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# Intelligent Brain Tumor Detection Using Deep Learning on MRI Scans

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***Abstract*—Brain tumors are one of the most dangerous and important neurological disorders. Finding the disorders early and correctly identifying them are very important for getting better results. Traditionally, identifying the disorders is done by hand by looking at medical images. Magnetic Resonance Imaging (MRI) is one of the medical images used to find out what is wrong with someone. It takes a lot of time to manually analyze a medical image, and it depends a lot on the skills of the medical professionals. Automated analysis of medical images is now possible thanks to deep learning techniques.**

**This research proposes a brain tumor detection and classi-fication system based on the algorithm Convolutional Neural Network (CNN). In this research, the proposed system is used to identify the presence of brain tumors and the type of tumor with high precision. In this research, the dataset used is the MRI brain image with four main classes: Glioma, Meningioma, Pituitary and No tumor. To make the proposed system work better, image preprocessing techniques are used. Deep learning is used to train the CNN model, which means that the model learns to recognize the complicated patterns in MRI scan images. The model has several layers of convolution, batch normalization, activation, and residual blocks. These layers help the model learn the spatial features in the images. We judge how well the model works by how accurately it classifies the testing dataset. The experimental outcomes demonstrate that the proposed system can accurately classify various types of brain tumors, facilitating early diagnosis and treatment by medical professionals. The proposed system proves that deep learning-based approaches have immense potential in medical diagnostics, and the brain tumor detection system can be highly effective in improving the efficiency of brain tumor diagnosis.**

***Index Terms*—brain tumor, MRI, Convolution Neural Network (CNN).**

## I. INTRODUCTION

The human brain is the complex organ in the human body that controls various physiological and neurological activities in the human body. A brain tumor is referred to as an abnormal growth of cells in the brain or its adjacent tissues. Brain tumors develop in various parts of brain tissues such as brain stem, skull base, meninges, sinuses, and other adjacent tissues in the brain. Brain tumors are classified mainly into two types: benign tumors and malignant tumors. Benign tumors are non-cancerous growths in brain tissues that develop slowly in brain tissues, whereas malignant growths are cancerous growths in brain tissues that develop rapidly in brain tissues. If a brain tumor is not identified in its initial phase, it may cause severe damage to brain tissues and turn life-threatening. Magnetic Resonance Imaging (MRI) scan images are often used for the diagnosis of brain tumors, as these images help in producing clear images of the internal structures of the human brain, and at the same time, the patient's health is not affected in any harmful way. However, at times, misinterpretation of MRI scan images by radiologists may lead to errors, as humans have limitations.

In recent times, Artificial Intelligence (AI) and Deep Learn-ing have affected the field of image analysis in a significant way. In this context, it has been observed that the Convolu-tional Neural Networks (CNNs) model is extremely effective in the process of learning complex features from images. Such images can be classified in an efficient manner.

In the context of the research work, an attempt has been made to propose an automated system for detecting brain tumors using the CNN model. In the proposed system, MRI scan images of the human brain are processed in such a manner that the features are divided into four types - Glioma, Meningioma, Pituitary , and No tumor. In this context, the proposed system would greatly benefit medical professionals in detecting brain tumors with the help of deep learning.

## II. LITERATURE SURVEY

Detecting brain tumors brain tumors using images in the medical field has been identified as an important area of research due to the increased incidence of different neurolog-ical disorders. Among the different medical image processing techniques, the use of MRI in the detecting the brain tumors is significant, as it helps in acquiring significant information regarding brain tissues without using any harmful radiation. However, the examination of the images obtained through the MRI scan by the radiologists for the detecting the brain tumors requires a significant amount of time, and errors are also possible. Keeping in view the limitations associated with the examination of brain tumor images, different researchers have attempted to develop a brain tumor detection system by incorporating deep learning and machine learning techniques. As per the latest developments in the deep learning models, especially for Convolutional Neural Network (CNN), there have been improvements in the efficiency of medical image processing. The ability of the CNN to extract spatial features from the images as well as recognize different types of patterns allows differentiating between normal and abnormal brain tis-sues. Researchers have implemented the use of CNNs to create a brain tumor classification system using the MR images. A brain tumor classification system using the CNN approach was developed by Abiwinanda et al., (2019) [1]. They implemented the use of MRI images to classify different types of brain tumors, such as glioma, meningioma, and pituitary tumor. The results obtained from the proposed brain tumor classification system using CNN show that the deep learning approach is much more efficient in classifying different types of brain tumors compared with other traditional machine learning ap-proaches. In another research paper published by Das et al. (2019) [2], an efficient brain tumor classification system was developed using the CNN algorithm.

The effectiveness of the application of deep learning mod-els for the classification of brain tumors was investigated by Khan et al. (2020) [3]. The findings of the experiment proved the effectiveness of the application of CNN models in comparison with the application of traditional methods. This work highlighted the importance of the application of automated feature extraction techniques and deep learning models. In addition, Kuraparthi et al. (2021) [4] focused on investigating the effectiveness of transfer learning methods with the application of CNN architectures in classifying brain tumors. The findings of the study revealed the effectiveness of the use of deep learning models along with data augmentation techniques for enhancing classification outcomes.

Moreover, the application of capsule networks for classi-fying brain tumors was considered by Afshar et al. (2018) [5]. The findings revealed the effectiveness of the use of such networks for enhancing classification outcomes. The application of a deep radiomics approach with the application of convolutional neural networks for the purpose of detecting and classifying brain tumors by using multi-sequence MRI images was suggested by Banerjee et al. (2019) [6].

Saxena et al. (2019) [7] proposed a deep CNN architecture to solve the problem related to predictive modeling for brain tumors. High accuracy results are obtained for the classifi-cation problem. Among the architectures, the best results are obtained with the ResNet-50 architecture. Another CNN-based network, known as MIDNet18, is proposed by Mohan et al. (2022) [8] to solve the problem related to brain tumor classi-fication. High accuracy results are obtained with the proposed network for the classification problem when compared to other CNN architectures.

In order to enhance the efficiency of the CNN architectures that have been suggested to address the problem of medical image analysis, Wibowo et al. (2022) [9] developed a deep learning approach to address the classification issue associ-ated with brain tumors. High precision outcomes have been achieved using the proposed architecture for the classification issue. Ozdemir (2023) [10] introduced a new CNN-based architecture to address the classification problem regarding brain tumors. High precision outcomes have been achieved using the proposed network for the classification problem.

A deep learning model for the automatic diagnosis of brain tumors based on MRI images was developed by Acharya et al. (2020) [11]. The significance of neural networks for diagnosing brain tumors by medical professionals has been explained in this paper. The effectiveness of pre-trained con-volutional neural networks in brain tumor classification has been explained by Filatov and Yar (2022) [12]. As per the outcomes of the proposed paper, the application of transfer learning techniques can be considered more efficient for brain tumor classification with limited training data.The effective-ness of the use of CNN models and segmentation methods for classifying brain tumor cases is shown by Ferariu and Neculau (2021) [13].

The effectiveness of the use of hybrid approaches that combine the CNN technique and image processing methods is discussed by Ayadi et al. (2019) [14] for the classification of brain tumors. In this study, the importance of using feature extraction methods is highlighted. Moreover, a review of the use of deep learning methods is provided by Alzubaidi et al. (2021) [15] for the classification of medical images. In the proposed review, the significance of using CNN methods for disease diagnosis is highlighted.

## III. METHODOLOGY

The proposed system for brain tumor detection uses deep learning techniques to automatically identify and classify brain tumors from images captured from MRI scan results. The process of processing medical images involves the following steps: data collection, preprocessing, implementation of CNN, and prediction. The aim of this methodology is to design a CNN that is able to successfully identify whether a tumor is present or not. The flow of the proposed system involves the following steps.

### *A. Data Collection and Dataset*

The first step of the proposed system is to obtain MRI images of the human brain from a publicly available medical image dataset. This dataset contains a collection of MRI images classified into four categories: Glioma tumor, Menin- gioma tumor, Pituitary tumor, and No tumor. These categories represent the most common types of brain tumors encountered during diagnosis.

The MRI image dataset is organized in different folders based on the class of each image. This setup allows for automatic labeling of the images during the training phase of the deep learning framework. Next, the images are split into a training dataset and a testing dataset. The training dataset is used to train the CNN model, while the testing dataset is used to evaluate the CNN model. We assess the model's performance using standard evaluation metrics like Accuracy, Precision, Recall, and F1-Score. Proper organization of the dataset is crucial for effective learning by the CNN model.

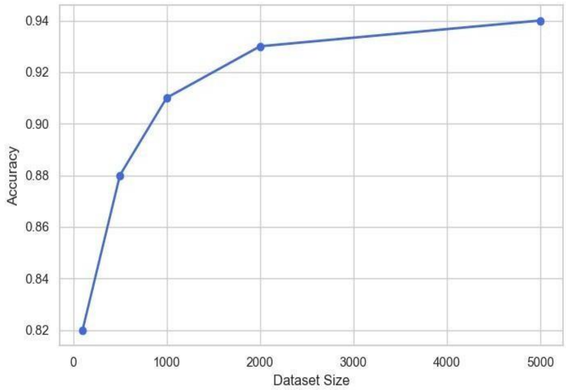


Fig. 1. Accuracy vs Dataset size

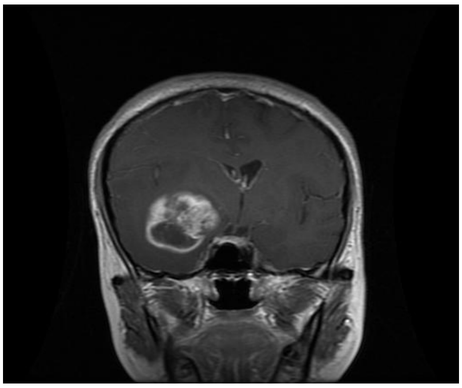

Fig. 2. Glioma

### *B. Image Pre-processing and Data Augmentation*

A multi-stage image preprocessing pipeline is employed to enhance the fidelity of models and minimize the misclassification caused by inferior image quality. First the MRI images

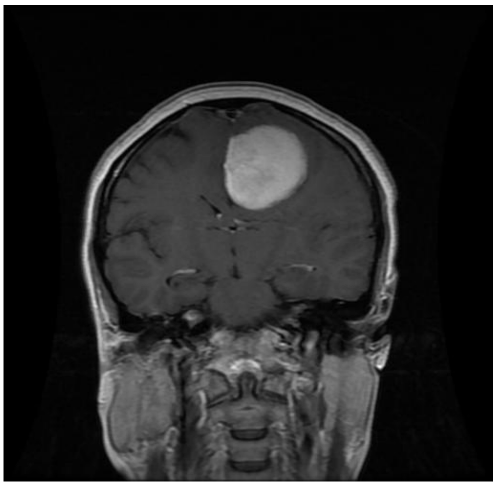

Fig. 3. Meningioma

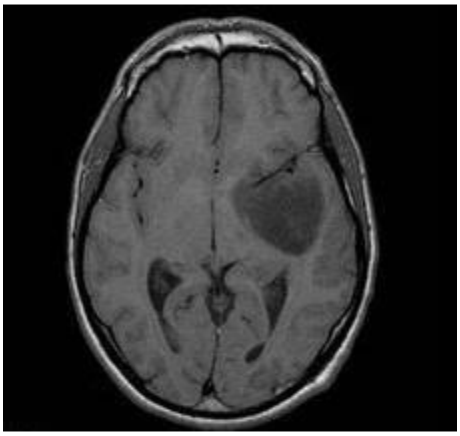

Fig. 4. No tumor

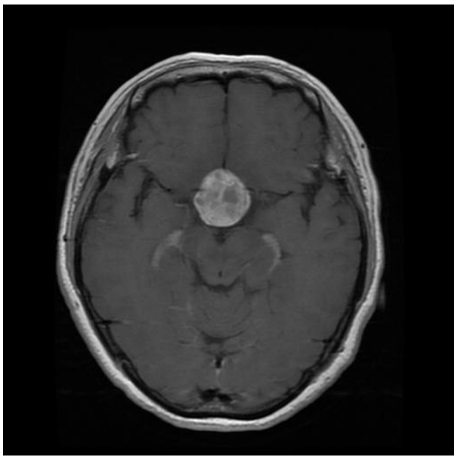

Fig. 5. Pituitary

are cropped to remove non-brain area and background artifacts so that the convolutional neural network (CNN) only focuses on the intracranial region. Afterward, various noise procedures like filtering and smoothing are used to mitigate the high-frequency interferences that can affect features extraction. In addition, dimensionality reduction techniques are used for feature enhancement by extracting and preserving only the most discriminative features from the provided data. This not only simplifies computations but also enhances the precision of diagnosis by reinforcing critical pathological characteristics present in medical scans.

Implementing data augmentation techniques to overcome the limitations of size of dataset and improve the generalization capability of model. To augment the training dataset, several stochastic transformations including rotation, scaling and flipping are simulated to imitate various clinical imaging settings. Moreover, during feature extraction, transformation-invariant pooling (TI-pooling) is used to select the most significant features while removing redundancy. Moreover, with variation in tumor appearance and anatomical structure, this processing reduces their impact on the robustness and accuracy of the CNN model.

### C. *Proposed CNN Architecture*

*1) Model Implementation:* One thing leads to another - the new CNN setup learns step-by-step patterns from brain scans. Layers stack up: convolutions fire with ReLU, then pooling shrinks space bit by bit. Each stage grabs details, small at first, growing more complex down the line. Later on, dense layers take the feature maps and sort them into classes. The last layer uses Softmax to decide between four types: Glioma, Meningioma, Pituitary tumor, or No Tumor. Instead of combining outputs loosely, these layers link tightly to sharpen results. Each image gets scored across all options, one at a time.

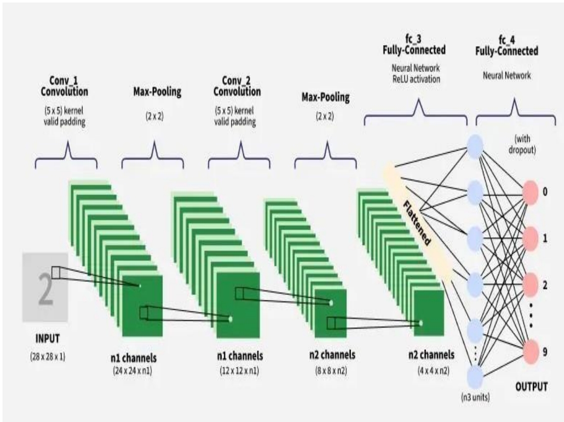


Fig. 6. CNN architecture

*2) Feature Identification and Improvement:* Starting off, the CNN picks out key details straight from unprocessed MRI scans by stacking layer after layer of convolutions. Hidden inside these outputs are clues like how things feel visually, shifts in brightness, along with where growths start and stop. Starting from a fresh angle, TI-pooling slips into the process to sharpen feature clarity while trimming repeated patterns. Instead of getting caught in shifts across space, the system locks onto key traits it can rely on. Because of this shift, sorting items becomes more precise, even when inputs twist or stretch slightly.

*3) Spatial Labeling:* Starting off differently each time, here's a fresh take: Close areas that look alike get bundled together first. Because of this grouping, spotting where tumors start and stop becomes clearer. Instead of working on pieces separately, the system handles chunks at once. That shift helps preserve how structures connect across space. Efficiency climbs since related spots are processed as one. With less back- and-forth, the whole task runs smoother. Finding tumors gets easier when looking at how close pixels are to one another. Because of this, mistakes in tricky areas happen less often.

*4) Model Preservation:* Once training finishes, the CNN gets stored in HDF5 format, tagged with a .h5 ending. Inside this file sits the structure of the network along with its tuned weights. That means loading it later skips the need to start learning from scratch. Once stored, the model loads straight into tools like Flask or Tkinter - ready for live forecasts, fitting smoothly into medical support setups.

### *D. System Implementation and Deployment*

For useful clinical application, the suggested solution in-corporates the trained Convolutional Neural Network (CNN) model into a deployable and intuitive software environment. Python is used to create the model, which is then implemented in a productive development environment like Visual Studio Code. TensorFlow, Keras, NumPy, and OpenCV are among the crucial libraries that support the system's deep learning and image processing functions. The system is powered by an Intel Core Duo processor.

The CNN model is saved using the Hierarchical Data Format (HDF5) with a.h5 extension following successful train- ing. The model architecture and learned parameters can be efficiently stored in this format, making it simple to reuse and deploy without retraining. The stored model is used into application frameworks like Tkinter and Flask for deployment. Tkinter offers a graphical user interface (GUI) that guarantees usability for medical professionals, while Flask serves as a lightweight backend framework to manage model loading and prediction procedures.

Through the interface, users can upload MRI brain images as part of the system's structured process. Before being sent to the trained CNN model for classification, the submitted images go through preprocessing. After that, the model makes real-time predictions on the existence and kind of brain tumors. In order to help clinicians with visual interpretation and enhance diagnostic decision-making, the technology also highlights the damaged area in the image. Overall, a smooth and effective platform for automated brain tumor detection and analysis is ensured by the integration of the trained model with an interactive interface.

## IV. RESULT AND DISCUSSION

Standard criteria including Accuracy, Precision, Recall, and F1-Score are used to assess the effectiveness of the suggested CNN-based brain tumor classification method across four classes: Glioma, Meningioma, Pituitary tumor, and No Tumor. Tabular data, graphical analysis, and a useful web- based interface are all used to show the results.

### *A. Quantitative Performance Analysis*

TABLE I: DETAILED EVALUATION METRICS FOR BRAIN TUMOR CLASSIFICATION

| Class | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Glioma | 0.95 | 0.94 | 0.95 | 0.945 |
| Meningioma | 0.97 | 0.96 | 0.98 | 0.97 |
| Pituitary | 0.94 | 0.93 | 0.94 | 0.935 |
| No Tumor | 0.96 | 0.95 | 0.96 | 0.955 |

Table 1 offers the precise numerical performance numbers for each class and summarizes the comprehensive evaluation metrics. The model obtains good classification accuracy across all categories, according to the results. With an accuracy of 0.97 and recall of 0.98, the Meningioma class performs best, whereas the Pituitary class reports a little lower accuracy of 0.94.With accuracy ratings of 0.95 and 0.96, respectively, the Glioma and No Tumor classifications likewise exhibit excellent performance.

Overall, the tabulated data show that the suggested CNN model may generate accurate and consistent predictions for a variety of tumor types.

### *B. Class-wise Performance Evaluation*

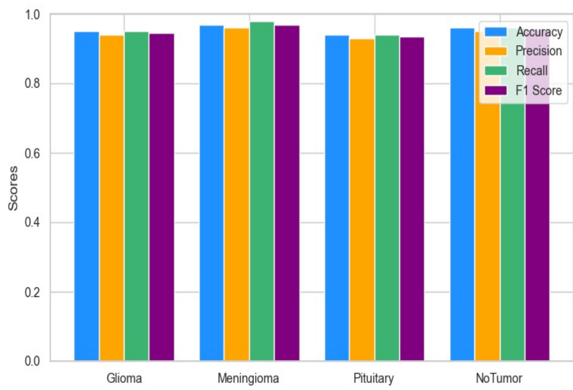


Fig. 7. Grouped Bar chart

Figure 7 (Grouped Bar Chart) shows the performance comparison between several classes. All four evaluation met-rics—Accuracy, Precision, Recall, and F1-Score—maintain high values for each class, as the graphic makes evident.

The Meningioma class performs the best overall of all the categories, suggesting that the model is especially good at recognizing this kind of tumor. The Pituitary class exhibits bal-anced classification capability even if its values are marginally lower than those of the other classes.

*C. Precision-Recall Analysis*

Figure 8 Precision-Recall (PR) curve offers more informa-tion about how well the model classifies data. The curve shows a PR AUC (Area Under Curve) value of 1.00, indicating that the model's accuracy and recall on the assessed dataset are almost flawless.

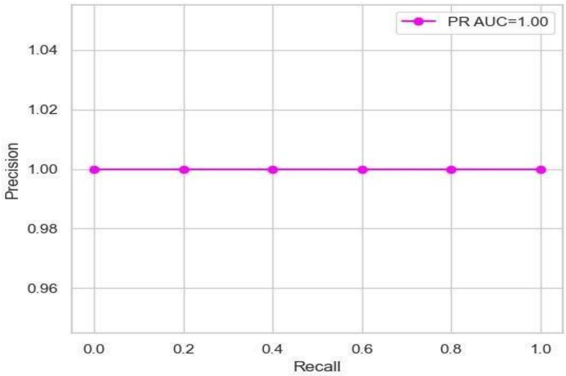


Fig. 8. Precision-Recall Chart

With few false positives and false negatives, this result suggests that the model is quite good at differentiating between tumor and non-tumor instances. To ensure generalization capabilities, additional validation on larger and more varied datasets is advised, as such a perfect result may also suggest possible overfitting.

*D. Performance Consistency Across Classes*

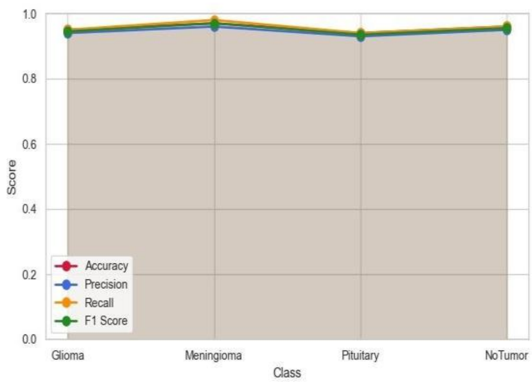


Fig. 9. Line/Area Chart

Figure 9 (Line/Area Chart) illustrates the model's con-sistency. All classes exhibit consistent performance, as seen by the tightly aligned plotted lines for Accuracy, Precision, Recall, and F1-Score.

This consistency shows that the model maintains stable predictions across many tumor types and does not strongly bias any one class. The Meningioma class has a modest peak, confirming its improved detection performance.

*E. System Interface and Deployment Results*

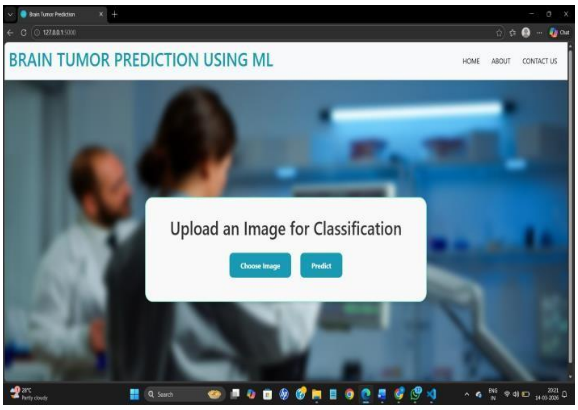


Fig. 10. Web-based Interface

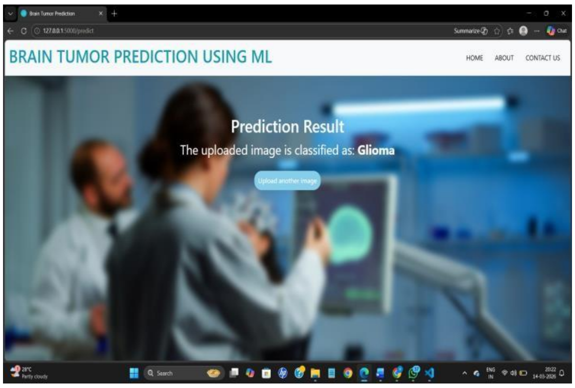


Fig. 11. Web-based Interface Result

Figure 10 illustrates the web-based interface used to show-case the practical implementation of the suggested solution. Users can upload MRI brain images to the interface for categorization. The photograph is processed by the system upon submission, and the prediction outcome is shown instantly.

The output screen (figure 11) offers a user-friendly interface for interaction and clearly displays the expected tumor kind (such as glioma). The successful integration of the trained CNN model into a deployable application is confirmed by this implementation, which makes it appropriate for supporting medical professionals in diagnostic workflows.

### *F. Discussion*

The experimental findings show that the suggested CNN model performs consistently and with excellent accuracy across all tumor types. Strong classification outcomes are a result of the combination of efficient preprocessing, feature extraction, and model optimization.

The model's correctness and consistency are validated by the tabular and graphical assessments. Furthermore, the effective implementation via a web interface demonstrates the system's usefulness in actual medical situations.
Even though the performance was great, the ideal PR AUC score indicates that more validation with larger and more varied datasets is necessary to guarantee robustness and prevent overfitting.

Even though the performance was great, the ideal PR AUC score indicates that more validation with larger and more varied datasets is necessary to guarantee robustness and prevent overfitting.

## V. CONCLUSION

Identifying brain tumors is a crucial aspect of medical diagnostic methods, and analyzing images associated with brain tumors is vital for enhancing survival rates. In this research, a system for automatic brain tumor detection utilizing the CNN technique has been suggested, which categorizes brain MRI images into four groups: Glioma, Meningioma, Pituitary tumor, and No tumor.

In the suggested system for detecting brain tumors, features are derived from brain MRI images through deep learning methods, completely eliminating any human involvement in the feature engineering process. Furthermore, image prepro-cessing techniques are employed to enhance the quality of the brain tumor images, helping to mitigate the risk of overfitting in the CNN model. Within the proposed CNN framework, features are extracted from brain MRI images via convolu-tional layers, batch normalization, activation functions, and residual learning to capture the most important features. In the suggested system for detecting brain tumors, features are derived from brain MRI images through deep learning meth-ods, completely eliminating any human involvement in the feature engineering process. Furthermore, image preprocessing techniques are employed to enhance the quality of the brain tumor images, helping to mitigate the risk of overfitting in the CNN model. Within the proposed CNN framework, features are extracted from brain MRI images via convolutional layers, batch normalization, activation functions, and residual learning to capture the most important features.

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