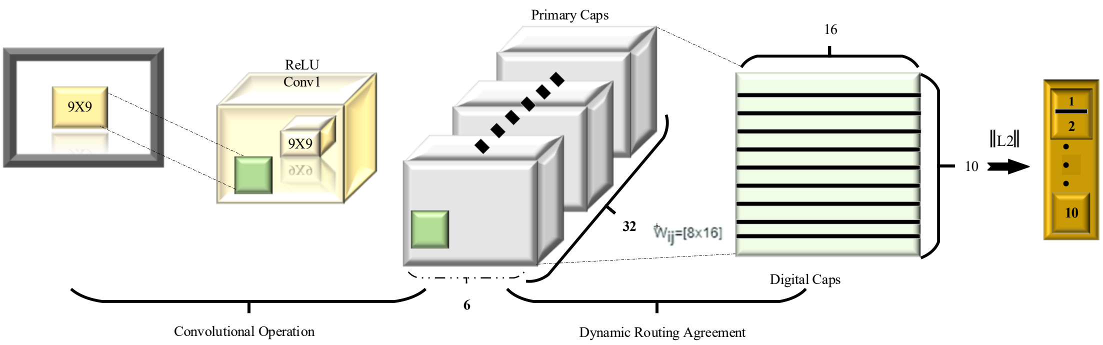


**Figure 3** CapsNets Diagram

Capsule Networks (CapsNet) primarily rely on capsules, which stand for groups of neurons that activate to detect particular features in an image and are aimed at modeling spatial arrangements between the features. The crucial equation for a capsule network spectacularly falls around transforming activations through dynamic routing between capsules.

To compute the output of a capsule, the equation used in the forward pass through a capsule is:

$$\mathbf{u}_j = \sum_i \mathbf{c}_{ij}\hat{\mathbf{u}}_i \quad (5)$$

Where uj is the $uj$ Output vector of capsule j, The routing procedure iteratively modifies these coupling coefficients cij in a manner so that the relevant information to be sent to the next layer comes only from the most relevant capsules. The output vector is fed through a non-linear activation function, commonly known as a squashing function, to enable the length of the vector to represent the possibility of the presence of a feature:

$$\text{squash}(\mathbf{u}_j) = \frac{\mathbf{u}_j}{\left(1+\|\mathbf{u}_j\|^2\right)^{\frac{1}{2}}} \quad (6)$$

Where, $\|\mathbf{u}_j\|$ is the norm (magnitude) of the vector $\mathbf{u}_j$.

## 5. DATASET DESCRIPTION

The Brain Tumor MRI Dataset is available on Kaggle and it is a collection of MRI images for constructing models for detection and classification of brain tumors. Glioma, meningioma, pituitary tumor classification, and healthy brain tissues are among the different types of tumors presented in this dataset. These images are pre-labeled so that any supervised learning task can take place because every single image has a tab, which denotes whether it has a tumor, and of what type, or is normal concerning the scan done. The dataset helps researchers and practitioners design and test machine learning models using, specifically, CNNs to try to provide classification and detection automation in medical imaging for brain tumors. This in turn will contribute significantly towards medical image analysis, in which some tools could be developed to help radiologists and medical professionals in the diagnosis of brain tumors in a more efficient way.

**Dataset Link:** https://www.kaggle.com/datasets/rishantenis/brain-tumor-mri-dataset

## 6. RESULT AND DISCUSSION

The system configuration in which the work is hosted is the 12th Gen Intel(R) Core (TM) i5-12400 Processor (speed 2.50 GHz), 8.00-GB RAM (usable 7.75 GB), and 64-bit OS with an x64-based processor. The system requirements to run the work should be at least 4GB of RAM (8GB recommended), an OS of Windows 7 or above, a new CPU (Intel i3 or above), and good storage capacity (100GB recommended). The project was executed using PyCharm 3.11.

### *6.1 Confusion Matrix*

A confusion matrix, as such, is used for other classification nearness evaluations such as models for classifying brain tumors. It has four components, namely, True Positives, True Negatives, False Positives, and False Negatives. It also derives computations for performance indicators, such as accuracy, precision, recall, and F1-score. This set of indicators provides insights into the overall usefulness of the model in classifying different types of tumors.

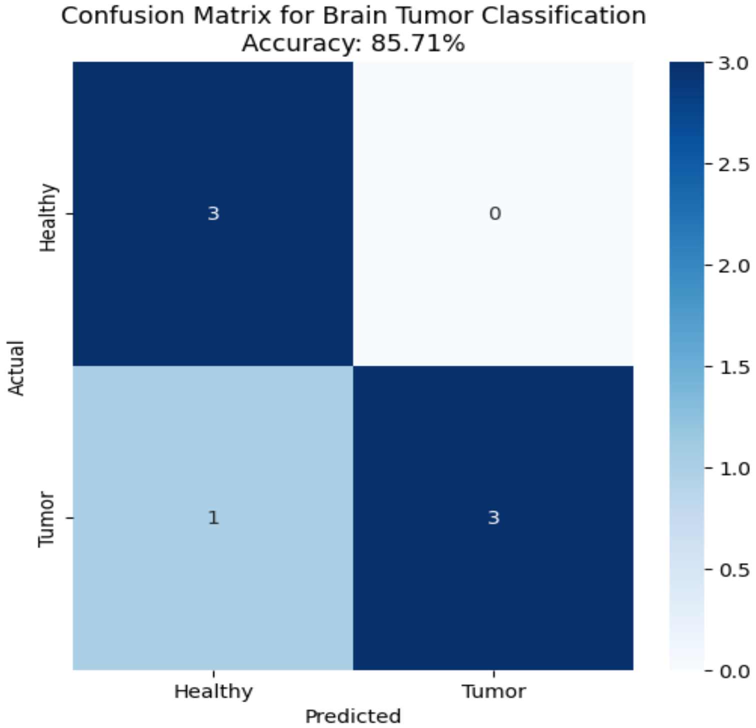


**Figure 4 Confusion Matrix**

A confusion matrix **(Figure 4)** is a graphic vector visualization to interpret a model performance by occurrences and predictions made by the model. In this scenario, the performance of the model is being evaluated for both classes of brain tumor, namely "Healthy" or "Tumor." The accuracy mentioned in the title of this graph stands for the percentage of correct predictions made by the model (TP + TN) out of the total predictions made. A high accuracy indicates the model is performing well at distinguishing tumor scans from healthy brain scans.

### *6.2 Performance matrix*

The performance metrics appropriate for the classification of brain tumors are accuracy, precision, recall, and F1-measure, which assess the capability of the model to distinguish between tumor and healthy brain scans. Accuracy measures the percentage of correct predictions, precision is the percentage of true tumor predictions, recall considers the number of actual tumors that were correctly identified, and the F1-score is the harmonic mean between precision and recall. All those metrics are critical in the medical field.

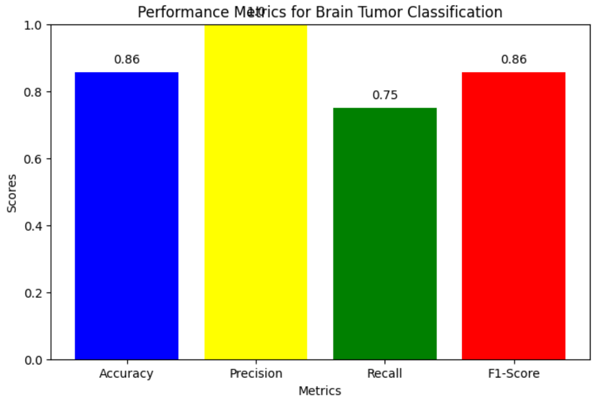


**Figure 5** Performance Matrix

The bar graph **(Figure 5)** depicts performance metrics for a brain tumor classification model based on four key evaluation measures: Accuracy, Precision, Recall, and F1-Score. The x-axis gives the name of the evaluation metric, while the measurement value is plotted along the y-axis. Different colors represent the different metrics represented in the bar graph. Accuracy shows the proportion of all correct predictions; Precision and Recall deal with the model diagnosing the tumor cases as positives while not generating false positives or false negatives. The F1 Score is the average of Precision and Recall. Each of the bars denotes its respective value, in the title, the accuracy percentage: thus, giving a clean and detailed view of the model performance based on different evaluation criteria.

## 7. CONCLUSION

The research aims to analyze the performance capabilities of Capsule Networks (Capsnet) when incorporated with a more improved feature-extraction paradigm called Local Binary Patterns (LBP). Such research questions are directed toward an image classification problem concerned with MRI scan-sourced images of brain tumors. Pre-processing methods on noises such as Gaussian filtering and feature enhancement, among others, are said to improve a lot the quality of inputs; in the same way, they have proven improvements of feature classification data Overall, the proposed system would provide a robust automated solution for substantial fast and accurate diagnoses in the classification of brain tumor, while it minimizes human errors in medicine by employing such deep-learning techniques into it.

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