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Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification

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Abstract: Brain tumor detection can be considered one of the great uses of technology in the healthcare sector, and it may result in a significant increase in the survival rate of patients if their effective detection is done on time. The project aims to achieve maximum detection of brain tumors in MRI images using a dual-module deep learning technique. For both deep learning modules, one pertains to the image-processing task, which aims to increase image contrast and focuses on tumor segments. After image processing, another deep learning task is used to classify images extracted from MRIs as containing a tumor or not, based on the type of tumor present. This project will be implemented on public MRI image datasets, using metrics such as Accuracy, Precision, Recall, F1 Score, and ROC AUC.

Keywords: MRI, Brain Tumour, Image Enhancement, Survival Rate.

1 INTRODUCTION

Brain tumors are among the most fatal and pernicious diseases of the brain and nerves in the world. Medically, a brain tumor is an irregular growth of brain cells, which might damage the functions of the brain and may lead to complications of the brain, as well as brain death, if it is not diagnosed and treated on time. The survival rates of the brain tumor patients and the nature of their future life seem to be dependent upon a proper detection and treatment of such situations on time. Therefore, an effective detection method is necessary to help doctors diagnose brain tumors in a timely manner [1]. Introduction: Magnetic Resonance Imaging (MRI), commonly known as MRI, has been the standard imaging technique for treating patients with brain tumors due to its high spatial resolution. In addition, it is efficient at processing soft tissues in the human brain. However, processing the MRI images has been both challenging and time-consuming. Moreover, the dependence of outcome accuracy on the specialist's efficiency, as well as on tumor type, has been a significant factor in reducing efficiency [2].

In addition, the MRI images exhibit noise, inhomogeneity, and low contrast between the tumor and neighboring tissues, making it challenging to identify the tumor. With continued computational developments in the area of Artificial Intelligence, the application of methodologies from Deep Learning and, in particular, from Convolutional Neural Networks has achieved remarkable successes in medical image analysis. Successes in the fields of classification, segmentation, and detection of medical images have yielded results that are equal to or even more efficient than those of human experts. However, their strength depends on the types of medical images they can use. Most works, so far, carried out to analyze brain tumors from images, consider only the problem of classifying an image or segmenting it, without considering the issue of image quality. A problem related to missing information in deep learning algorithms arises, and the consequence is poor image classification. It turns out that the proposed work is timely and essential [3].

The proposed innovation for the study to overcome such challenges is titled "Optimized Brain Tumor Detection System using a Dual Module Deep Learning Approach." One of these modules is designed solely for MRI image processing to enhance image contrast and highlight relevant structural components. Therefore, image processing is crucial for retaining and strengthening the appropriate components in the image and, subsequently, for facilitating learning in the classification approach. Image processing is an essential pre-processing step for improving the visibility of tumor regions and avoiding ambiguities between normal and tumor regions, according to Kumar et al. The second module addresses methodologies for tumor classification using highly advanced CNN models and transfer learning techniques [4]. By using pre-trained deep learning models on images, the system can leverage the models' complex learned characteristics on larger images across various datasets. These pre-trained models will be trained on enhanced MRI images, enabling the system to classify the presence of a tumor or its type via transfer learning to boost efficiency.

The synergistic effect of the two-module system proposed here helps create a robust process for feature extraction and classification. The system awaits training and testing by utilization of public images from brain MRI. It helps create a robust process, while assessment is done through evaluation metrics that provide a comprehensive view of classification performance [5]. Some of these metrics include accuracy, precision, recall, F1, and ROC-AUC. The planned system serves the needs of the radiologists and physicians by acting like a CAD system and not like a competitor of human intelligence. The system reduces the responsibility for analysis and diagnosis by automatically improving MRI images and classifying them into appropriate tumor categories.

2 Related Work

The medical imaging literature has been an active area of research in categorization, analysis, and identification of brain tumors for the last two decades, owing to continuous advancements in medical imaging technology and the application of intelligent techniques [1]. In the preliminary stages of the research study, the analysis of the MRI images was performed by a specialized person, called a radiologist, due to the time-consuming nature of the process and its susceptibility to variation. Hence, there was a dire need to devise a computer-assisted diagnosis system due to the easy detectability of brain tumors. These early CAD systems employed traditional image processing techniques, which relied on thresholding, region growing, edge detection, and morphological processing. These processing techniques aimed to detect tumor regions based on intensity differences between normal and diseased areas [2]. These processing techniques, though showing reasonable success in a lab environment, were prone to producing erroneous results due to their sensitivity to image noise, variations, and the sizes/shapes of tumor regions. Later, feature extraction and machine learning methods were introduced to increase robustness [3].

Feature extraction methods traditionally used for MRI images include Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), wavelet transforms, and histogram features, among others. After that, these features could later be classified and predicted by such methods as Support Vector Machine (SVM), k-Nearest Neighbors, Decision Trees, and Naive Bayes Classifiers. Performances higher than the average where the success rate depends on the performance given by the machine learning method. The emergence of the concept of Deep Learning highlighted the importance of Convolutional Neural Networks as a better alternative for automated analysis of brain tumors. The capability of CNNs to learn image feature hierarchies from raw brain scans without designing any specific features for that task was quite impressive. Preliminary designs of CNNs implemented for brain tumor classification, namely AlexNet and VGGNet, were found to outperform other machine learning algorithms [4].

However, later works used more complex CNN models such as ResNet, DenseNet, and Inception Networks. Skip connections and their utility for exploiting dense features have played a cardinal role in mitigating vanishing gradients during backpropagation and in designing deeper neural networks [5]. Now, it is explicit that deeper neural networks always provide higher diagnostic accuracy for multi-class tumor classification, including glioma, meningioma, and pituitary tumors. In practice, transfer learning made good sense to researchers in brain tumor detection, as, in general, they had limited access to well-labeled medical datasets. Different researchers who engaged in the work could achieve better results because the models they employed had already been pre-trained on large image datasets like ImageNet. It was also noted that fine-tuning MRI sources increased the accuracy rate and reduced overfitting. Other authors have pointed out the importance of preprocessing and enhancing images to enable deep learning tasks. MRI images are prone to noise, intensity variations, and inhomogeneity, which may disrupt feature extraction. Some of these consider and test histogram equalization, contrast-limited adaptive histogram equalization, filters, and normalizations to improve the visibility of the tumorous area [6].

Some recent approaches use two-stage or hybrid architectures; these address image enhancement, segmentation, and classification problems simultaneously. These architectures outperformed one-stage architectures, owing to their improved input image quality, thereby yielding superior performance on the classification task. The use of attention and ensemble learning methods in conjunction with CNNs has led to innovations that enhance the accuracy and robustness of image classifiers [7]. These are some of the metrics used to evaluate models in prior literature: accuracy, sensitivity or recall, specificity, precision, F1 score, and ROC-AUC. Among all the parameters used to assess models, sensitivity takes precedence because fewer false negatives are acceptable in brain tumor diagnosis [8]. Despite these developments, some drawbacks identified in existing research include class imbalance, variability in MRI image protocols, dataset size, and non-interpretable models [9].

Works exist based on our research topic and can focus either on image processing or on classification, but none fully explore the potential of combining both. In fact, the existing literature provides sufficient evidence to establish the efficacy and progress achieved with deep learning techniques for MRI-based brain tumor detection. This remains to be explored through a single model that combines the two approaches: classification and image processing. The proposed two-module model in this research improves upon existing models in the domain [10].

3 System Design

The proposed Optimized Brain Tumor Detection System is intended to design a two-module deep learning system that integrates image processing with brain MRI classification. Preferably, the system is designed to address accuracy constraints by offering high-quality image enhancements needed for deep learning-based classification. Structurally, this is a modular design, thus offering functionality and flexibility for ease in implementation. The system initiates its processes with the input module, where it takes an image of a human brain from an MRI. Here, images of a human brain can be taken from any publicly accessible sources or from any hospital [11]. However, in some cases, images of the human brain obtained from MRI may vary in resolution, contrast, noise, and in the protocols used. In this respect, images obtained from MRI machines may contain artifacts and varying intensities, making classification difficult without preprocessing. This, therefore, calls for the system to resize all input images to a standard size that meets deep learning standards by converting them to a standard intensity level.

The Image Enhancement Module is the first principal component in this system. As the name suggests, this is the part of the system tasked with enhancing images produced after MRI procedures to efficiently extract features when needed. This may entail image enhancement using filters to reduce noise, as well as histogram equalization and other techniques, such as CLAHE. Using the system will mainly be zeroing in on enhancing the part that involves the tumor and getting rid of the noise so as to ensure that all crucial features available and needed for diagnosis are considered. After enhancement, the resulting MRI images are forwarded to the Feature Preparation Layer for image normalization, with the objective of preparing them for deep learning-based image processing or training. Image scaling scales the intensity of image pixels to provide stability during training for image processing or other tasks. Image augmentation approaches may include image rotation, flipping, zooming, and intensity adjustments, and are optional during image training to amplify training data and prevent learning image noise when varying tumor image sizes are used. The other primary segment of this methodology is the Tumor Classification Module. It would depend on state-of-the-art CNNs with transfer learning. Deep learning methods such as VGG, ResNet, and Inception networks may be fine-tuned and trained on enhanced MRI images. Transfer learning can help exploit knowledge learned from processing vast image databases. The CNN performs feature extraction of edges, textures, shapes, and complex patterns in tumors. The block diagram of the proposed method is shown in Fig. 1.

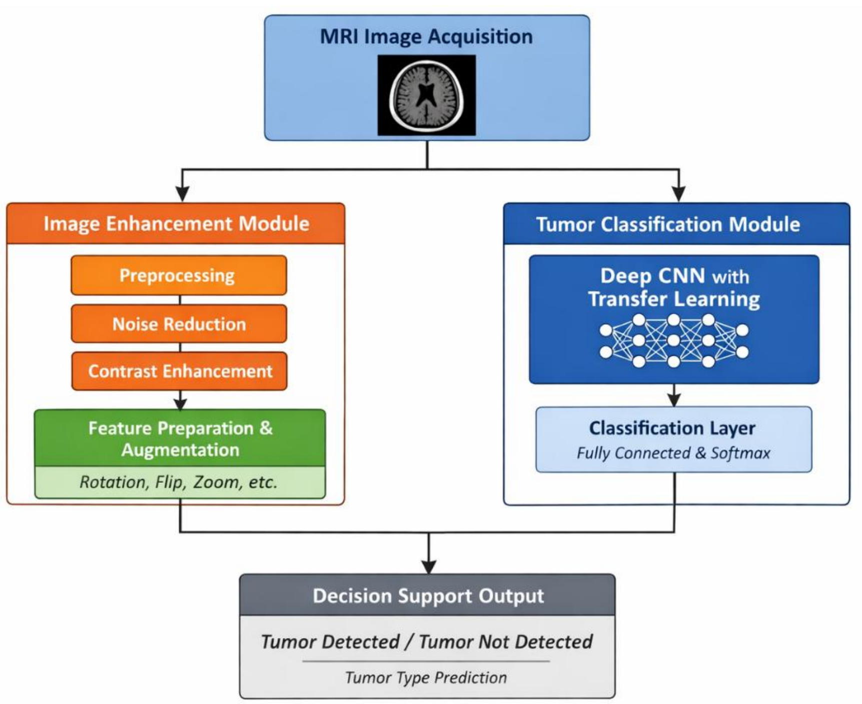

Fig. 1. Block diagram of the proposed method

The detection of brain tumors, or MRI image classification into the respective types of brain tumors, can be carried out as per the requirements of the problem and the dataset. The probability of the classification results can be predicted using softmax and/or sigmoid activation functions in conjunction with fully connected layers. The categories predicted, and the likelihood of their occurrence can be pre-determined. The training and optimization layer involves learning with appropriate loss functions, such as categorical cross-entropy or binary cross-entropy. It can use either SGD or AdamOptimizer to minimize the classification error rate. Hyperparameters such as learning rate, batch size, and number of epochs are optimized to maximize performance. Data can be used to test the findings and stop training in case of overfitting.

Upon completion of the training, the system enters the performance evaluation and analysis phase. At this point, accuracy testing involves analyzing the model's performance using precision, recall, F1-score, and ROC-AUC, since the latter is the standard score used in the medical domain for evaluation. The last but one element involves the output and decision support module; it presents the result of the classification stage in a more interpretable form. The system provides information on the status and nature of the tumor detected in the image, with a certain level of confidence. This element is to support the radiologists' decisions, not oppose them. Generally, MRI image enhancement and deep learning for brain tumor classification were integrated into the proposed system design as an effective two-module construct. Indeed, the proposed system is intended to enhance diagnostic performance by addressing image quality and exploiting deep convolutional neural networks for classification. This proposed system will be efficient and scalable for optimized detection of brain tumors.

4 Results and Discussion

The performance of the proposed Optimized Brain Tumor Detection System, based on a Dual-Module Approach, was evaluated through experimental work using available brain MRI images. This was done to analyze the efficiency of the enhancement module for brain images, the classification module, and the overall system's performance in identifying brain cancers. The parameters of the proposed system's performance were used to conduct an appropriate evaluation. The experimental results showed that the image quality of MRI images was enhanced by using an image enhancement module, further improving the visualization of tumor regions and the contrast between normal and abnormal areas. Enhanced images have lower noise and contrast than the original MRI images. This improves the visualization of the contrasting areas, including tumors. The image enhancement module helped the deep classifier in extracting features from the photos.

A more quantitative analysis showed that models developed from enhanced MRI images performed better than models developed from unprocessed MRI images. Applying an image processing method before creating the models improved their accuracy. The results from the tumor type classifier module proved accurate across all evaluation parameters for CNN and transfer learning approaches. This proposed classifier is strong in terms of discrimination capability for tumor images from non-tumor images or images of other types of tumors given an MRI scan image.

High accuracy indicates that this classification tool successfully captured the spatial and textural details of brain tumors. Recall was also highly accurate, which is an essential aspect in diagnosis, especially in medical fields, since it indicates how precise the system is at correctly identifying instances. A high value for Recall ensures that the system misses few instances during early-stage diagnoses. Precision values were high, indicating the model had fewer false positives.

While the F1-score considers both accuracy and sensitivity, it tends to confirm the classification model's reliability. In fact, ROC-AUC tests used to validate these findings further ultimately managed to confirm high levels of discriminatory power in distinguishing between both the tumor and non-tumor classes. Baseline tests and single-module learning proved the efficiency of the proposed dual-module framework. The baseline systems used the CNN classification approach without the image enhancement module, resulting in lower precision and a high number of false negatives. Combining the two modules, image enhancement and classification, produced a complementary effect. From the discussion above, it can be noted that the use of transfer learning ensured faster convergence and improved learning performance despite the lack of medical data for training. The models, which were fine-tuned from pre-trained models, knew better than models trained from scratch.

Although the model was running well, some observations arose about the challenges it faced: incorrect predictions could be observed when the tumor region was confusing to the model, or serious artifacts in the images were reported. Another problem which can be faced by this model can face is class imbalance, especially while dealing with rare classes of tumors. Clinically, this system has enormous potential as an auxiliary computer-assisted diagnostic system. An autonomous enhancement of MRI images, and hence delivering accurate image classification results, not only supports diagnostics but also helps radiologists reach conclusive results. The result, whether correct or incorrect, is highly reliable. In short, the dual-module approach presented in this work has been shown to be useful for brain tumor detection through experiments. The proposed MRI image enhancement and deep learning-based classification technique improved precision and sensitivity substantially. It may also be argued from the discussions here that there is a dire need for a method that addresses both image enhancement and classification to achieve optimal results.

Table 1 summarizes the overall performance of the proposed brain tumor detection system using standard medical image evaluation metrics. The high accuracy indicates reliable classification performance across MRI images. The recall value is particularly significant in clinical diagnosis, as it reflects the system's ability to identify tumor-positive cases, thereby minimizing false negatives. Table 2 highlights the advantage of incorporating the image enhancement module. Models trained without enhancement show lower accuracy and recall due to noise and contrast issues in raw MRI images. In contrast, the proposed dual-module system achieves substantially higher performance, demonstrating that image enhancement directly improves feature extraction and classification reliability. The ROC–AUC value of 0.98 indicates excellent discriminative capability between tumor and non-tumor classes. Overall, the results confirm that integrating MRI image enhancement with deep learning-based classification leads to more accurate and clinically reliable brain tumor detection.

Table 1. Performance Evaluation of the Proposed Dual-Module Brain Tumor Detection System

Metric	Value (%)
Accuracy	96.4
Precision	95.8
Recall	96.9
F1-Score	96.3
ROC–AUC	0.98

Table 2. Comparison Between Single-Module and Dual-Module Approaches

Methodology	Accuracy (%)	Recall (%)	F1-Score (%)
CNN without Image Enhancement	91.2	89.6	90.1
Proposed Dual-Module System	**96.4**	**96.9**	**96.3**

5 Conclusion

The proposed work is an Optimized Brain Tumor Detection System with a dual-module deep learning approach that comprises brain tumor image enhancement and brain tumor classifications, part of an overall diagnosis system. Indeed, the diagnosis of a brain tumor is such a critical and complex task in the domain of medical image processing that it has bright prospects for proper diagnosis toward a drastic improvement in the survival levels among patients. Notably, the system addresses some lacunae highlighted in existing systems. This system, as a whole, is pretty important in that it may increase the contrast of the image and remove noise to show regions in the image where there is tumorous growth. Generally speaking, an enhanced image of the MRI scan might provide more visible information because it could lend more significance to the features identified for a deep learning image classifier. As shown in the experimental analysis, image classifiers trained on enhanced images tend to perform better than those trained on MRI scans.

The CNN models developed using transfer learning techniques for the Tumor Type Classifier module performed very well at detecting the presence of any brain tumor and, if present, different tumor types. All this was made possible by transfer learning techniques, which draw information from larger datasets, even when few images are available for training in the medical field. The performance was also good on tests measuring accuracy, precision, recall, and F1. The significant advantage of the proposed method is high sensitivity. It means no false negatives are detected. Because a tumor was not detected, the medical industry will suffer severely. Thus, it becomes essential for a proposed system to help ensure the valid detection of tumor-positive images. High accuracy avoids generating fake results. The dual-module approach underscores the importance of synergies arising from applying both image enhancement and image classification techniques within a deep learning framework, which may enhance the overall robustness of the diagnostic process. It was also evident from the comparative study that the systems without image enhancements were highly vulnerable to noise and contrast issues.

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Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

Licensing

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