International Journal of Advances in
Soft Computing and Intelligent Systems (IJASCIS)
2025, Vol 04, Issue 02, 110-118
ISSN: 3048-4987

Original Paper

CLASSIFICATION OF BRAIN TUMOUR MRI IMAGES USING ENSEMBLE MODEL

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ABSTRACT

Research on Brain Tumours (BT) is increasingly moving toward automated diagnostic tools that can assist clinicians in making quicker and more accurate decisions. Since brain tumours are challenging to diagnose and can be life-threatening, early identification remains critical for improving treatment outcomes. Recent progress in machine learning (ML), deep learning (DL), and MRI-based imaging has helped overcome issues seen in manual interpretation, such as variation in expert judgment and the complex nature of tumour patterns. In this study, several deep learning architectures-including Convolutional Neural Networks (CNNs), ResNet50, VGG-16, and Inception V3-were used to develop an automated detection system capable of producing fast and dependable predictions. By combining MRI scans with features generated by these models, the system reduces manual effort and simplifies the diagnostic process. The study also uses an ensemble strategy, merging outputs from multiple networks to improve accuracy and model stability. When evaluated on 259 MRI images, the ensemble achieved 90% accuracy, supporting existing findings that DL methods are highly effective in tumour classification. Overall, the proposed system shows strong promise for improving automated brain tumour detection and aiding clinical workflows.

KEYWORDS

Brain Tumour, Ensemble model, CNN, ResNet50, VGG-19.

1. INTRODUCTION

Brain tumours affect millions of individuals across the globe and remain a major health concern. Among the various types, BT is particularly debilitating, often leading to significant pain, functional limitations,

and a reduced quality of life, especially among older adults (see Fig. 1) [1]. The growing impact of BT on daily living has increased the urgency to improve early detection and management strategies. Brain tumours are recognized as one of the more aggressive forms of cancer, and when diagnosed at a late stage, they are often associated with poor survival outcomes. Their effect on everyday activities and overall well-being further underscores the importance of timely and accurate diagnosis [2].
With advancements in technology, there is a rising interest in the use of computer-assisted methods, machine learning, and deep learning for medical diagnosis. These approaches have shown great promise in enhancing the identification and classification of various health conditions. By leveraging such advanced techniques, this work aims to contribute more accurate and efficient tools for detecting and categorizing brain tumours, ultimately supporting better clinical decisions and treatment planning. The adoption of these modern methodologies reflects a broader effort to strengthen medical diagnostics and address the unique challenges posed by life-threatening diseases like BT [3], [4]. In this study, ensemble methods combining ResNet50, VGG-16, and Inception-V3 are employed to boost overall model performance and improve diagnostic reliability.

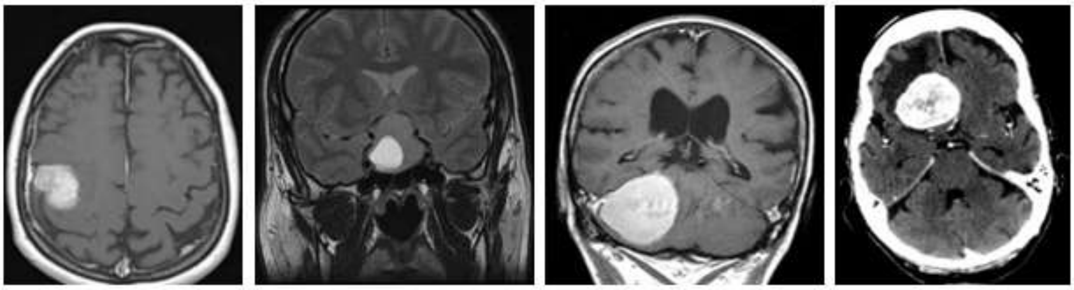

Fig. 1. Brain Tumor image.

2. LITERATURE SURVEY

Early identification and timely treatment of BT are essential for improving a patient’s quality of life. Recent advancements in machine learning and deep learning, including transfer learning techniques such as ResNet-34, have significantly contributed to improving the accuracy of BT classification. Several studies have also demonstrated that ensemble learning can further boost model performance by combining the strengths of multiple classifiers [5]. These approaches have reported strong outcomes, achieving high levels of accuracy, precision, recall, and F-score in BT detection tasks [6].

In another recent investigation, researchers used deep feature extraction with CNNs to capture the complex characteristics of BT images. The extracted features were then classified using traditional machine learning algorithms such as Naïve Bayes, K-Nearest Neighbour (K-NN), and Support Vector Machine (SVM). The study reported promising results, with an overall accuracy of 90% and SVM achieving up to 95% classification accuracy. A Restricted Boltzmann Machine was also explored as an alternative method for feature extraction, further validating the effectiveness of deep feature learning in this domain [7].

BT remains a serious global health challenge, significantly affecting daily functioning and overall well-being. As there is currently no permanent cure, treatment efforts mainly focus on symptom management. Key goals include reducing pain, improving neurological function, and maintaining patient stability to help preserve quality of life [8].

3. PROPOSED MODEL

The proposed ensemble framework is built around three main components: the training dataset, the ensemble of models, and the final output predictions. Together, these elements work to classify different types of BT images. An overview of this process is illustrated in the block diagram shown in Figure 2. Data collection, data augmentation, region of interest, and picture segmentation are the stages of the training dataset.

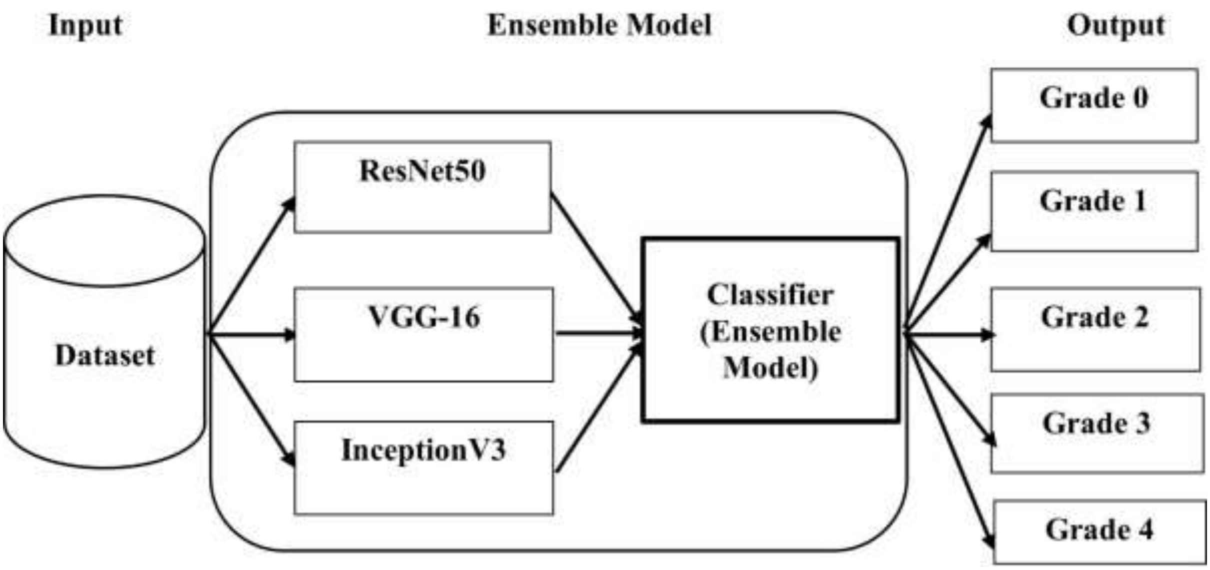

Fig. 2. Proposed ensemble model for brain tumor images classification.

3.1. Data description

Normal or non-tumorous brain images were sourced from the IXI Dataset. For this study, 259 T1-weighted volumes were randomly chosen as healthy samples, as T1 contrast-enhanced (T1ce) imaging is widely preferred for single-contrast tumor classification among the four common MRI types [9]. Figure 3 illustrates the grading of tumor severity based on image characteristics.

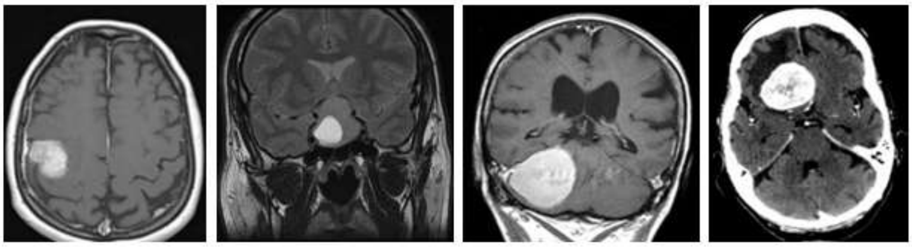

Fig. 3. Images of different grade based on severity level.

3.2. Data enhancement

Histogram equalization is applied in this study to improve the visual quality of the images. This technique is especially useful when the foreground appears too bright or too dark against the background, as it helps balance contrast and reveal hidden details. It can also enhance structural visibility in medical scans, such as highlighting bone features in radiographs (see Fig. 4). Once the MRI images are enhanced, further processing can be performed to remove unnecessary artifacts that may interfere with diagnostic calculations and reduce accuracy [10], [11].

- The probability of an occurrence of a pixel of level i in the image is (Eq. 1),

$$p_x(i) = p(x = i) = \frac{n_i}{n}, 0 \le i \ \le L \tag{1}$$

where n_i is the frequency of occurrence of i and n is the total number of observations.

- The cumulative distribution function $cdf_x(i)$ can be expressed as (Eq. 2):

$$cdf_x(i) = \sum_{j=0}^{i} p_x(x = j) \tag{2}$$

where p_x(x = j) is the probability distribution function for x.

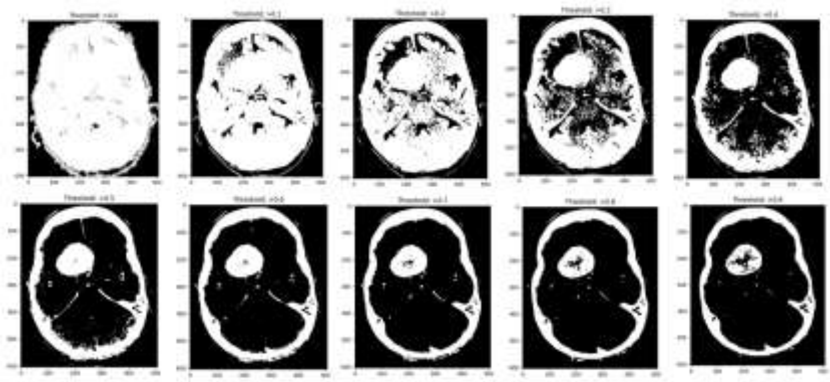

Fig. 4. Normal image and Enhanced images.

3.3. Region of Interest (RoI)

The meniscus region plays an important role in determining the severity of a BT, as it helps evaluate the extent of the affected area. To focus on this critical region, cropped MRI scans are used to generate Region of Interest (ROI) images. As shown in Fig. 5, a center pinhole filter is applied to limit exposure outside the ROI, which helps reduce the patient's dose while preserving-or even enhancing-the quality of the image [12].

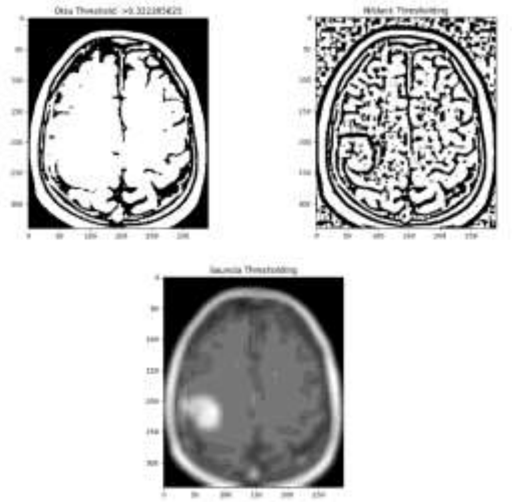

Fig. 5. Image shows the Region of Interest.

3.4. Image segmentation

Image segmentation refers to the process of dividing an image into several meaningful parts to simplify interpretation and analysis. This step is often used to define boundaries within an image and to identify specific structures. For MRI scans, K-means clustering is a widely used segmentation method. When applied with k = 3, it separates the image into three distinct regions, each represented by different color clusters, as illustrated in Fig. 6. Each cluster corresponds to a unique range of pixel intensities, helping highlight important anatomical or pathological differences [13].

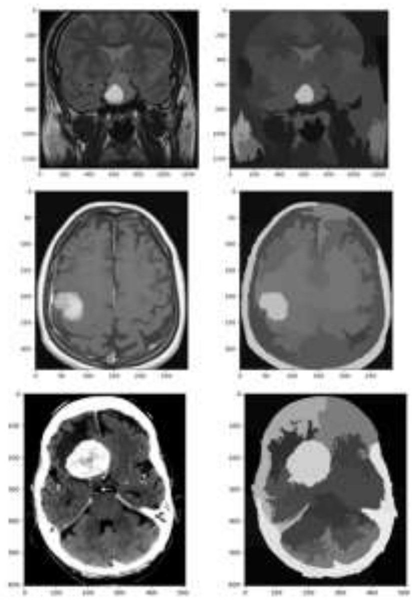

Fig. 6. Segmented MRI images.

3.5. Ensemble model

Ensemble learning has gained attention in recent years because of its ability to strengthen model performance and produce more reliable predictions. By combining the outputs of multiple models, ensemble methods reduce the limitations of any single approach and generate more accurate forecasting results. This strategy has been widely adopted across different domains, consistently demonstrating its effectiveness in improving prediction quality by leveraging the strengths of diverse models [14]. In this study, the proposed ensemble framework brings together three powerful deep learning architectures-VGG-16, InceptionV3, and ResNet50-to enhance overall classification accuracy. By merging their complementary capabilities, the ensemble provides a more robust assessment of BT images. Using this integrated approach, the system is able to grade BT based on their severity, offering a more dependable tool for clinical evaluation.

ResNet50: ResNet50 is a deep CNN made up of 50 layers, designed to handle a wide range of computer vision applications (see Fig. 7) [15]. Its ability to learn rich, high-level features from large datasets-such as ImageNet-makes it especially effective for transfer learning. Because these pretrained features can be repurposed for new visual recognition tasks, ResNet50 serves as a strong foundation for building accurate and efficient classification models [16].

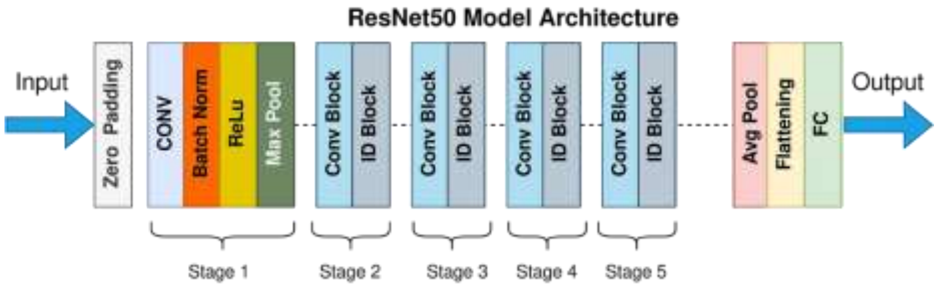

Fig. 7. ResNet50 architecture.

VGG-16: In VGG-16, the first CNN layer receives an input image of 224 × 224 pixels. The architecture relies on 3 × 3 convolutional filters with a padding of 1 pixel, which helps preserve the spatial dimensions after each convolution step. To further process the feature maps, VGG-16 uses max-pooling, a down-sampling method that reduces the spatial size while retaining the most important information. This pooling operation, defined by equations (3) and (4), allows the network to focus on the most relevant features during learning [17].

- The soft function of VGG-16 (Eq. 3):

$$y_i = \sum_{j=1}^{n} e^{z_j} \,.\, e^{z_i} \tag{3}$$

- The loss function will be (Eq. 4):

$$E = \frac{1}{3}\big(d(c_1, G_1) + d(c_2, G_2) + d(c_3, G_3)\big) \tag{4}$$

Inception-V3: Image classification is one of the key applications of deep neural networks, and Inception-V3 is widely recognized as a powerful CNN model for this purpose. It has been successfully used in various real-world scenarios-social media platforms like Facebook employ deep learning to enable automatic photo tagging, autonomous vehicles rely on similar models to detect obstacles, and medical professionals use them to identify cancerous regions in diagnostic images [16].

In this study, we applied a hard voting ensemble approach, also known as majority voting. This method works by combining the predictions from multiple base models and choosing the class that receives the most votes. Hard voting is particularly effective for classification problems where each class is distinct and mutually exclusive. Using this strategy, the final grade assigned to an image corresponds to the grade predicted by the majority of the models. For instance, if two out of three models classify an image as grade 0 and the remaining model predicts grade 1, the final output will be grade 0.

4. Results and Discussion

The purpose of the ensemble model is to classify brain images into five categories: Healthy, Doubtful, Minimal, Moderate, and Severe [14], [15]. Each model within the ensemble brings its own architectural features and learned representations, allowing their strengths to complement one another. By combining these diverse capabilities, the overall system achieves greater accuracy and robustness than any single model alone [16].

A total of 259 brain tumor images were used for the final training and testing phases. These images were randomly selected from the BT dataset and pre-processed before evaluation. The proposed ensemble model achieved an accuracy of 90%, demonstrating a clear improvement over the individual models. Specifically, ResNet, VGG-16, and Inception-V3 recorded accuracies of 68%, 77%, and 64%, respectively, whereas the ensemble significantly surpassed these results with its 90% performance, as summarized in Table 1. The training loss and ROC curve for the BT classification are also illustrated in Figure 8.

Table 1. Comparison of accuracy of other models with ensemble model

Model	ResNet50	VGG-16	Inception-V3	Ensemble Model
Accuracy	68%	77%	64%	**90%**

Because achieving high accuracy is a primary objective of this study, the ensemble model emerges as a strong and reliable choice due to its superior performance. However, accuracy alone should not determine the final selection. Other factors-such as model interpretability, computational demands, and the ability to operate in real-time-also need to be carefully evaluated before deciding on the most suitable approach.

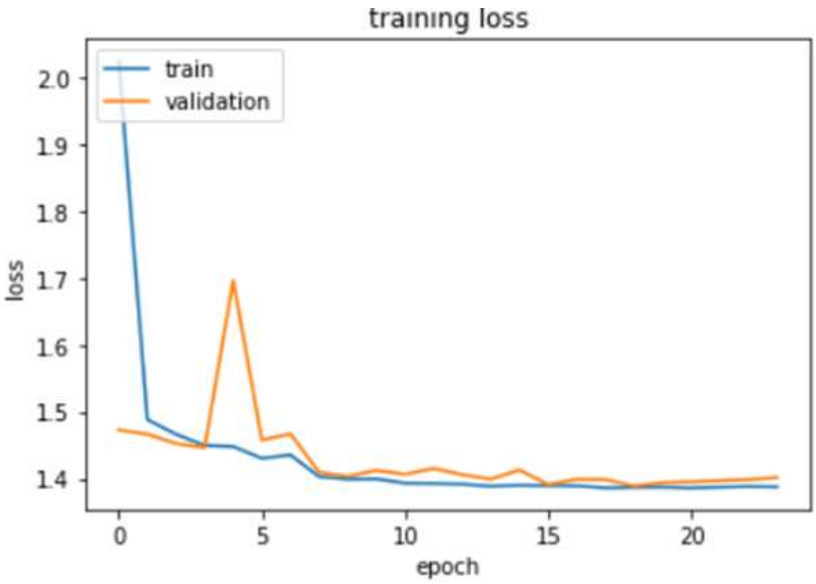

Fig. 8. ROC curve for BT training loss.

5. CONCLUSIONS

The main aim of the brain tumor study is to classify tumor severity using medical imaging through the development of an ensemble model. This model brings together three advanced architectures-VGG-16, Inception-V3, and ResNet50-allowing it to merge their individual strengths and deliver more accurate and reliable predictions. By drawing on the distinct features and learning abilities of each network, the ensemble provides a more comprehensive and robust approach to assessing tumor severity. One of the key advantages of this work is its potential to support medical professionals by enabling quick, informed decisions based on real-time predictions. Such immediate feedback can significantly enhance clinical efficiency and improve patient care. Looking ahead, the project aims to integrate real-time functionality more fully, allowing clinicians to receive diagnostic insights during examinations. This advancement has the potential to greatly improve current diagnostic workflows and revolutionize how brain tumors are identified and evaluated.

Acknowledgements

Authors would like to thank to the data providers.

Authors Contributions (Compulsory):

All authors have equally contributed.

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