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# Application of machine learning for brain tumor diagnosis using magnetic resonance images: a comparative analysis

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***Abstract*****—** A brain tumor is an abnormal growth of cells that may lead to cancer. MRI scans are the conventional method of diagnosing brain tumors. This paper investigates the potential of machine learning (ML) in interpreting MRI images for brain tumors. The study described applies and evaluates three different methods. The study applied and evaluated three different methods for identifying brain tumors: a self-defined a support vector machine (SVM), a Random forest (RF), and a convolution neural network (CNN). The Bra-TS 2018 dataset is used in this study on MRI brain images containing images of glioma, meningioma, pituitary, and no tumors. Python 3.11 was used for interpreting MRI images for brain tumors. The accuracy of the proposed CNN, RF, and SVM were found to be 99.29%, 99.06%, and 98.36%, respectively. The CNN approach has higher accuracy than innovative techniques.

**Keywords**: magnetic resonance imaging, support vector machine, random forest, convolutional neural network, brain tumor, machine learning.

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# I. INTRODUCTION

The human Central Nervous System (CNS) consists of the brain, which is the primary component of the human nervous system, and the spinal cord [1]. The brain is responsible for overseeing the majority of the body's basic functions, including processes such as perception, integration, organization, selection, and control. The structure of the human brain is highly complex. Finding a suitable treatment for specific CNC issues, like infections, headaches, strokes, and brain tumors, can be quite challenging [2]. A brain tumor is an aggregation of anomalous cells located within the inflexible cranium that safeguards the brain [3], [4]. Any expansion inside this limited area has the potential to result in complications. The presence of a tumor within the skull poses a substantial risk to the brain, leading to brain damage [5], [6]. Brain tumors rank as the tenth leading cause of death in both children and adults [7]. Based on their texture, location, and form, brain tumors come in various varieties, all of which have very poor survival rates [8], [9]. There are several kinds of tumors, according to "The American Association of Neurological Surgeons (AANS)," as shown in Figure 1 [10].

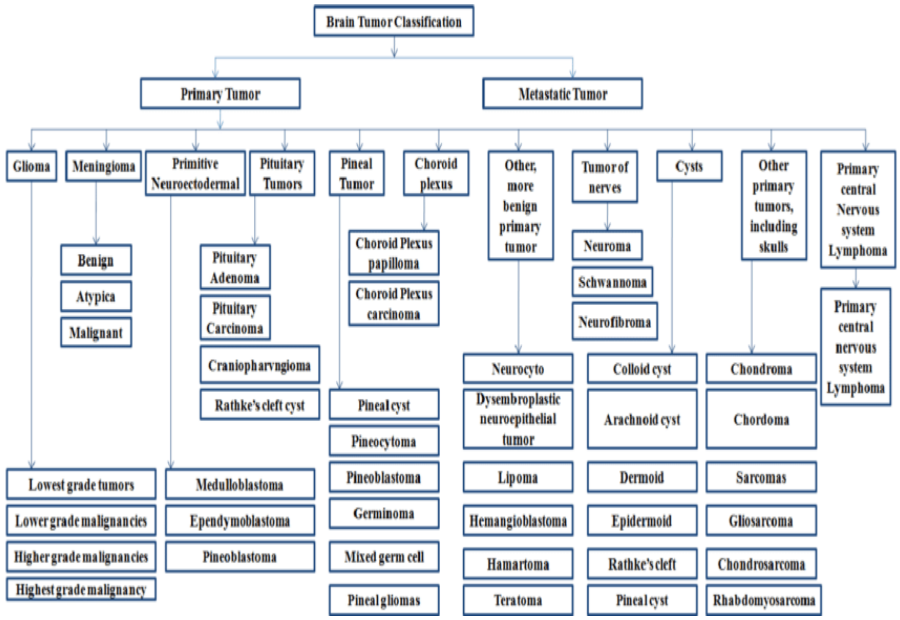


Figure 1: Brain Tumor Classification According to AAN.
Source: Own elaboration based on contributions from [11].

The most common methods for detecting abnormalities in the brain are Computed Tomography (CT), MRI, Magnetoencephalography (MEG), and Positron Emission Tomography (PET) [12]. Due to its ability to generate a wide variety of tissue contrast for all imaging methods, MRI is commonly considered the most widely used and effective tool for detecting brain diseases [13]. MRI is the predominant medical imaging technology used to visualize particular regions of the brain and get multimodal images [14]. Trained neuroradiologists have the ability to manually segment and interpret structural MRI scans of brain tumors due to their expertise and the amount of time required for this task [15], [16]. Thus, the identification and treatment of brain tumors would be significantly improved by automated and robust segmentation of the tumors.

There have been various suggestions for automatically categorizing brain tumors in recent years. They could be separated into Deep Learning (DL) and ML techniques depending on feature selection, feature fusion, and the learning process. Feature selection and extraction are critical in ML algorithms for categorization [17], [18]. Contrarily, DL techniques can be learned by taking cues from actual images. Medical image analysis involving MRI analysis substantially utilizes the novel DL methods, mainly Convolutional Neural Networks (CNN), because of their high accuracy [19], [20], [21].

CNN, fuzzy C-mean (FCM), RF, Sequential Minimal Optimization (SMO), Naive Bayes (NB), Decision Tree (DT), SVM, and K-Nearest Neighbor (KNN) are just some of the ML-based classifiers used for brain tumor Categorization and detection. There is less computational and geographical complexity involved in implementing a CNN. These classifiers have attracted a lot of study because of their low computing complexity, simplicity of use by non-experts, and modest training dataset requirements [22]. The objectives of the study are:

- Implement ML models for precise MR image-based segmentation and classification of brain tumors.
- Examine feature extraction techniques to improve the capacity of the models to recognize tumor features.
- To evaluate the effectiveness of the proposed strategies in relation to established methodologies.

## a. Grade System for Brain Tumors

A brain tumor is an anomalous growth of tissue inside the cranium resulting from uncontrolled cellular proliferation. Above than 150 distinct forms of brain tumors have been identified; however, they can be broadly categorized as either primary or metastatic [23]. Brain tumors originating from either brain tissue or the tissue surrounding it are known as primary brain tumors. They are further divided into glial cells, which are made up of glial cells, and virtual cells, which develop from brain structures that comprise nerves, blood arteries, and sweat glands [24]. Metastatic brain tumors are cancerous growths that begin in another organ, likes the breast or lungs and metastasize (travel) to the brain via the bloodstream. Annually, brain tumors are diagnosed in 25% of cancer patients, estimated to affect more than 150,000 people [25]. Metastatic brain tumors can occur in as many as 40% of people with lung cancer, and the prognosis for individuals identified with these tumors is quite poor; generally, the time span from diagnosis to mortality is typically limited to a few weeks.

The World Health Organization (WHO) created a grading system to categorize tumors according to their histological characteristics that can be seen under a microscope, including their propensity for aggressive necrosis, rapid recurrence, and most malignant characteristics (Table 1) [26].

Table 1: WHO Grades of Brain Tumors.

| Grade | | Tumor Types | Characteristics |
|---|---|---|---|
| Lower Grade | Grade I | Craniopharyngioma<br>Chordomas<br>Ganglioglioma<br>Gangliocytoma<br>Pilocytic astrocytoma | Surgical treatment may be sufficient to cure the condition.<br>Persistence over time Least malignant (benign)<br>Without penetration |
| | Grade II | Pineocytoma<br>“Diffuse” astrocytoma<br>Pure oligodendroglioma | Slightly penetrating<br>moderate in rate of expansion<br>Can Come Back as a Better Grade |
| High Grade | Grade III | Anaplastic ependymoma<br>Anaplastic astrocytoma<br>Anaplastic oligodendroglioma | Malignant<br>Infiltrative<br>The tendency to recur as advanced level |
| | Grade IV | Glioblastoma multiforme<br>Medulloblastoma<br>Ependymoblastoma<br>Pineoblastoma | The most cancerous<br>Rapidly expanding and hostile<br>Deeply pervasive<br>Repeated occurrence inclination for necrosis |

Source: Own elaboration [27].

Summary of scientific progress: The next section evaluates numerous significant research endeavors from diverse scholars. After that, it outlines the recommended research procedure, describes the proposed methodology, and concludes with a tool simulation-based experimental evaluation of the methodology. The study's conclusion is given in the final paragraph.

## II. LITERATURE OF REVIEW

Scientists have previously researched, notably in the last several years, on applying ML approaches to interpret MR images for brain tumors. Medical image analysis, and particularly illness detection, has benefited greatly from the creation of model-based innovative technologies. This section reviews the research on brain tumors using various techniques. Various perspectives can be used to analyze literature research. For example.

Asiri et al., (2023) [28] suggested a Fine-Tuned Vision Transformer (FT-ViT) method to precisely detect any images showing indications of a brain tumor in the provided data by using DL and sophisticated image processing methods. Data processing, patching, interpreting, combination and fine-tuning, learning, and, feature selection are all steps in the proposed model FT-ViT. The accuracy of the FT-ViT model was 98.13%. The suggested approach is realistic regarding medical research because it has a high degree of accuracy and could greatly lessen the burden on radiologists.

Chang et al., (2023) [29] developed a model Dual-Path Attention-Fusion Convolutional Neural Network (DPAF-Net) for efficient 3D segmentation. The experimental findings of this study's Brain Tumor Segmentation (BraTS (2018-2020)) are positive, offering a high degree of accuracy and a high Dice score compared to earlier work in this field. Experiments on BraTS2018 reveal that the proposed DPAF-Net performs well. On Bra-TS 2019, the dice results for tumor improvement, entire tumor and tumor center are 78.2%, 89.0%, and 81.2%, respectively.

Zhu et al., (2023) [30] developed a method for segmenting brain tumors using multimodal MRI and deep semantic fusion to enhance segmentation accuracy and facilitate better cross-modal communication. The edge detection module was created using CNNs, and its characteristics were enhanced with the help of an Edge Spatial Attention Block (ESAB). The new method is validated using the well-known Bra-TS benchmarks. Based on the research findings, the proposed technique outperforms previous methods in the segmentation of brain tumors.

Saeedi et al., (2023) [31] Proposed two DL techniques and many ML methods for the diagnosis of pituitary gland, Meningioma, and glioma tumors, along with healthy brains with tumors, utilizing MRI brain scans. The proposed 2D CNN obtains a training accuracy of 96.47% and a recall rate of 95%. The Multilayer Perceptron (MLP) achieved an accuracy of 28%, making it the worst performing ML technique. On the other hand, the KNN algorithm achieved the highest accuracy of 86%, making it the best performing ML technique among those utilized.

Zahoor et al., (2022) [32] developed a unique approach to distinguishing tumor MRIs from healthy ones by using DBFS-EC (Deep-Boosted Features Space and Ensemble Classifiers). The experimental findings show that the recommended DBFS-EC detection method has better F1-Score (99.45%), Recall (98.99%), Precision (99.91%), accuracy (99.56%), mean classification accuracy (0.9892), and area under the receiver operating characteristic curve (99.90%) than the gold standard. F1-Score (99.09%), accuracy (99.20%), precision (99.06%), and Recall (99.13%) on the CE-MRI dataset show that the categorization system depends on the fusion of feature spaces of the suggested HOG (Histogram of Gradients) and (BRAIN-RE-Net) Brain Region-Edge Net significantly surpasses other methods.

Younis et al., (2022) [33] developed a CNN for automated detection of brain cancers using MRI data. The researchers utilized a dataset consisting of 253 brain MRI scans, out of which 155 exhibited malignancies, to evaluate the efficacy of their proposed approach in identifying brain cancers. Brain cancers in MR images could be detectable by using the method. When compared to other methods for identifying brain cancers, the algorithm demonstrated superior performance in the test data, with CNN (96%), VGG16 (98.5%), and Ensemble Model (98.14%) achieving great accuracy.

Gab et al., (2021) [34] analyzed the performance of a novel strategy for the categorization of brain tumor MRIs using a VGG19 features extractor in conjunction with one of 3 classifiers (CNN, Gated Recurrent Unit (GRU) and Bi-GRU). To compensate for the scarcity of excellent images needed for deep learning, researchers have developed a model that uses a PGGAN (Progressive Growing Generative Adversarial

Network) to simulate brain tumor MRIs. Compared to prior research, the method employed by the authors yielded a superior accuracy rate of 98.54% in identifies pituitary, meningiomas and gliomas tumors.

Arora et al., (2021) [35] presented a system for segmenting and identifying brain tumors, which was assessed through experiments using the Bra-TS 2018 dataset. This system employs a fully automated approach to segment gliomas within pre-operative MRI images, utilizing a U-Net-based DL model. The system demonstrated consistently high accuracy across all phases, including training, validation, and testing, on the Bra-TS 2018 dataset. Specifically, when tested on the dataset, the model yielded remarkable results, achieving a dice coefficient of 0.9815 for HGG-1, 0.9844 for HGG-2, 0.9804 for HGG-3, and an outstanding 0.9954 for LGG-1. The comparison table of the reviewed literature can be found in Table 2.

Kshirsagar et al., (2020) [36] introduced a MRI based brain tumor detection technique. According to the author, tool reading algorithms are used to identify tumors in magnetic resonance imaging. The proposed paintings are divided into three parts: On images captured using magnetic resonance imaging, preprocessing steps are applied, and texture skills are extracted using the prevalence of grey diplomas. The use of a tool-mastering set of suggestions is completed after the matrix.

Raut et al., (2020) [37] proposed a CNN model for detecting a brain tumor. The images are then preprocessed to eliminate any noise and prepare them for the upcoming processes. The system under consideration was trained using pre-processed MRI brain pictures. Subsequently, it was capable of categorizing new input images as either tumorous or normal based on the features that were extracted during the training process. Backpropagation was employed to enhance precision and reduce the duration of training. Autoencoders were employed to generate an image that removes unnecessary information and accurately separates the tumor area. K-means was a form of machine learning that falls under the category of unsupervised learning.

Çınarer et al., (2019) [38] analyze the efficacy of tumor classification techniques in categorizing MR brain image features into four distinct categories: gliomatosis, multicentric, n/a, and multifocal. During the categorization process, an analysis was conducted on the statistical characteristics of the input images, and then using those, Various groups were created from the data in a systematic manner. The data underwent testing using machine learning algorithms including LDA (linear discriminant analysis), SVM, RF, and KNN. The SVM technique demonstrated superior performance compared to alternative algorithms, achieving a 90% accuracy rate.

Zhao et al., (2018) [39] developed a novel methodology for the detection of brain tumors by combining CRFs (conditional random fields) and FCNNs (fully convolutional neural networks) within a unified framework. The objective is to achieve segmentation results that exhibit both appearance and spatial consistency. Using image slices and two-dimensional image patches, the author trained a segmentation model based on deep learning as follows: FCNNs are trained using image patches; CRFs are trained as CRF-RNN (recurrent neural networks) utilizing Parameterized FCNN image slices fixed; and FCNNs and CRF-RNN are fine-tuned using image slices. To segment brain tumors, the author specifically trains three segmentation models utilizing slices and Patches of a 2D Image obtained from sagittal, coronal, and axial views, respectively, and then merges them using a voting-based fusion strategy. Slice-by-slice segmentation of brain images using this technique was much faster than using image patches. The Multimodal Brain Tumor Image Segmentation Challenge (BRATS) 2016, BRATS 2015, and BRATS 2014 imaging data were used by the author to evaluate this method. According to the experimental findings, this method can create segmentation models using T1c, Flair, and T2 scans that perform as well as those created using T2 scans, T1c, T1, and Flair.

Table 2: Comparison of Literature of Review.

| Authors [Reference] | Techniques Used | Outcomes | Dataset |
|---|---|---|---|
| **Asiri et al., (2023)** [28] | FT-ViT | The FT-ViT performed better and correctly and consistently detected 98.13% of the complicated forms of brain tumors compared to all the previous studies. | Brain Tumor MRI Dataset |
| **Chang et al., (2023)** [29] | DPAF-Net | Using the proposed DPAF-Net, authors improved BraTS2018 in all three tumor categories (augmentation, total, and tumor core) by a Dice score of 79.5%. | BraTS2018, BraTS2019 and BraTS2020 |
| **Zhu et al., (2023)** [30] | Deep learning | The study's results confirm the efficacy of the core elements of the method. The recommended technique achieves better-than-average results (86.93 for Dice, 4.193 HD) compared to several other algorithms on the BraTS benchmarks. | Training and testing datasets are sourced only from the BraTS2018, BraTS2019, and BraTS2020 datasets. |
| **Saeedi et al., (2023)** [31] | 2D CNN, SVM, RF, KNN, LR, SGD, and MLP | The proposed 2D CNN exhibited a training precision of 96.47%, whereas the training efficiency of the auto-encoder network was found to be 95.63%. This study employed two deep neural networks, with an additional six ML methods created for brain tumor classification. Accuracy levels of 86% for KNN, 82% for RF, and 80% for SVM were achieved. | MRI dataset |
| **Zahoor et al., (2022)** [32] | DBFS-EC | The recommended approach achieved exceptional results on a benchmark dataset used for brain tumor classification, with precision, Recall, accuracy, and F1-score all reaching 99%. | CE-MRI dataset |
| **Younis et al., (2022)** [33] | CNN | Regarding accuracy, the architecture suggested included CNN, VGG 1, and Ensemble, with CNN achieving 96%, VGG 16 achieving 98.5%, and the Ensemble Model achieving 98.14%. | Brain MRI Images Dataset |
| **Gab et al., (2021)** [34] | VGG19 + GRU, VGG19 + CNN, and VGG19 + Bi-GRU | In previous studies, all other models were outperformed by the VGG19 additionally with PGGAN augmentation framework and CNN model, achieving accuracy scores of 98.54% for gliomas, 98.54% for meningiomas, and a perfect 100% for pituitary tumors. | Public data set |

| | | | |
|---|---|---|---|
| **Arora et al., (2021)** [35] | U-Net-based deep learning | The proposed study demonstrated outstanding performance in identifying brain tumors, with an accuracy of approximately 0.99 on the validation set and 0.98 on the test set during training. | Bra-TS 2018 dataset |

Source: Own elaboration.

## III. PROBLEM FORMULATION

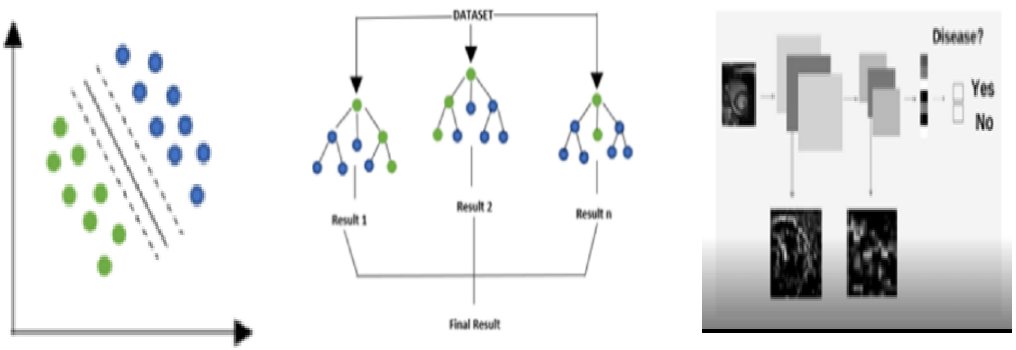
The purpose of this problem statement is to study the unused potential of ML in the context of improving the interpretation of MR images to perceive and analyze brain tumors. This research aims to increase the accuracy, speed, and consistency of diagnosing and characterizing brain tumors via automated image processing by using more sophisticated approaches for ML. The function of this study is to tackle the issues connected with the complexity and unpredictability of MR images to contribute to clinical decision-making that is more effective and efficient in neuro-oncology.

## IV. TECHNIQUES USED

In this study we have used ML techniques namely CNN, RF, and SVM for interpreting MRI images for Brain Tumors.

### a. Fundamental of ML

ML algorithms are categorized into three main types: Unsupervised Learning (UL), Supervised Learning (SL), and Reinforcement Learning (RL) [40-41]. A machine in SL is provided with a dataset that has been labeled. The settings for both input and output are already included. Subsequently, when a machine is presented with a new dataset, the SL algorithm scrutinizes it by taking into account the labeled data and produces the suitable output. UL involves the absence of a labeled dataset, requiring the algorithm to independently identify patterns and relationships. The process entails the classification of information. RL algorithms are designed to enable the machine to actively pursue the optimal solution by utilizing the principles of reward and punishment to guide its behaviors, ultimately leading to the attainment of the desired outcome. Logistic Regression (LR), SVM, RF, cluster analysis, CNN, and ANN are among the most popular machine learning methods [42-46] (Figure 2). Our study uses SVM, RF, and CNN models to interpret MR Images for Brain Tumors.




SVM RF CNN

Figure 1: the most widely used machine learning techniques for cardiac imaging [46].
Source: Own elaboration.

- **Support Vector Machine**

The SVM is a widely used and advanced ML technique. The main purpose of this is to arrange and structure data. SVM, being an algorithm, depends on the concept of calculating the margin. Essentially, it creates false divisions among socioeconomic groups. The classes are maximally detached from the margin in order to minimize the classification error during the process [47].

- **Random Forest**

One regression methodology that makes use of ensemble learning is the RF method, which builds multiple decision trees during training. For classification problems, a RF is advantageous since it produces the class that the majority of trees choose. In regression tasks, the only output is the mean forecast from all the trees.

- **Convolutional Neural Network**

A CNN is a type of ANN that use a technique known as convolutional operation to modify the value of each node in a layer, taking into account its spatial relationship with a node in the layer above. These models were specifically designed for image processing, taking into account the spatial information of nodes (pixels) while formulating predictions. ANNs are provided with access to both the advantages and disadvantages. These models differ greatly from their predecessors by directly using photos as input without doing any feature extraction.

It explains the pros and cons of the most popular ML methods for the general public, as well as their potential use in interpreting MRI scans for neurological malignancies. For further, please refer to Table 3.

Table 2: Overview of ML methods.

| Techniques | Description | Advantages | Disadvantages |
|---|---|---|---|
| SVM | Identifies the optimal division between classes | • High accuracy.<br>• Objects Discovered Recently Categorized Rapidly. | • The choice of the kernel might not be immediately obvious.<br>• Quite computationally demanding. |
| RF | Generates a sequence of a hierarchical decision queries that are performed on both the input and output data. | • Strong Performance.<br>• Derive variable measures. | • Computation intensive.<br>• Overfit problem. |
| CNN | ANNs tailored to perform image data processing and classification | • Flexible design tailored to meet the specific needs of the application.<br>• Proficient in extracting optical parameters directly from images. | • Same limitations as ANNs. |

Source: Own elaboration based on contributions from [48].

## V. RESEARCH METHODOLOGY

The study's recommended methodology can be seen in Figure 3. Initially, we collect MR images that are as varied and representative as possible and labeled ground truth information regarding tumors' existence, locations, and types. Include images with a variety of tumor sizes, locations, and any other variants that are pertinent.

Dataset Description: In the research methodology, we are using a BraTS 2018 dataset for the identification of brain tumors combined with various machine learning models like SVM, RF, CNN, etc. The BraTS 2018 dataset is frequently employed within the healthcare domain. The dataset offers multimodal 3D brain MRI (magnetic resonance imaging) scans along with accurately descriptions brain tumor segmentations performed by medical professionals. Each case in the dataset includes four Magnetic Resonance Imaging (MRI) techniques: FLAIR, T2, T1c, and T1. The three sub-regions of tumors that are commonly annotated are the improving tumor, the the non-enhancing tumor core, the necrotic, and the peritumoral edema. The annotations were organized and grouped together within three hierarchical sub-regions, namely the tumor core (TC), enhancing tumor (ET), and whole tumor (WT). The data were obtained from a total of 19 institutions, employing a range of magnetic resonance imaging (MRI) scanners [49].

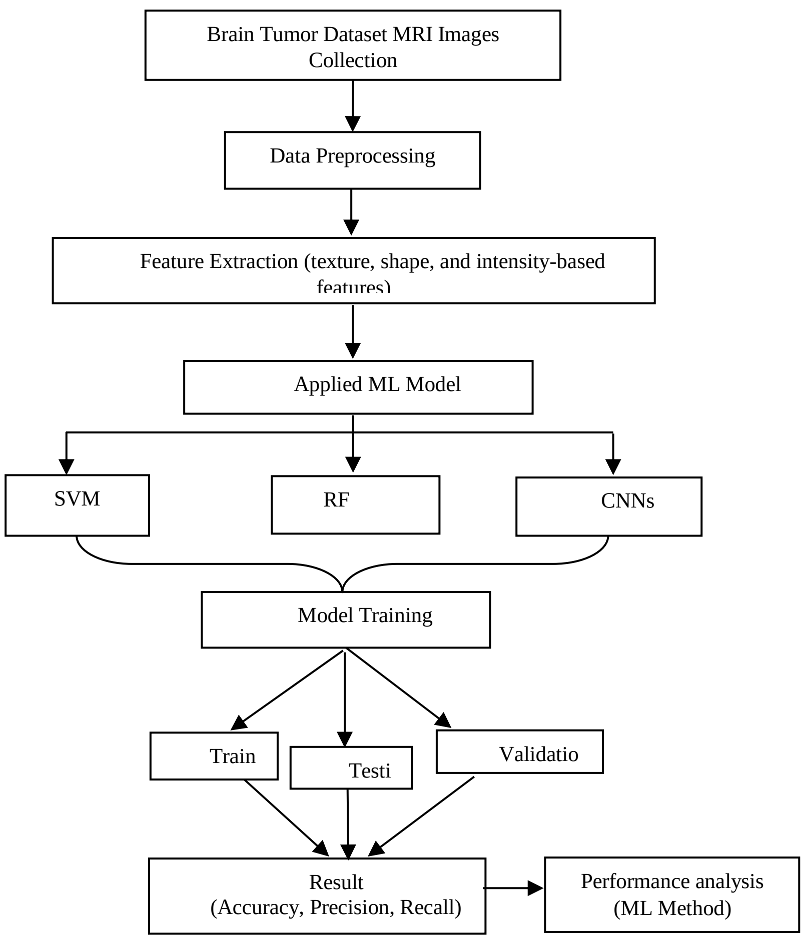



Figure 3: Block diagram of Proposed Work.
Source: Own elaboration.

Firstly Brain Tumor MRI images dataset is collected then, make the data ready for ML model by carrying out the necessary preprocessing processes:

- **Image normalization:** Ensure that the intensity levels are consistent across all images.
- **Noise reduction:** Improving the quality of images can involve the use of denoising or filtering methods.
- **Image registration:** Aligning images to a standardized coordinate system is necessary for maintaining consistency.
- **Region of interest (ROI) extraction:** Concentrate on the brain area to reduce the amount of computing complexity.

The preprocessed data is prepared for the next process, which is feature extraction. It will extract significant features from the MR images to be input for ML models. The intensity histogram, the texture characteristics, the form descriptors, and the spatial correlations are all examples of common features. Following this, it will choose the most suited ML models for the position by considering the data's characteristics and the intricacy of the issue. Some techniques are:

- RF
- SVMs
- CNNs

After the feature extraction procedure is finished, the data needs to be divided into training, testing, and validation sets. Utilize the selected models to train them with the data from the training set, and subsequently refine the hyperparameters using the validation data. Enhancing the ability of a model to apply its knowledge to new data can be achieved through various methods, including data augmentation. During the final phase, evaluate the model's efficacy by employing relevant measures such as F1-score, Recall, precision, and accuracy. Cross-validation can enhance the reliability of an assessment.

## VI. IMPLEMENTATION AND RESULTS

This research section details the implementation using the suggested technique, and the implementation tools and dataset are provided below. The authors used the Matrix Laboratory (MATLAB) tool to obtain the results of this research. MathWorks created MATLAB, a commercial programming language and numerical computing environment supporting many examples. Matrix processes, charting of functions and information, procedure development, user interface design, and linking with other programming languages are all probable with MATLAB. The findings provided to support the suggested effort stated below are as follows.

### a. Dataset Collection

The dataset was gathered from data available on kaggle.com and to detect malignant growths in the brain. The dataset was built with the use of MRI pictures. MRI was chosen for this study due to its superiority over other methods. Glioma tumor (221 images), No tumor (194 images), Meningioma (216 photos), and Pituitary tumor (225 images) were the four types of brain tumor data that they utilized in this research. In total, our dataset comprises 857 MRI data samples.

### b. Performance Measures

They considered metrics such as F1-Score, Recall, Precision, and Accuracy and to evaluate and analyze the ML models' performances.

- Accuracy

The proportion of true positive and negative values to the overall amount of values.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Positive} \quad (1)$$

True Positive (TP): Detected the altered images without error.
False Positive (FP): Images mistakenly recognized as genuine or manipulated.
True Negative (TN): Validated as authentic on visual inspection.
False Negative (FN): Falsely recognized manipulated images or images mistakenly thought genuine.

- Precision

The word precision is used to describe the unavoidable variation in measuring results. Thermal effects probably cause a random fluctuation in the observed value. It can be calculated as:

$$\frac{TP}{TP+FN} \quad (2)$$

- Recall

One of the other most crucial parameters for testing an ML model is Recall. The formula for determining the Recall is:

$$Recall = TP/(TP + FN) \quad (3)$$

- F1-Score

F1-score is a single metric that combines a model's precision and Recall, providing a balanced assessment of its performance in binary classification tasks.

$$F1\ score = \frac{2(Precision * Recall)}{Precision + Recall} \quad (4)$$

## c. Performance Analysis

### 1. Training and Validation Accuracy CNN

The F1 score, Recall, precision, and accuracy and were only a few metrics for evaluating the effectiveness of the CNN model while categorizing images of brain tumors. The validation accuracy of the model was 99.13%, proving its capacity to detect brain cancers. Figure 4 also displays validation accuracy vs. training and loss graphs created to demonstrate the model's learning process. The accuracy of the training procedure gradually increased during the training iterations, eventually achieving a remarkable value of 99.29%, as seen by the accuracy graph.

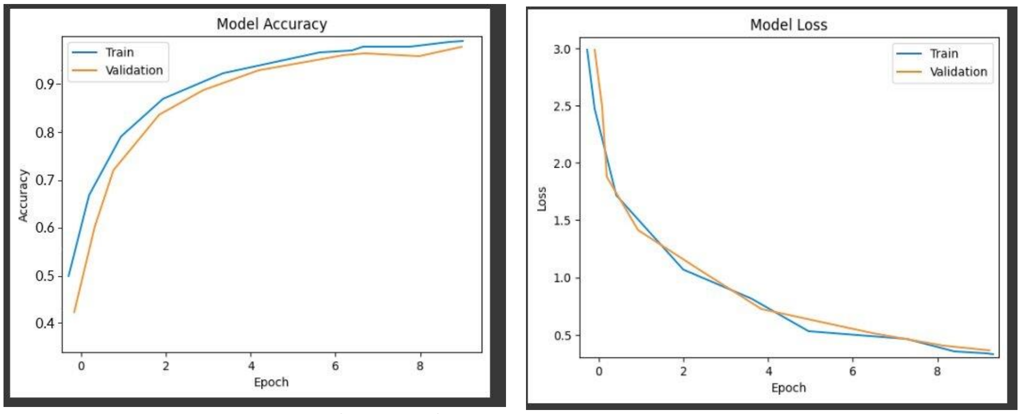
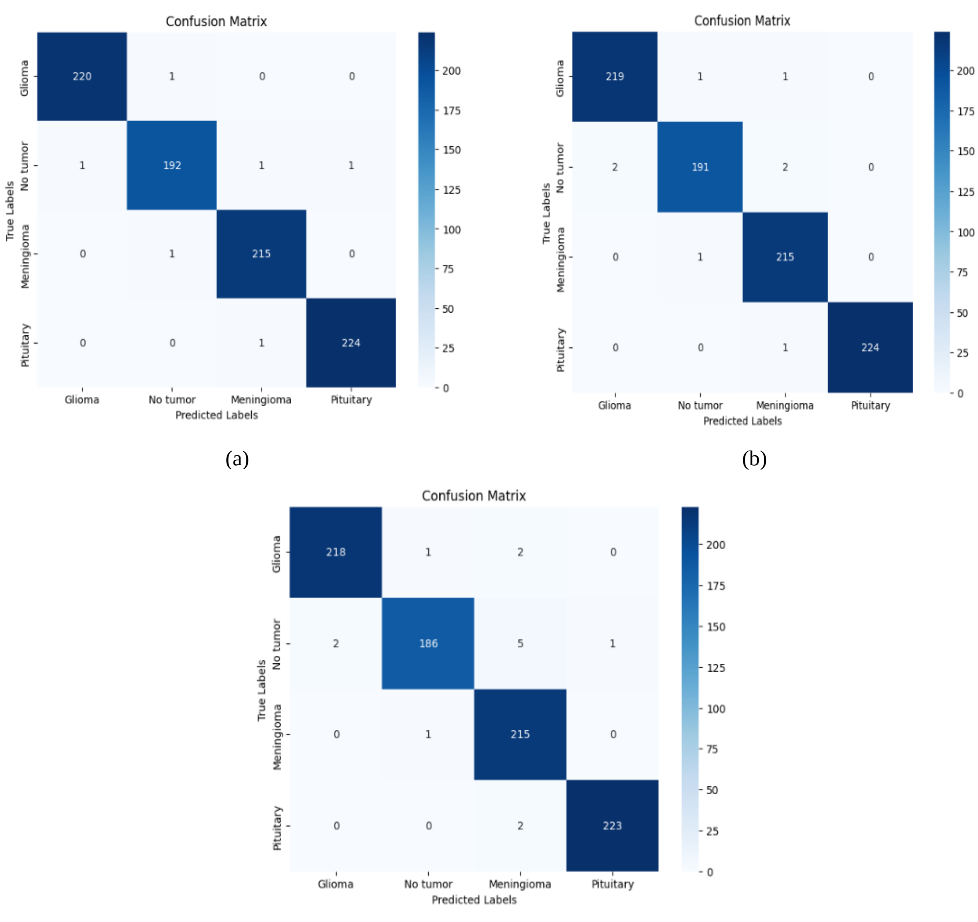



Figure 4: Training and Validation Performance of Accuracy and Loss.
Source: Own elaboration.

### 2. Testing Confusion Matrix

The confusion matrix summarized the properly and incorrectly categorized examples, giving us further information about the model's accuracy. As shown in Figure 5 (a), out of 857 pictures used for validation, the model correctly labeled 851. As shown in Figure 5 (b), out of 857 pictures used for validation, the model properly labeled 849 images. Out of 857 pictures used for validation, the model was properly labeled 842 (Figure 5 (c)). The remaining 15 images were incorrectly labelled.




(a) (b)

(c)

Figure 5: The suggested model's Confusion Matrix, which shows the TP, TN, FP, and FN ratio in the validation dataset of the (a) CNN, (b) RF, and (c) SVM.
Source: Own elaboration.

### 3. Classification of model performance of Tumor class

Figures 6 and 7 depict the proposed study's findings, showcasing accurate and inaccurate classifications. It depict the MRI images produced by our machine learning model which demonstrates the classification of the brain tumor diseases by visualizing these process images. The model classifies the meningloma or pituitary brain tumor with an images of no brain tumor.

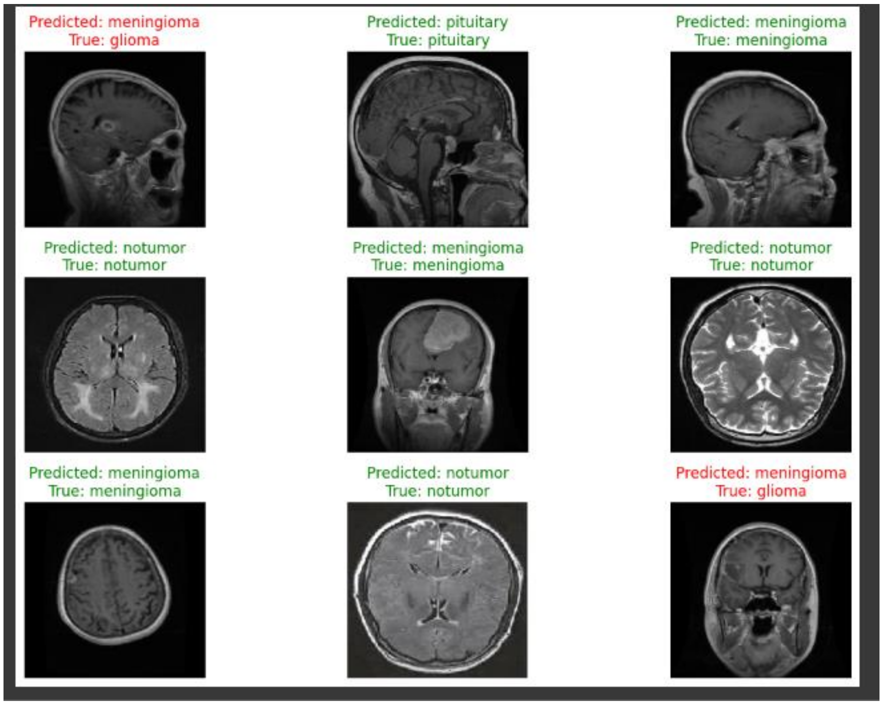



Figure 2: Correct and Incorrect classification findings of the suggested model.
Source: Own elaboration.

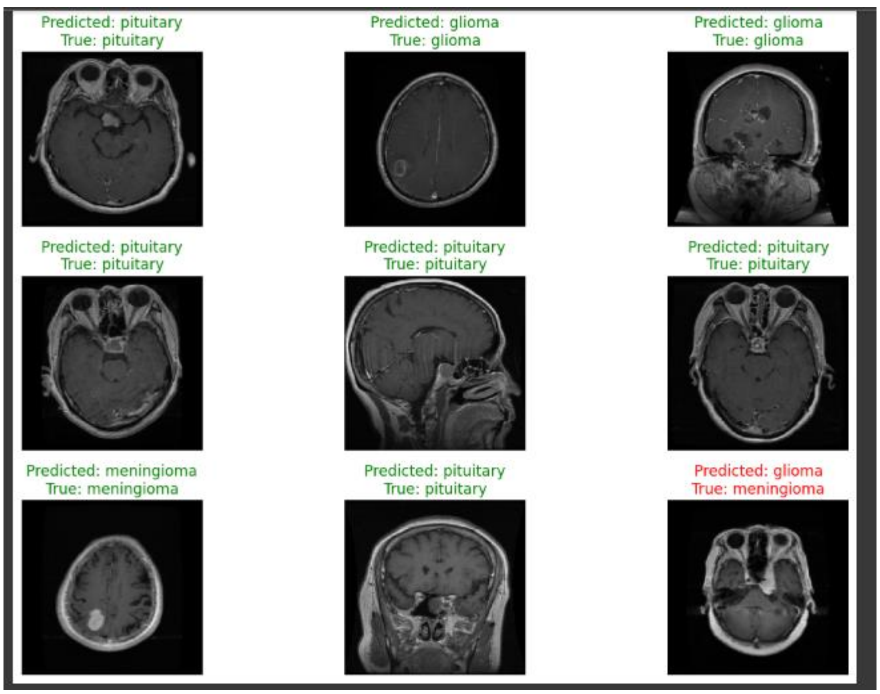



Figure 7. shows the proposed model's classification successes and failures.
Source: Own elaboration.

Tables 4, 5, and 6 describe the precision, Recall, and F-measure of the four classes generated with CNN, RF, and the SVM, respectively. Table 4 depicts the CNN (convolutional neural network) based model classification of different tumors like glioma, meningioma, and pituitary with no tumor, with an accuracy rate, recall, and FI-score.

(b)

Table 3: Precision, Recall, and F-Measure of CNN.

| Brain Tumor | Precision | Recall | F1-score |
|---|---|---|---|
| Glioma tumor | 100% | 100% | 100% |
| No tumor | 99% | 98% | 99% |
| Meningioma | 99% | 100% | 99% |
| Pituitary | 100% | 100% | 100% |
| Weighted avg | 99% | 99% | 99% |
| Accuracy | - | - | 99% |

Source: Own elaboration.

Table 5 depicts the RF (random forest) based model classification of different tumors like glioma, meningioma, and pituitary with no tumor, with an accuracy rate, recall, and FI-score.

Table 4: Precision, Recall, and F-Measure of RF.

| Brain Tumor | Precision | Recall | F1-score |
|---|---|---|---|
| Glioma tumor | 99% | 99% | 99% |
| No tumor | 99% | 98% | 98% |
| Meningioma | 98% | 100% | 99% |
| Pituitary | 100% | 100% | 100% |
| Weighted avg | 99% | 99% | 99% |
| Accuracy | - | - | 99% |

Source: Own elaboration.

Table 5 depicts the SVM (support vector model) based model classification of different tumors like glioma, meningioma, and pituitary with no tumor, with an accuracy rate, recall, and FI-score.

Table 5:. Precision, Recall, and F-Measure of SVM.

| Brain Tumor | Precision | Recall | F1-score |
|---|---|---|---|
| Glioma tumor | 99% | 99% | 99% |
| No tumor | 99% | 96% | 97% |
| Meningioma | 96% | 100% | 98% |
| Pituitary | 100% | 99% | 99% |
| Weighted avg | 98% | 98% | 98% |
| Accuracy | - | - | 98% |

Source: Own elaboration.

## 4. Comparison Analysis

The proposed models are contrast to the latest models currently available in this study, illustrated in Table 7. To illustrate in [50], the 2D-CNN-based method was employed, achieving an accuracy of 96.47% with 3064 images. In another study, [51] the CNN model achieved an accuracy of 97.8% with 3064 images. The DL approach [52] achieved 98.3% accuracy on 3264 images. The success rate of our CNN method was 99.29% with the 857 images. The success rate of our RF method was 99.06% with the 857 images. Our SVM approach resulted in a 98.36% rate of success with the 856 images. In this paper, we have achieved a higher accuracy of the CNN technique at 99.29% than the other approaches. Figure 8 depicts the comparison of the proposed work with the other methods.

Table 6: Comparative analysis of proposed work with state-of-the-art models.

| Authors | No. of Images | Models | Accuracy |
|---|---|---|---|
| **Saeedi S. et al., (2023)** [50] | 3064 | 2D CNN | 96.47% |
| **Khan S. et al., (2022)** [51] | 3064 | CNN | 97.8% |
| **Mahmud Md. et al., (2023)** [52] | 3264 | DL | 93.3% |
| **Proposed** | 857 | CNN | 99.29% |
| **Proposed** | 857 | Random Forest | 99.06% |
| **Proposed** | 856 | SVM | 98.36% |

Source: Own elaboration.

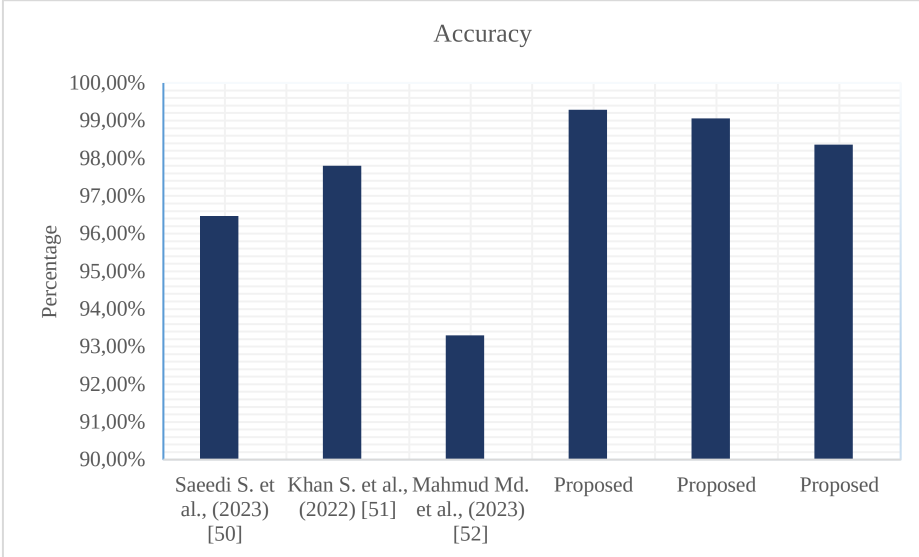



Figure 3. Comparison of the proposed work with the other methods
Source: Own elaboration.

## VII. CONCLUSION AND FUTURE SCOPE

Prompt identification of brain tumors is essential for optimal treatment outcomes. The location, texture, size and varied shape of malignancies in medical images make accurate tumor analysis challenging. MRI is suggested to be analyzed using ML to detect and classify brain cancers. ML algorithms also have a major effect on these detection and classification tasks. They indicated a CNN, RF, and SVM model for early identification of brain cancers, and encouraging results were achieved using a large set of MR data. The authors utilized a range of metrics to assess the effectiveness of the ML models throughout the assessment process. They evaluated the findings using the proposed approach and other alternative ML models. Accuracy levels of 99.29%, 99.06%, and 98.36% were measured for the suggested CNN, RF, and SVM training methods. With a CNN Accuracy of 99.29%, the model accurately classified pituitary tumors, no tumors, meningiomas, and gliomas in a dataset of 857 MRI scans. In the future, researchers could employ patient data from any source to accurately diagnose brain cancer. The use of machine learning to read MRI images to find and diagnose brain tumors looks like it will make big steps forward in the area of medical imaging in the future. Learning algorithms that use machine learning are getting better at finding brain tumors early on. They will get even better at finding subtle or complicated patterns in tumors, which will help with early diagnosis and planning treatment. Machine learning can help make treatment plans that are more effective by taking into account the specifics of each patient's tumor. Drafting and recognizing the tumor area in an MRI scan is called tumor segmentation. Machine learning models can automate this process. As portable MRI machines and cloud-based processing get better, models using machine learning may be able to give diagnoses in real time or at the point of care. This can be especially helpful in an emergency because it lets patients make decisions more quickly. The use of MLto read MRI pictures for brain tumor diagnosis will likely change the field by making it more accurate, tailoring treatment to each patient, and speeding up the diagnosis and decision-making process.

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