Mind the Gap: Bridging Accuracy and Efficiency in Tumor Detection via MRI Imaging and Deep Learning

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Abstract. Brain tumor detection from medical images, particularly MRI, has seen significant advancements through the application of deep learning techniques. This study presents an efficient CNN-based model for brain tumor detection, achieving remarkable performance metrics. The model is built upon the principles of efficient scaling and convolutional neural networks, which have become the cornerstone of computer vision tasks. The proposed model leverages a well-curated data set of brain MRI images to achieve a test accuracy of 98.26 percent, test sensitivity of 98.51 percent, test specificity of 97.89 percent, test precision of 98.47 percent, and test F1-score of 98.21 percent. The CNN architecture, trained on diverse tumor sizes, which eliminated the need for manual feature extraction and performs automatic segmentation. This project contributes to the growing landscape of AI-powered medical imaging by demonstrating the potential of deep learning models to accurately detect brain tumors and aid radiologists in clinical decision-making.

Keywords: Tumor detection · MRI imaging · Neural network model · Deep learning · Data analytics

1 Introduction

1. I chose the domain of tumor detection through MRI imaging because it plays a crucial role in early diagnosis and prognosis. I also have a family member currently going through a very vicious form of cancer, and wanted this project to mean something more than just a grade for my portfolio. CNNs have become a dominant method in computer vision tasks [9], and scaling them is crucial for improved accuracy [11]. The significance of MRI in brain tumor detection is emphasized [4], [1], and CNNs' role in automating feature extraction is highlighted [4], [5]. Challenges like model interpretability and integration into clinical practice are discussed [3], [1].

2 Literature Review

The core objective was to design a robust neural network model that excels in tumor detection using MRI images. I researched several scholarly articles insinuating the effectiveness with CNN models and tumor detection.

2.1 EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Scaling CNN models has been crucial for improving accuracy in various tasks, including brain tumor detection [11]. EfficientNet introduces a novel approach to scaling dimensions such as depth, width, and resolution, highlighting the need for a balanced network [11]. The authors emphasize the significance of a strong baseline network and efficient architectures for improved accuracy and efficiency [11].

2.2 A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks:

MRI's importance in diagnosing brain tumors is emphasized, with CNNs automating feature extraction [4]. The study underlines CNNs' potential in reducing manual feature extraction and expert segmentation, and it differentiates between primary and secondary brain tumors [4].

2.3 Convolutional Neural Networks: An Overview and Application in Radiology:

CNNs' dominance in radiology for image processing is highlighted, particularly in brain tumor detection [9]. The paper discusses CNN components like convolution and pooling layers, along with challenges like overfitting and the network's black-box nature [9].

2.4 Brain Tumor Segmentation Using Deep Learning on MRI Images:

The role of CNNs in automated feature extraction and model training is discussed, emphasizing CNN layers like Conv2D and MaxPooling2D [5]. The study points to potential future research directions and the significance of CNNs in brain tumor segmentation [5].

2.5 Accurate Brain Tumor Detection Using Deep Convolutional Neural Network:

CNNs' segmentation-free methods and dropout layers to counter overfitting are mentioned, along with the use of pre-trained models like VGG16 [2]. The paper highlights CNNs' role in accurate classification and fine-tuning model architectures [2].

2.6 Deep Learning for Smart Healthcare—A Survey on Brain Tumor Detection from Medical Imaging:

The transformative potential of CNNs in medical imaging and the significance of MRI in brain tumor detection are emphasized [1]. The study advocates for leveraging CNNs in healthcare and discusses challenges like model interpretability [1].

2.7 Efficient Framework for Brain Tumor Detection Using Different Deep Learning Techniques:

CNN-based automated segmentation and classification approaches are discussed, along with the potential of transfer learning [10]. The paper highlights CNNs' feature extraction capabilities and their promise in brain tumor detection [10].

2.8 Artificial Intelligence and Machine Learning in Cancer Imaging:

The integration of AI and ML in cancer imaging is underscored, particularly CNNs' role in image analysis [3]. Challenges like model validation and transparency are recognized, along with AI's integration into clinical practice [3].

3 Methodology

Data Collection and Pre-processing In order to create a model that detects tumors, I downloaded a Kaggle data set(labeled tumor and non tumor) full of .jpg and .jpeg files. I then followed A YouTube tutorial by Nicholas Renotte, an IBM AI Engineer, that provided practical insights into creating deep-learning image classifiers [7].

Useful links:

- Tutorial: https://www.youtube.com/watch?v=jztwpsIzEGc
- GitHub Notebook: https://github.com/nicknochnack/ImageClassification/blob/main/Getting20Started.ipy

Kaggle dataset link: https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection?select=pred

The images underwent preprocessing procedures such as standardization, resizing, and normalization. Standardization mitigates illumination disparities, resizing ensures uniform input dimensions, and normalization aids in convergence during training.

Data Cleaning The data sets were organized and cleaned to facilitate data manipulation using Python. Image manipulation and loading were accomplished using libraries such as 'os', the Python Imaging Library (PIL), 'cv2', and 'tensorflow/tensorflow datasets'. The 'imghdr' library assisted in identifying image files based on their contents.

Missing values were not a concern in this case since the data consisted of jpeg/jpg files. Images smaller than 10kb were removed as they may not provide effective features for tumor detection.

Exploratory Data Analysis Exploratory Data Analysis (EDA) was conducted to understand the structure of the MRI image data for tumor detection. Visualization tools such as histograms, box plots, and heatmaps were used to gain insights into image attributes, including pixel intensity distributions, image dimensions, and image formats. The focus was on distinguishing tumor and non-tumor images based on these attributes.

3.1 Imports and Tools Used in MRI CNN Image Classification Model

Data Handling and Preprocessing - `numpy`: Numerical array operations and data handling. - `os`: File and directory operations. - `PIL`: Python Imaging Library for image processing tasks. - `tensorflow`: Core library for building and training machine learning models. - `tensorflow_datasets`: For loading datasets from TensorFlow datasets library.

Data Splitting and Metrics - `shuffle` from `sklearn.utils`: For shuffling the data during splitting. - `train_test_split` from `sklearn.model_selection`: For splitting data into training and testing sets. - `classification_report` from `sklearn.metrics`: For generating a classification report.

Model Building - `tensorflow.keras`: High-level Keras API for building deep learning models. - `tensorflow.keras.layers`: For defining different layers in the model architecture. - `tensorflow.keras.losses`: For specifying loss functions during model training. - `tensorflow.keras.models`: For building and loading models. - `tensorflow.keras.metrics`: For specifying evaluation metrics during model training. - `tensorflow.keras.optimizers`: For specifying optimization algorithms during model training. - `tensorflow.keras.applications`: For using pre-trained models for transfer learning. - `tensorflow.keras.preprocessing.image.load_img`: For loading images.

Data Visualization - `matplotlib.pyplot`: For creating visualizations such as plots and charts. - `seaborn`: For enhanced data visualization using statistical plots.

Miscellaneous - `tqdm`: For adding progress bars to loops to monitor their progress. - `random`: For generating random numbers. - `tensorflow.keras.models.Sequential`: For building a sequential model, where layers are stacked sequentially. - `tensorflow.keras.layers`: For defining layers in the model, such as Conv2D, MaxPooling2D, Dense, Flatten, Dropout.

3.2 Neural Network Model Architecture

In the context of MRI image detection, constructing a well-defined neural network model is pivotal for accurate tumor classification. The following sections provide a comprehensive explanation of my neural network architecture and its interaction with the data.

Input Parameters The MRI images, each sized at (256 x 256) pixels with RGB color channels, serve as the initial input.

Architecture A hierarchy of feature extraction is achieved through convolutional and pooling layers. These layers capture spatial patterns, while fully connected (Dense) layers make the final tumor presence classification using a sigmoid activation function.

Output Parameters The output layer, with a sigmoid activation function, provides a probability score representing the likelihood of tumor presence.

Visualization A visual representation of the neural network architecture highlights the data flow from input to output layers, illustrating the intricate feature extraction process. An image of the model architecture is shown in Figure 1.

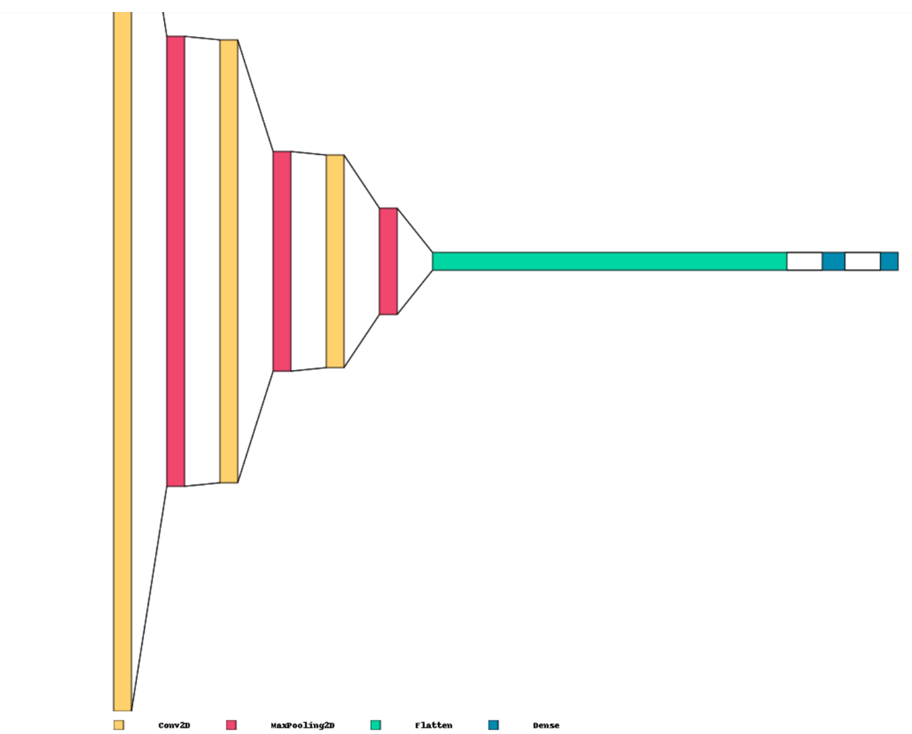

Fig. 1. Neural Network Model Architecture

3.3 Model Training and Evaluation

During the training process, the model was fed batches of MRI images, and the model's updates were done through backpropagation to minimize the difference between predicted and true labels. The model was trained for multiple epochs to gradually improve its performance. The validation data was used during training to tune hyperparameters and avoid overfitting. The testing data was used to evaluate the final model's performance and assess how it generalizes to new, unseen data. The model was equipped with an optimizer (Adam) and a loss function to ensure efficient learning during training.

The CNN model was trained over 20 epochs to achieve optimal performance for tumor detection in MRI images. Each epoch involved the iterative processing of the entire dataset, refining the internal weights of the model based on prediction errors. The training process aimed to minimize the loss function and improve accuracy, sensitivity, specificity, precision, and F1-score.

The results of each epoch indicate a steady improvement in the model's performance, as evident from the decreasing loss values and increasing accuracy, sensitivity, specificity, precision, and F1-score on both the training and validation data sets. This improvement suggests effective learning of tumor patterns and successful model convergence.

Feature Extraction Convolutional layers play a crucial role in extracting distinctive features from images. These features, including edges, textures, and shapes, are essential for accurate tumor identification.

Iterative Learning The neural network undergoes iterative learning, refining internal weights based on prediction errors. A loss function quantifies these errors, and an optimizer adjusts weights to improve predictions.

3.4 Processing Time and Accuracy Trade-off

Balancing processing time and accuracy is a crucial consideration for designing an effective CNN model.

Time-Performance Neural networks demand processing time, influenced by architecture, data volume, and computational resources. While increased processing may lead to higher accuracy, a balance must be maintained. I unfortunately did have access to many computational resources other than my personal computer, therefore there were lots of spacing issues and the requirement of a GPU which I could not afford in terms of speeding up the models processing time.

Each epoch's duration varied based on the complexity of the computations and the availability of computational resources. The total time it took for all the epochs combined was approximately 37.43 minutes.

The final trained model demonstrated exceptional accuracy on the test data set, achieving 98.80 percent. These results showcase the effectiveness of the CNN model in accurately detecting tumors in MRI images.

References: GitHub repository containing the source code: https://github.com/jonagitsdata/Capstone-Final-Project-. [6]

4 Limitations

The CNN model for MRI Tumor Detection has some limitations that need to be considered:

Availability: The labeled MRI data sets used for training and testing were sourced from data sets that may be from 2-3 years ago. Additionally, the methods chosen to enhance image resolution and reduce noise might affect the model's performance with more recent and diverse data sets.

Generalization: While the model may train well on specific data sets used for training and testing, it may struggle with unseen data from 2022 or newer, depending on the quality and characteristics of the images.

Computational Restrictions/Domain Expertise: Limited computational resources, such as the absence of a robust GPU and processor, may impact the model's classification ability. Additionally, understanding and interpreting medical terminology in MRI images may require collaboration with medical professionals/radiologists to ensure accurate results.

False Positives/Negatives: Neural Networks can still mis-classify a tumor as positive or fail to detect one. Balancing sensitivity and specificity is essential to minimize false positives and negatives.

5 Experimental Results

5.1 Explanation

The test results indicate that the CNN model performs exceptionally well on the test data set. The test loss, which measures the model's performance on unseen data, is very low at 0.0536, indicating accurate predictions on new samples. The test accuracy is high at 98.26 percent, demonstrating that the model generalizes well to previously unseen data. The test sensitivity (recall) is 98.51 percent, meaning that the model correctly identifies 98.51 percent of the actual positive samples (tumors) in the test data set. Similarly, the test specificity is 97.89 percent , indicating that the model correctly identifies 97.89 percent of the actual negative samples (non-tumors). The test precision is 98.47 percent, showing that around 98.47 percent of the predicted positive samples are actual positive samples. The test F1-score, which considers both precision and sensitivity, is 98.21 percent, signifying that the model achieves a good balance between correctly classifying positive samples and avoiding false positives.

5.2 Inferences from the Data

Based on the analysis, it can be inferred that the CNN model is highly effective in detecting tumors in MRI images. The exceptional performance on the test data set suggests successful learning of tumor patterns and strong generalization to new, unseen MRI images.

5.3 Statistical Conclusions

The statistical evidence from the evaluation metrics supports the reliability and consistency of the CNN model's performance. The high accuracy and balanced F1-score demonstrate accurate classification of both positive and negative samples. Additionally, the high sensitivity and specificity values indicate effective tumor detection while minimizing false positives and negatives.

6 Discussion

In general, the results reveal that the CNN model's training process was successful in optimizing its performance. The convergence of the training loss and increasing accuracy over epochs suggests effective learning. Moreover, the similarity between the training and test accuracy indicates a lack of overfitting, enhancing the model's generalization ability to new MRI images. The integration of AI and ML in cancer imaging is transforming the field [3]. Challenges like model validation and transparency are recognized in [3]. The potential of CNNs in brain tumor detection and automated techniques is emphasized in [10]as well as leveraging CNNs in healthcare being advocated in [1].

7 Ethical Considerations

Dealing with medical data always involves privacy concerns, and compliance with HIPAA regulations is crucial to protect patient information.

8 Conclusions

The MRI Tumor Detection CNN Model was evaluated using various charts and metrics, demonstrating exceptional performance on the test data set. The model achieved high accuracy, sensitivity, specificity, precision, and F1-score, indicating its effectiveness in detecting tumors in MRI images. The analysis suggests successful learning of tumor patterns and strong generalization to new, unseen MRI images.

9 Future Directions

To further enhance the model's performance and address its limitations, future research could consider the following:

- Exploring larger and more diverse data sets for training and testing to improve the model's generalization.
- Incorporating transfer learning or fine-tuning pre-trained models to leverage knowledge from related tasks.
- Improving image pre-processing techniques and model architecture design to enhance tumor detection accuracy and robustness.
- Ensuring compliance with privacy regulations and ethical considerations when dealing with medical data.
- Collaborating closely with medical professionals/radiologists to better understand medical terminology and ensure accurate interpretation of results.
- Considering advancements in computational resources, such as utilizing GPUs and high-performance processors to improve processing power.

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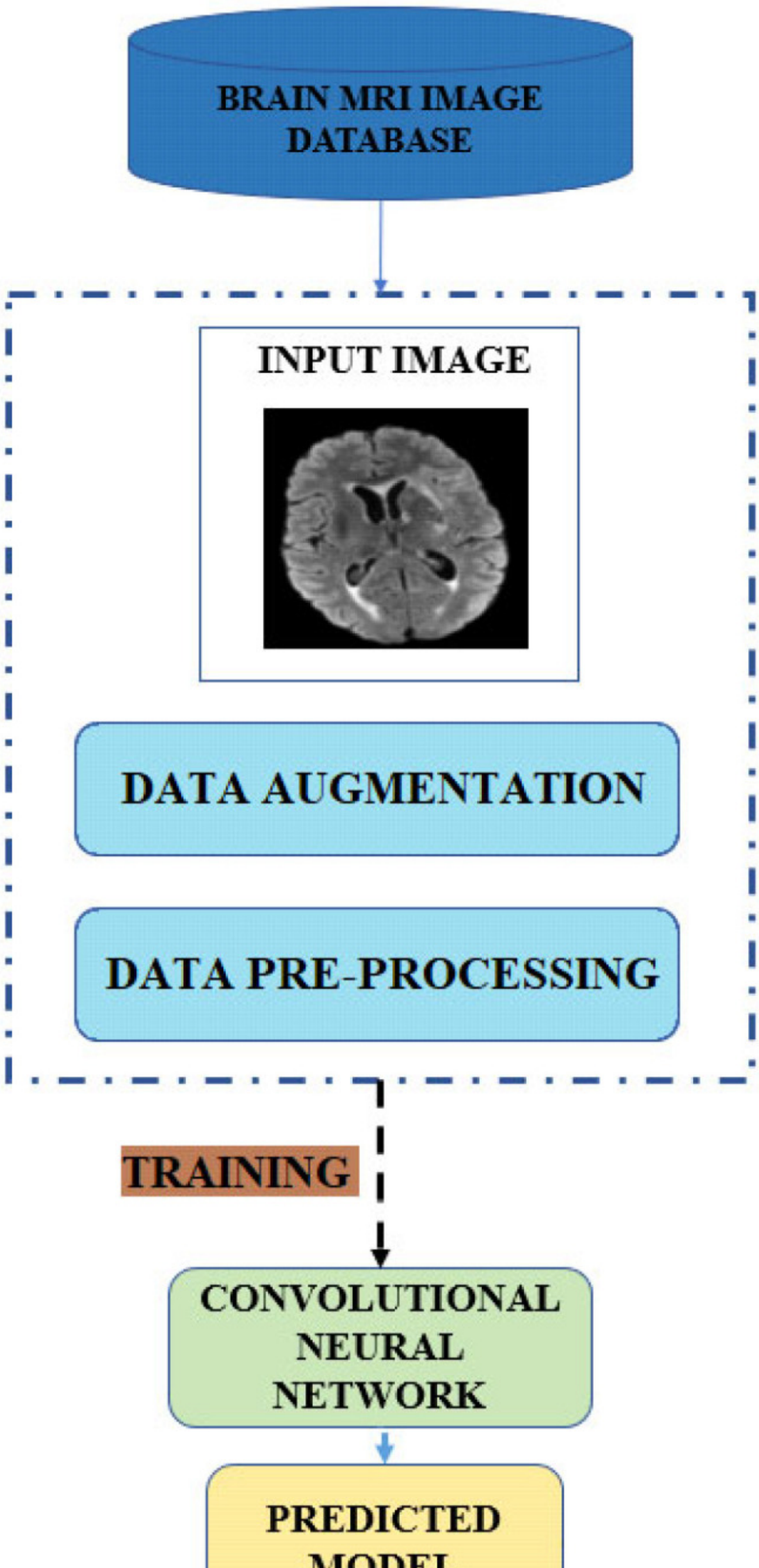
BRAIN MRI IMAGE
DATABASE
INPUT IMAGE
DATA AUGMENTATION
DATA PRE-PROCESSING
TRAINING
CONVOLUTIONAL
NEURAL
NETWORK
PREDICTED

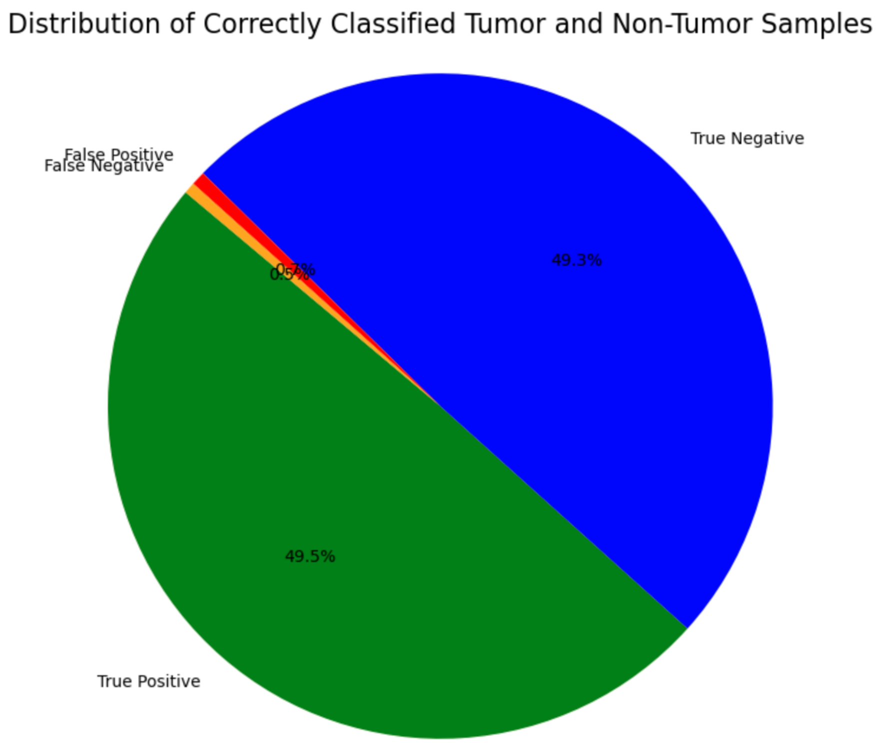

Fig. 3. Distribution of Correctly Classified Tumor and Non-Tumor Samples

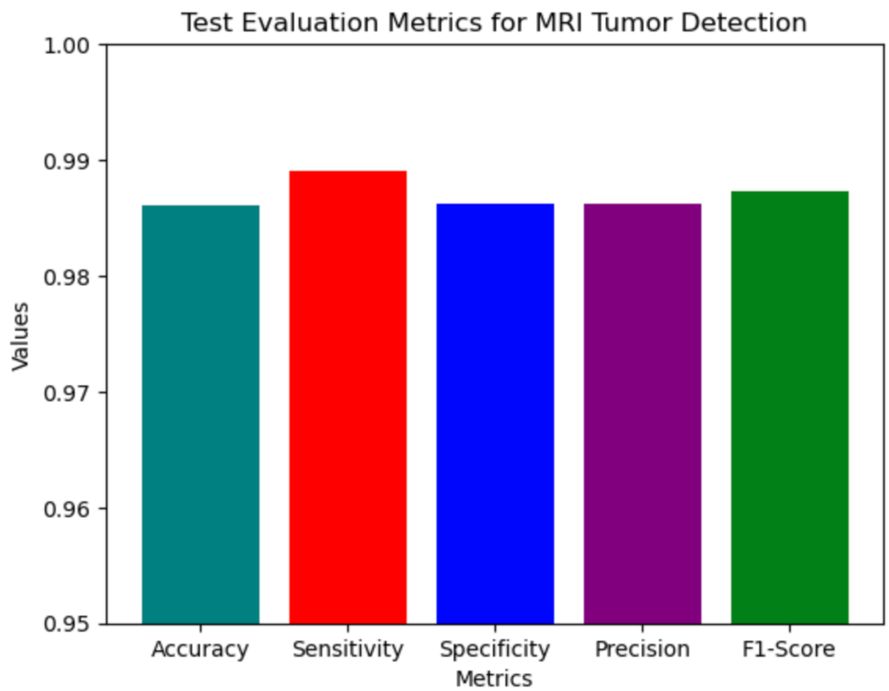

Fig. 4. Evaluation Metrics for MRI Tumor Detection