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Brain Tumor Detection Using Machine and Deep Learning

Rachit Kumar

Maharaja Agrasen Institute of Technology Delhi, India.

ABSTRACT :

Uncontrolled growth of cells in the brain results in the development of brain tumors. When a tumor increases in size by more than fifty percent, the likelihood of recovery for the patient significantly decreases. As the tumor grows larger, it elevates intracranial pressure, potentially leading to serious complications such as brain herniation. Therefore, prompt diagnosis and treatment are crucial to mitigate these complications and slow down the progression of the tumor. This underscores the necessity for rapid and precise diagnosis of brain tumors. MRI imaging plays a vital role in the assessment, identification, and treatment planning for brain tumors. Gaining insight into the growth history of a brain tumor is crucial information for medical professionals. MRI scans provide substantial benefits in recognizing human soft tissues. MRI scans can be classified into three categories: Brain Tumor, Brain Glioma. The dataset was sourced from Kaggle and utilized for testing and validation purposes. To achieve swift and reliable classification outcomes from MRI scans, deep learning is among the most efficient methods available.

The application of deep learning methodologies has proven to improve the accuracy of the early detection of human diseases. Brain MRIs often struggle to reliably show whether tumors are present or absent. This research proposes a hybrid deep learning strategy that combines Convolutional Neural Networks (CNNs) for feature extraction with machine learning classifiers like Support Vector Machines (SVM) and Random Forest to improve brain tumor detection in MRI scans. Additionally, the combination of both handcrafted and automated features—including texture, shape, and intensity—has resulted in better detection outcomes. Our study presents deep learning frameworks aimed at detecting, segmenting, and classifying tumors from MRI scans to tackle this significant challenge.

Keywords: Brain tumor detection, MRI imaging, Convolutional Neural Networks (CNNs), Hybrid deep learning, Feature extraction, Support Vector Machines (SVM), Random Forest, Brain glioma classification, Tumor segmentation, Intracranial pressure,Texture features

Introduction

The brain is a fundamental component of the Central Nervous System (CNS), overseeing all physiological and cognitive functions such as thinking, emotions, sensation, movement, sight, and breathing. Brain tumors arise from uncontrolled cell growth within the brain or other regions of the CNS, leading to impairment. The malignancy of a tumor is determined by the speed at which the cells proliferate.

Non-malignant tumors, which are benign and not cancerous, develop slowly and do not metastasize to surrounding tissues. In contrast, malignant brain tumors are cancerous, often proliferating and invading adjacent healthy structures. Brain tumors are becoming an increasing health issue in India, with an estimated 40,000 to 50,000 new cases reported annually. Approximately 20% of these cases occur in children. The incidence of central nervous system tumors in India varies from 5 to 10 cases per 100,000 individuals, influenced by genetics, environmental factors, and lifestyle choices. Brain tumors account for about 1.6% of all cancer diagnoses in the country. Males are more commonly affected than females, with a male-to-female ratio of approximately 2.1:1. The highest incidence is seen in individuals aged 31 to 40 years, who represent nearly 23% of total cases.

Among adults, meningiomas (28%) and glioblastomas (25%) are the most frequently diagnosed types of brain tumors. In pediatric patients, gliomas are the most common, making up around 46.3% of cases. Recent studies show that brain tumors, including meningiomas, gliomas, and other malignancies, exhibit significant variability within classes, complicating accurate identification. This has created an increasing demand for advanced computational methods to improve diagnostic precision and assist radiologists in making well-informed choices.

Deep learning and machine learning are emerging technologies that have significantly progressed various sectors. One critical area of impact is medical image processing, where extensive research is actively being pursued. A primary focus within this domain is the automation of brain tumor segmentation and classification, which enhances both the accuracy and efficiency of diagnosis and treatment. Our research employs the Kaggle Brain Tumor MRI Dataset, a detailed collection of 7,023 MRI images categorized into three specific brain tumor types: glioma, meningioma, and pituitary.

Literature Review: AI Recommendation Algorithms in Education Settings

Recent progress in machine learning and deep learning has transformed the detection of brain tumors, emphasizing automated feature extraction and classification through MRI scans. Abd-Ellah Mohammed K et al. (2018), a distinguished researcher from Al-Azhar university, performed a comprehensive review of the techniques employed in the diagnosis of brain MRI scans, highlighting the advantages and disadvantages of both conventional machine learning and deep learning methods.

Badža et al (2020). performed a study to classify glioma, meningioma, and pituitary tumors using a convolutional neural network (CNN). Their network design included an input layer, two "A" blocks, two "B" blocks, a classification block, and an output layer, totaling 22 layers. They assessed the model's effectiveness through k-fold cross-validation, reaching a peak accuracy of 96.56% with tenfold cross-validation. The dataset utilized in their research comprised 3,064 T1-weighted contrast-enhanced MRI images gathered from Nanfang Hospital, General Hospital, and Tianjin Medical University in China.

In 2018, Phaye S. S., Sikka A., Dhall A., and Bathula D. presented two innovative models, DCNet (Capsule Algorithm Networks) and DCNet++ (Diverse Capsule Networks), to address the problem of classifying brain tumors. DCNet was crafted using a deep convolutional network aimed at effectively capturing distinctive and relevant features, while DCNet++ advanced this approach by integrating a hierarchical framework, improving its capacity to process complex data. The researchers employed a dataset consisting of 3,064 MRI images from 233 patients diagnosed with three different brain tumor types, intentionally leaving out healthy cases to concentrate exclusively on tumor classification. To boost the performance of DCNet, they streamlined the model by cutting down the original eight convolutional layers to four, each featuring 16 kernels, and trained it through eightfold cross- validation. The outcomes were remarkable, with DCNet achieving an accuracy of 93.04%. DCNet++ surpassed this by attaining an even greater accuracy of 95.03%, highlighting the effectiveness of these models in delivering accurate and dependable tumor classification.

Several techniques for identifying brain tumors through MRI images were explored by Somasundaram S. and Gobinath R. et al (2018), emphasizing the application of 3D Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and multi-class SVMs to enhance tumor segmentation. Their study underscored the efficacy of deep learning methods, especially CNNs, in the realm of medical image processing for brain tumor detection. In comparison to conventional machine learning classifiers, the deep learning models demonstrated superior performance in both classification and segmentation tasks.

G. Kumar, P. Kumar, and D. Kumar (2021) examined a range of machine learning and deep learning methods for detecting and segmenting brain tumors, such as support vector machines (SVMs), k-nearest neighbors, multi-layer perceptrons, Naïve Bayes, and random forest algorithms. Among these techniques, the traditional SVMs exhibited the highest classification accuracy of 92.4%. Furthermore, the authors introduced a custom CNN architecture consisting of five layers for detecting brain tumors in MRI scans, which showed an impressive accuracy of 97.2%.

Methodology

Research Design

The research framework emphasizes the application of machine learning and deep learning methods to improve the precision of brain tumor detection. A collection of brain MRI scans is processed, which includes normalization and augmentation, to guarantee the robustness of the model. Convolutional neural networks (CNNs) are utilized for extracting features and classification purposes, and performance metrics such as accuracy, sensitivity, and specificity are assessed. Cross-validation techniques are implemented to mitigate overfitting, and a comparison with conventional methods is performed to demonstrate enhancements in the efficiency of tumor detection.

Tools Used

Several tools were used during the devlopment of the project. Some of them are listed below :

- **Python** : Used for overall development, including data manipulation and model training with libraries like NumPy, Pandas, and Matplotlib.
- **TensorFlow/Keras** : Built and trained CNN models for brain tumor classification from MRI scans.
- **React.js/HTML/CSS** : Designed a user-friendly frontend interface for uploading MRI scans and displaying results.
- **OpenCV :** Preprocessed images (resizing, noise reduction, augmentation) to improve model performance.

Dataset Description

The Brain Tumor MRI Dataset comprises 7,023 MRI images divided into three categories of tumors: gliomas, which are known for their ability to infiltrate the brain or spinal cord; meningiomas, which develop in the protective membranes surrounding the brain and spinal cord; and pituitary tumors, which can affect hormone levels as well as neurological functions. The dataset is organized with distinct folders for each type of tumor, making processing and management easier. The grayscale images vary in resolution, size, and contrast, reflecting the diverse characteristics found in real-world MRI scans, and are extensively used for training deep learning models focused on detecting, classifying, and segmenting brain tumors. Additionally, the dataset features scans of healthy brains without tumors, which aids in multi-class classification (differentiating between various tumor types), thereby boosting productivity.

Data Processing

After data acquisition, the next step is Data Preprocessing, which prepares the images for analysis. This stage includes improving image quality through various methods like histogram equalization, Gaussian or median filtering, and adjusting contrast, among other techniques. Since the dimensions of each image in the dataset differ, they are resized to a standardized size. Then, every image is converted into a two-dimensional array. Following this, each image is normalized to ensure that all array element values fall within the range of [0,1].

Model Training

This stage involves training the chosen models using the training dataset. In deep learning models, the parameters of the model are modified through optimization techniques like backpropagation. Specifically, hyperparameters such as the learning rate and batch size are fine-tuned to minimize overfitting and achieve better model performance by making use of the validation set.

Model Evaluation

In the end, Model Evaluation was conducted to gauge how well the trained Model performed on the test dataset. We used metrics such as accuracy, precision, recall, F1-score, and ROC-AUC [2]. The F1-score offers a balance between precision and recall. The ROC-AUC score evaluates the model's ability to clearly distinguish between different tumor types.

Algortihms Used

Algorithms Used

Convolution Neural Networks (CNNs) : A convolutional neural network (CNN) functions using a multi-layer structure. It analyzes pixel matrices in images and automatically recognizes unique features. The core of deep neural networks is found in the convolution layer. This model was created by testing different methods to fine-tune the hyper-parameters. The best configuration is determined by conducting a random search through various combinations of the model's hyper-parameters while using Keras Tuner. The convolution layer improves feature representation by combining the functions of convolution, activation, and pooling to extract low-dimensional features from high-dimensional inputs. CNNs enable the extraction of features from intricate, high-dimensional data. In manual feature extraction, the focus is on identifying and emphasizing key attributes of the tumor, such as its shape, size, texture (using the Gray Level Co-occurrence Matrix, GLCM), and intensity. In contrast, CNNs automatically extract hierarchical features from images without requiring any manual input, while deep learning models such as Convolutional Neural Networks (CNNs) can also support automated feature extraction. Feature extraction in Convolutional Neural Networks (CNNs) occurs in a hierarchical manner. The initial layers identify fundamental visual elements like edges and corners, the mid-level layers recognize patterns such as textures or areas, and the deeper layers understand high-level semantic features related to the tumor's characteristics. This automated hierarchical approach to feature extraction distinguishes CNNs from conventional manual techniques. In the manual method, expert knowledge is utilized to pinpoint crucial features such as the tumor's shape, size, texture (which can be quantified using techniques like the Gray Level Co-occurrence Matrix, GLCM), and intensity levels. Although these manual techniques can be effective, they are often labor-intensive and susceptible to personal biases. In contrast, CNNs simplify this procedure by learning to derive important features directly from unprocessed input images, thereby removing the need for human involvement and enhancing the system's flexibility in adapting to new datasets.

Machine Learning Classifiers : Machine learning classifiers greatly improve feature extraction and classification by utilizing their capability to pinpoint the most important features within datasets, thereby enhancing overall prediction accuracy. While convolutional neural networks (CNNs) independently derive hierarchical features from raw data, machine learning classifiers such as Support Vector Machines (SVM), Random Forests, and Decision Trees function as additional layers of refinement. These classifiers concentrate on refining decision boundaries, ensuring better separation between classes, and tackling situations where deep learning may struggle, such as with small or imbalanced datasets. The integration of machine learning classifiers with deep learning models results in hybrid approaches that leverage the advantages of both techniques. For instance, CNNs can be utilized as feature extractors, delivering rich, high-dimensional representations, while classifiers like SVM or Random Forests manage the ultimate decision-making process. This structured integration proves especially beneficial in medical imaging tasks like brain tumor detection, where accuracy is critical. Hybrid models frequently attain greater accuracy and robustness by alleviating the shortcomings of individual models, such as the risk of overfitting in deep learning or limited feature extraction abilities in conventional machine learning. In the realm of medical imaging, hybrid strategies also aid in addressing domain-specific challenges like noise, artifacts, and variations in imaging methods. Preprocessing methods such as denoising, histogram equalization, and normalization can be combined with feature extraction and classification workflows to enhance input quality. Furthermore, transfer learning can be employed in hybrid models to use pre-trained CNNs as feature extractors, adjusting them on domain-specific data to achieve quicker convergence and improved performance. Ultimately, incorporating hybrid models into clinical practices allows for solutions that are both scalable and interpretable. By integrating their results with visualization techniques like Grad-CAM or SHAP (SHapley Additive exPlanations), healthcare professionals can gain insights into the reasoning behind predictions, which enhances trust in the system and supports decision-making. This collaboration between machine learning classifiers and deep learning models possesses significant potential to revolutionize medical diagnostics and treatment strategies.

Results

The results section presents the discoveries from our suggested framework for detecting brain tumors, highlighting its capability in precisely classifying and segmenting MRI images. These findings illustrate the efficacy of our hybrid method that merges CNN and computer vision techniques to aid radiologists in accurately identifying and classifying tumors.

Train And Val Plots :

Fig. 1. Model Training History

The image showcases a graph representing the history of model training, emphasizing the variations in both accuracy and loss during the training epochs. The green line represents the model's accuracy, which shows a steady upward trend, approaching a value of 1.0, signifying improved learning over time. In contrast, the red line illustrates the loss, which progressively decreases, indicating that the model is successfully minimizing errors throughout the training period. Some results that are observed are :

1. The model starts with an initial accuracy of approximately 0.82, which gradually improves with increase in the number of epochs (iterations). This shows that with increase in the number of tests the model improves gradually.

2. The loss decreases from about 0.45 to a lower value, demonstrating enhanced optimization.

3. The steady pattern suggests that the model is learning successfully without major fluctuations.

4. This graph shows no signs of overfitting; however, it is crucial to assess validation performance for confirmation.

TABLE 1. Model Classification Report

EPOCH	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.97	0.98	0.98	300
1	0.93	0.90	0.91	300
2	0.95	1.00	0.97	405
3	0.93	0.91	0.92	306

The table depicts Model Classification Report and shows the following results :

1. Precision: Measures the fraction of accurately identified positive predictions, showing values from 0.93 to 0.97 throughout the epochs.
2. Recall: Indicates the capability to identify all relevant cases, with values between 0.90 and 1.00.
3. F1-Score: Represents the harmonic average of Precision and Recall, demonstrating a balance between the two metrics, and it ranges from 0.91 to 0.98.
4. Support: Denotes the count of instances in each epoch for which these metrics have been calculated, ranging from 300 to 405.

Confusion Matrix :

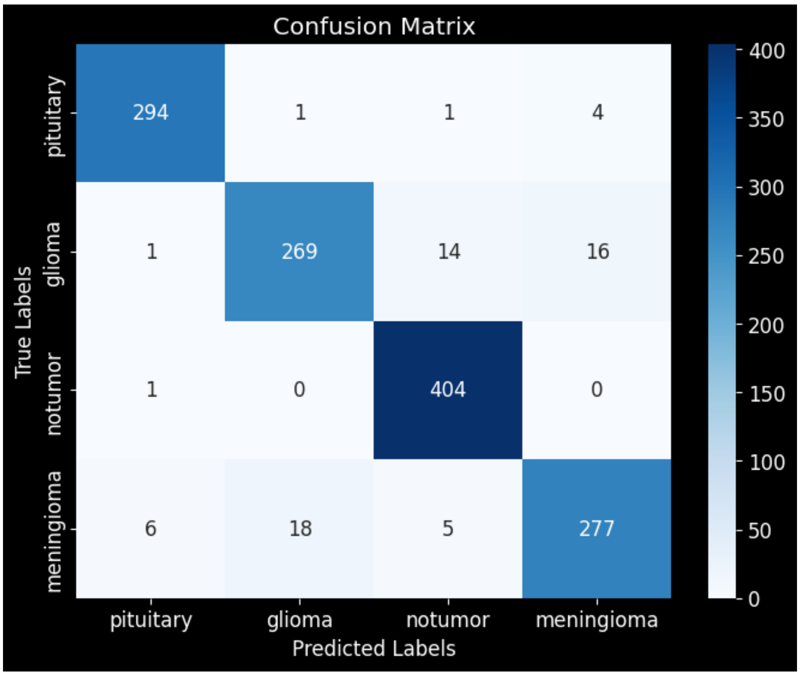

Fig. 2. Confusion Matrix for the model

The confusion matrix illustrates the effectiveness of the model in distinguishing between various types of brain tumors and cases without tumors. The significant numbers along the diagonal indicate a strong accuracy level in classification, particularly for non-tumor cases (404 correctly identified), pituitary tumors (294), gliomas (269), and meningiomas (277). The results that are displayed in the image are :

1) The confusion matrix assesses predictions across four categories: pituitary, glioma, notumor, and meningioma.
2) The most accurate classifications are seen in the notumor (404) and pituitary (294) categories.
3) Misclassification rates are higher for glioma and meningioma, with glioma frequently misidentified as meningioma (16 instances) and the opposite occurring in 18 cases.
4) The model shows excellent performance for the notumor category, displaying very few misclassifications.
5) Enhancements are necessary to better differentiate between glioma and meningioma, given their similar characteristics.

ROC Curve :

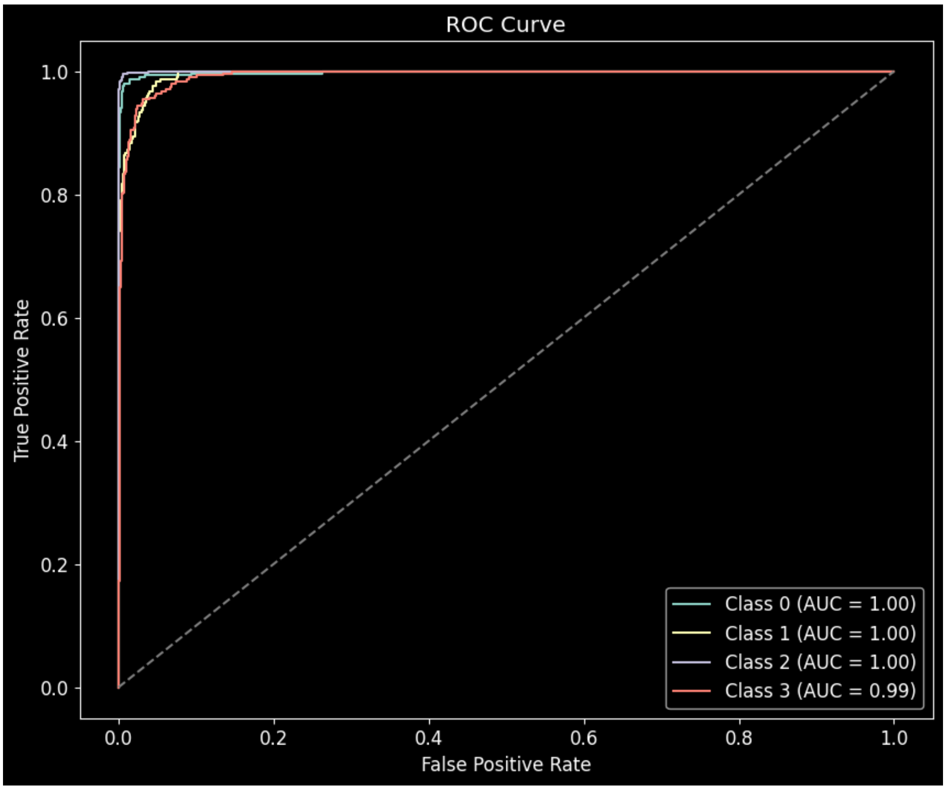

Fig. 3. ROC Curve

The ROC curve demonstrates the model's efficacy in distinguishing between four distinct categories, emphasizing the relationship between the true positive rate (sensitivity) and the false positive rate.Green Line (Class 0) Represents the performance of the model in classifying data belonging to Class It has an AUC of 1.00, indicating perfect classification with no trade-off between sensitivity (true positive rate) and specificity (1 - false positive rate). Red Line (Class 3): Represents the performance of the model in classifying data for Class 3. It has an AUC of 0.99, showing near-perfect classification with a very slight decrease in performance compared to the other classes.Some Observations include :

1) The AUC (Area Under the Curve) values for Class 0, Class 1, and Class 2 are all 1.00, demonstrating perfect classification for these categories.
2) Class 3 has a slightly reduced AUC of 0.99, which still indicates high accuracy but suggests that there may be a few minor misclassifications.
3) The positioning of the curves close to the top-left corner further supports that the model is skilled at distinguishing between tumor and non-tumor cases.
4) Close-to-Perfect Classification: The curves for all classes are nearly at the top-left corner, reflecting high sensitivity and specificity for the model across the classes.

Future Scope And Conclusion

The automated segmentation of brain tumors is essential for computer-assisted diagnosis in glioma patients. This paper presents a hybrid model designed to improve the efficiency and effectiveness of segmentation methods. The deep learning technique employed for identifying brain tumors, which merges CNN and computer vision, demonstrates high accuracy and reliability in analyzing MRI scans. The confusion matrix indicates strong classification performance across different tumor types with minimal misclassifications. The ROC curve and AUC values further support the model's exceptional capacity to distinguish between classes. This research affirms the potential of AI-based diagnostic systems to revolutionize medical imaging by reducing manual errors and assisting radiologists in the early detection of tumors.

Looking ahead, there is considerable potential for enhancing the performance of the system. Implementing sophisticated feature extraction methods, like attention mechanisms or multi-scale analysis, could further boost the model's capability to identify subtle differences in tumor features. Increasing the dataset with a variety of imaging modalities and augmenting classes that are underrepresented can improve the model's generalizability and reliability. Furthermore, incorporating explainable AI techniques will offer greater insights into the decision-making process, making the system more transparent and trustworthy for use in clinical settings.

In summary, this study marks a significant progress in creating automated, efficient, and precise tumor detection systems. Although the outcomes are encouraging, continuous improvements in data augmentation, model refinement, and real-time implementation can facilitate its practical use in healthcare, ultimately contributing to earlier and more accurate diagnoses.

Limitation and ethical consideration

Although the proposed brain tumor detection system shows promising results, it has several limitations. Firstly, the effectiveness of the model is significantly influenced by the quality and variety of the dataset, which may not fully reflect real-world situations. Insufficient data for uncommon tumor types or underrepresented groups could result in biased or less accurate predictions. Additionally, while the integration of CNNs and machine learning classifiers improves performance, the high computational demands of training and implementing such models may restrict their use in settings with limited resources. Another concern is the risk of overfitting to particular datasets, which could impair the system's ability to generalize when faced with new data. Finally, the lack of transparency in deep learning models might pose difficulties for clinicians in comprehending and trusting the predictions, particularly in critical decision-making scenarios.

Another drawback is the computational demands tied to training and implementing deep learning models, which can impede their use in environments with limited resources, like smaller clinics or rural locations. The challenge of real-time application is exacerbated by the time and resources needed to process high-dimensional data, especially when large-scale systems are required.

Additionally, the absence of transparency in deep learning models continues to be a major obstacle. In the absence of clear understanding of how the model makes decisions, healthcare professionals may be reluctant to fully trust its forecasts, particularly in critical medical contexts. Ensuring the system operates effectively in dynamic and diverse real-world situations remains a significant hurdle.

Implementing a brain tumor detection system in clinical environments brings forth significant ethical issues. One major concern is ensuring equity and avoiding biases, especially if the training dataset does not adequately represent various patient demographics. Incorrect diagnoses or missed cases could lead to serious repercussions for patients, highlighting the necessity for thorough validation prior to implementation. The privacy of patient information is another vital consideration; it is imperative to establish strong measures to anonymize and safeguard sensitive medical data.

Additionally, transparency is crucial, as both healthcare professionals and patients need to grasp the model's decision-making process to have faith in its suggestions. Furthermore, the risk of traditional diagnostic jobs being supplanted by automation needs careful handling, ensuring that such systems are created to complement rather than replace human expertise. Tackling these ethical issues is essential for the responsible advancement and application of AI-based healthcare solutions.

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