Brain Tumor Classification Using Deep Ensemble Learning Based on Voting Technique

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https://doi.org/10.59222/ustjet.4.1.4

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Abstract:

Brain tumor classification is a crucial process in the medical diagnosis field of brain lesions for obtaining a correct diagnosis and then beginning treatment planning. In this study, an ensemble learning approach using a VGG19 model is proposed to achieve high classification accuracy. Three VGG19 models with varying parameters are trained independently. The predictions of the three models are combined using ensemble learning based on the voting technique. The models were trained on a comprehensive dataset of brain MRI scans containing 7,041 MRI images, split into 80% training and 20% testing sets. The raw train dataset is resized and then fed to the three VGG19 models individually. The entire test dataset is preprocessed with sharpening techniques to enhance the details of brain images. The proposed approach achieved an impressive accuracy of 99.33 % on the test dataset, surpassing state-of-the-art methods in brain tumor classification. Furthermore, the proposed approach obtained high precision, specificity, recall, and F1-score, showing its strength. The results demonstrate the effectiveness of the proposed approach compared to individual models, with significant improvements observed through ensemble learning. This study contributes to the field of medical diagnosis by providing an accurate framework for auto-brain tumor classification.

Keywords: Brain tumor classification, deep learning, ensemble learning, convolutional neural network, voting technique, magnetic resonance imaging
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https://doi.org/10.59222/ustjet.4.1.4

تصنيف أورام الدماغ باستخدام التعلم العميق التجميعي المعتمد على تقنية التصويت بالأغلبية

الملخص:

يُعدّ تصنيف أورام الدماغ عملية حاسمة في مجال التشخيص الطبي لآفات الدماغ، لما له من دور كبير في الوصول إلى تشخيص دقيق والبدء في تخطيط العلاج. في هذه الدراسة، تم اقتراح منهجية تعلّم تجميعي بالاعتماد على نموذج VGG19 بهدف تحقيق دقة عالية في التصنيف. حيث جرى تدريب ثلاثة نماذج من VGG19 بمَعلمات مختلفة بشكل مستقل، ثم دمج تنبؤاتها باستخدام أسلوب التعلّم التجميعي المعتمد على تقنية التصويت. تم تدريب النماذج على قاعدة بيانات شاملة من صور الرنين المغناطيسي للدماغ، تضم 7,041 صورة MRI، قُسمت بنسبة 80% للتدريب و20% للاختبار. وتمت إعادة تحجيم بيانات التدريب الأولية قبل تمريرها لكل نموذج من النماذج الثلاثة بشكل منفصل. كما خضع كامل بيانات الاختبار لعمليات معالجة مسبقة باستخدام تقنيات زيادة حدّة الصور بهدف تعزيز تفاصيل صور الدماغ. وقد حقق النهج المقترح دقة عالية بلغت 99.33% على بيانات الاختبار، متفوقا على أحدث الأساليب في مجال تصنيف أورام الدماغ. إضافة إلى ذلك، سجّل النهج المقترح نتائج عالية في الدقة (Precision) والخصوصية (Specificity) والاسترجاع (Recall) ودرجة F1، مما يدل على كفاءته. وتُظهر النتائج فعالية هذا النهج مقارنة بالنماذج الفردية، مع تحسينات كبيرة حققها التعلّم التجميعي. تُسهم هذه الدراسة في مجال التشخيص الطبي من خلال تقديم إطار دقيق لتصنيف أورام الدماغ تلقائيا.

الكلمات المفتاحية : تصنيف أورام الدماغ، التعلّم العميق، التعلّم التجميعي، الشبكات العصبية الالتفافية، تقنية التصويت، التصوير بالرنين المغناطيسي.

1. Introduction

A brain tumor is defined as an abnormal and uncontrolled proliferation of brain cells [1, 2]. The exact underlying causes of brain tumor development remain unclear to date. According to the World Health Organization (WHO), brain tumors are classified into two primary categories: benign and malignant [3]. Patients diagnosed with benign tumors generally exhibit better survival outcomes, particularly when the tumor is detected at an early stage and appropriate treatment is administered. In contrast, patients diagnosed with malignant tumors often face more severe and critical clinical conditions [23, 26]. Glioma, meningioma, and pituitary tumors represent the three most prevalent types of brain tumors [4, 5].

Brain tumor detection and classification constitute a crucial task within the field of medical imaging [6]. This process plays a vital role in ensuring accurate diagnosis and facilitating effective treatment planning. Magnetic Resonance Imaging (MRI) is among the most widely used medical imaging modalities, especially for soft tissues such as the brain [7]. MRI offers numerous advantages, including its non-invasive nature, absence of harmful radiation, and ability to provide detailed anatomical information [8]. However, MRI generates a large volume of data, which poses challenges for radiologists, including increased time consumption and the risk of diagnostic errors associated with human judgment [9].

To address these challenges, researchers have increasingly adopted deep learning models to develop fast, automated, and more reliable brain tumor classification systems. Pre-trained Convolutional Neural Network (CNN)-based models have demonstrated remarkable performance across various image classification tasks, including medical imaging applications [10, 25]. Despite their effectiveness, individual models still suffer from certain limitations [11]. Some models exhibit superior performance in classifying specific classes within the same dataset [24, 27], while others perform better for different classes or are more susceptible to overfitting. Consequently, ensemble learning techniques have been employed to overcome these limitations and enhance classification accuracy [12, 13]. Utilizing multiple models enables the capture of diverse characteristics from medical images. Ensemble learning generates the final prediction by combining the outputs of several models into a unified decision, leveraging their strengths while mitigating their weaknesses [28]. This model diversity contributes to constructing an

https://doi.org/10.59222/ustjet.4.1.4

ensemble system with higher accuracy and reliability compared to single-model approaches [29].

In this study, an ensemble learning-based approach for brain tumor classification is proposed. The proposed framework integrates three VGG19 models with different parameter configurations. Each model is trained on a comprehensive brain MRI dataset comprising 7,041 images distributed across four distinct classes. VGG19 is a well-established architecture in image classification tasks due to its deep structure and strong capability to learn complex feature representations [30]. By combining the strengths of these models, the overall brain tumor classification performance is significantly enhanced [31].

Through multiple stages of extensive experiments and evaluations, the proposed approach achieved impressive classification accuracy, surpassing the performance of several state-of-the-art methods in brain tumor classification. In addition, the model demonstrated strong performance across other evaluation metrics, including precision, recall, specificity, and F1-score, thereby confirming the robustness and efficiency of the proposed framework.

Beyond achieving high accuracy, this study also explored the integration of multiple VGG19 models with varying parameters. Furthermore, it demonstrated that employing models with different architectural configurations contributes to extracting diverse tumor characteristics more effectively. The results highlight the effectiveness of ensemble learning for brain tumor classification and encourage further research toward advancing computer-aided diagnosis systems.

The remainder of this paper is organized as follows: Section Two presents a comprehensive review of related work on deep learning-based brain tumor classification. Section Three describes the proposed methodology, including the ensemble strategy for combining the three VGG19 models with varying parameters, as well as the experimental setup, dataset, preprocessing steps, and implementation details. Section Four presents and discusses the experimental results and evaluation metrics, demonstrating the superior performance of the proposed ensemble approach. Finally, Section Five concludes the paper by summarizing the main findings and outlining potential directions for future research.

2. Literature Review

Several studies have been conducted on brain tumor classification using deep learning techniques. In this section, a number of state-of-the-art research works related to this domain are reviewed and discussed.

Hossam H. Sultan et al. [14] proposed a computer-aided diagnosis (CAD) system for classifying brain tumors in MRI images into three categories: meningioma, glioma, and pituitary tumors. In addition, the study addressed the classification of glioma grades (Grade II, Grade III, and Grade IV) using a custom-designed deep neural network architecture. To enhance classification performance, data augmentation techniques were employed due to the relatively small size of the dataset. The proposed system achieved classification accuracies of 96.13% and 98.7% on the two datasets utilized in the study.

Hareem Kibriya et al. [4] introduced a novel CNN-based approach for the detection and classification of three brain tumor types (glioma, meningioma, and pituitary) using MRI images. The proposed method was evaluated on 3,064 MRI images obtained from the publicly available Figshare dataset. Experimental results demonstrated that the proposed model achieved an accuracy of 97.2%.

In the work presented by Ayesha Younis et al. [15], a pre-trained VGG16 CNN model was employed for the automatic detection of three types of brain tumors using MRI scans. Several preprocessing techniques, including N4ITK bias field correction, amplitude normalization, and thresholding, were applied to improve the model's performance. The approach was evaluated on a local dataset, and the results indicated that the proposed architecture achieved an accuracy of 98.15%, outperforming conventional CNN-based methods.

Mohammed Rasool et al. [16] proposed a hybrid CNN-based framework for classifying three types of brain tumors from brain MRI images. The study explored two hybrid classification strategies. In the first approach, a pre-trained GoogleNet model was utilized for feature extraction, followed by classification using a support vector machine (SVM). In the second approach, a softmax classifier was integrated with a fine-tuned pre-trained GoogleNet model. The experimental results showed that using only the fine-

https://doi.org/10.59222/ustjet.4.1.4

tuned GoogleNet model achieved a classification accuracy of 93.1%, while combining GoogleNet as a feature extractor with an SVM classifier improved the accuracy to 98.1%.

Özkaraca et al. [17] conducted a study to investigate the limitations and drawbacks of previous research by analyzing the simple structure of CNN architectures and identifying classification weaknesses arising from limited network depth. The authors examined VGG16Net and DenseNet architectures to assess the influence of transfer learning and dense layers on classification performance. The study reported that transfer learning did not significantly affect success rates in the medical domain and was therefore excluded from the final model. Analysis of DenseNet revealed positive effects due to dense layer connections; however, when combined with transfer learning, the performance did not meet expectations. As a result, the authors concluded that a manually designed architecture incorporating dense layers and a high number of layers during preprocessing could enhance feature extraction. The model was evaluated on a Kaggle dataset and achieved precision, recall, and F1-score values of 96%, 96.5%, and 96%, respectively.

3. Materials and Methodology

The methodology of this study is based on combining three VGG19 models with varying parameters. This process is done by using ensemble learning based on voting techniques.

3.1. Dataset and Preprocessing

The dataset utilized in this study was obtained from Kaggle [18] and comprises a total of 7,041 brain MRI images. The dataset was divided into two subsets, with 80% allocated for training and 20% reserved for testing. Both subsets include four classes: Glioma, Meningioma, No Tumor, and Pituitary. To prepare the raw images for model training and evaluation, several preprocessing steps were applied, as described below:

a. Resizing: All input images were resized to a resolution of 224 × 224 pixels to ensure compatibility with the input requirements of the VGG19 models [32, 33].

b. Contrast-Limited Adaptive Histogram Equalization (CLAHE): This preprocessing technique has been reported to yield performance improvements for certain models and datasets [40]. CLAHE was applied to enhance relevant image details and salient features within the training dataset by improving local contrast.

The decision to apply CLAHE exclusively to the training dataset was motivated by the suitability of the VGG19 architecture for processing contrast-enhanced images. CLAHE enhances feature visibility, thereby improving the model's capability to extract discriminative features, which is critical for accurate classification [47]. In contrast, the VGG19 model was also trained using raw images to preserve its inherent ability to operate on unmodified data, consistent with its pre-trained configuration and strong generalization capabilities. This preprocessing strategy leverages the complementary strengths of each model within the ensemble learning framework [48, 51].

c. Sharpening: To further enhance structural details in the brain MRI images, a sharpening technique was applied to all classes within the test dataset. The ensemble learning model was then evaluated using this sharpened test set [50]. Figure 1 illustrates the dataset classes along with the applied preprocessing steps.

Glioma Meningioma No Tumor pituitary

a

b

c

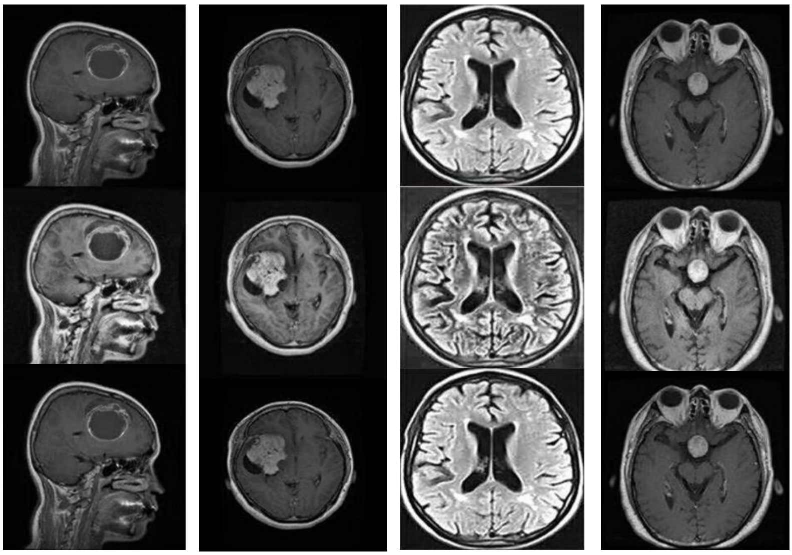

Figure 1: Brain dataset classes and preprocessing steps (a) Original Image (b) CLAHE Technique (c) Sharpening Technique

3.2. VGG19 Model Architecture

The VGG19 model is a pre-trained model based on deep convolutional neural network architecture [34]. This pre-trained model has shown remarkable performance in computer vision field, especially images classification tasks [19]. The model consists of 19 layers, including 16 convolutional layers and

https://doi.org/10.59222/ustjet.4.1.4

3 fully connected layers [35]. It applies small-sized convolutional filters (3x3) with a stride of 1, which help in extract the significant features of medical brain images [20]. The VGG19 model was chosen for build the proposed ensemble learning approach due to it has a deep architecture and a good ability to learn complex features from medical images [21]. The VGG19 Model Architecture is illustrated in Figure 2.

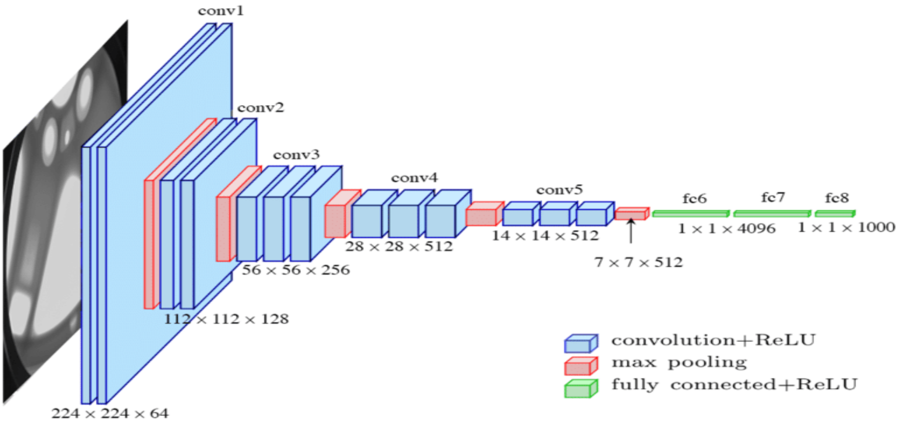

Figure 2: VGG19 Model Architecture [22]

3.3. VGG19 Model Training

Three VGG19 models varying with parameters are trained individually on the raw training dataset. The Stochastic Gradient Descent with Momentum (SGDM) optimization algorithm is used. This algorithm combines the benefits of stochastic gradient descent and momentum updates to accelerate convergence [36,37]. As presented in Table 1, the hyper-parameters were set as follows: In the first model (VGG19 A), Learning Rate: 0.001, Minibatch Size: 64 and epoch numbers: 9. In the second model (VGG19 B), Learning Rate: 0.001, Minibatch Size: 64 and epoch numbers: 21. In the third model (VGG19 C), Learning Rate: 0.001, Minibatch Size: 64 and epoch numbers: 30. The purpose of these procedures is to explore the impact of different training parameters on the model's performance. This process led to obtain three different confusion matrices, especially in Class 1 and Class 2. The variance in the obtained confusion matrices is an important factor to build an efficient ensemble learning model.

Table 1: Parameter values of trained models

Model	Learning Rate	Minibatch Size	Optimization	Epoch Numbers
VGG19 A	0.001	96	SGDM	9
VGG19 B	0.0001	64	SGDM	21
VGG19 C	0.001	64	SGDM	30

3.4. Ensemble Learning with Voting

After training the three VGG19 models, ensemble learning based on the voting technique is applied to combine their predictions and generate the final ensemble prediction. Ensemble learning is a powerful deep learning technique where multiple models, often referred to as "weak learners," are combined to form a robust model with improved predictive performance [39,52]. One of the most straightforward and widely used ensemble methods is voting. In voting-based ensemble methods, each model in the ensemble makes a prediction for each instance, and the final prediction is determined by aggregating these predictions. The aggregation can be done through majority voting [38]. For classification, each model votes for a class, and the class with the most votes is chosen as the final prediction. This method leverages the idea that while individual models might make errors, the majority decision is more likely to be correct, thereby reducing the overall error. Research has shown that ensemble methods, such as those based on voting, can significantly enhance model performance and robustness [46]. Figure 3 shows the block diagram of ensemble learning based on voting.

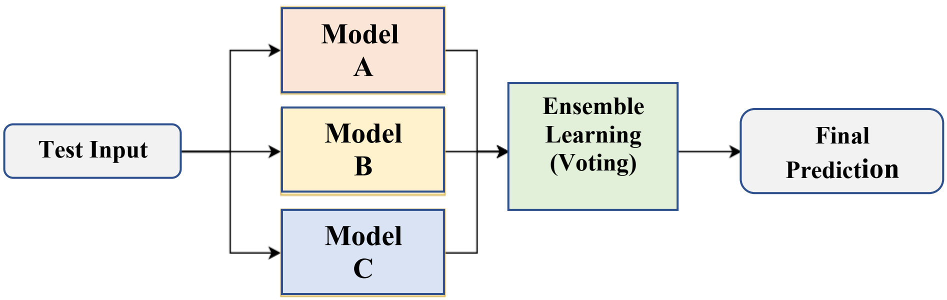

Figure 3: Block diagram of ensemble learning based on voting

3.5. Materials (Software and Hardware)

All training, testing and evaluation processes are performed using MATLAB R2022a environment on a PC computer. Full specification details are given in Table 2.

https://doi.org/10.59222/ustjet.4.1.4

Table 2: Information about hardware

CPU	RAM	Hard Drive	Operating System	Language
Intel(R) Core(TM) i7-10700 CPU @ 2.90GHz	32 GB	1 TB SSD	Windows 11	MATLAB R2022a

4. Experimental Results

In this section, the experimental results of this study are presented. The results aimed to classify brain tumor images into four different classes: Glioma, Meningioma, No Tumor, and Pituitary. The performance of the proposed approach is evaluated using various metrics, such as accuracy, precision, specificity, recall, and F1 score.

4.1. Performance Metrics and Evaluation

The performance of the proposed approach is evaluated using the following metrics: accuracy, specificity, sensitivity, precision, f1-score and confusion matrix. The formulas for accuracy, F1-score, precision, and recall metrics calculated from the confusion matrix are presented. Accuracy, Precision, Recall, Sensitivity, Specificity and F1-score have been calculated as in the following equations.

$$\mathbf{Accuracy} = \frac{N_{TP} + N_{TN}}{N_{TP} + N_{TN} + N_{FP} + N_{FN}} * 100$$

$$\mathbf{Precision} = \frac{N_{TP}}{N_{TP} + N_{FP}} * 100$$

$$\mathbf{Specificity} = \frac{N_{TN}}{N_{TN} + N_{FP}} * 100$$

$$\mathbf{Recall} = \frac{N_{TP}}{N_{TP} + N_{FN}} * 100$$

$$\mathbf{F1\ score} = \frac{2 * (\mathrm{Precision} * \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})}$$

Where true Positive (NTP) is the number of positive predicted cases and they are actually positive. True Negative (NTN) is the number of negative predicted cases and they are also actually negative. False Negative (NFN) is the number of negative predicted cases while they are actually positive, also called (type two) error. False Positive (NFP) is the number of positive predicted cases while they are actually negative, also called (type one) error. The numbers of TP, TN, FP and FN that obtained from the confusion matrix are presented in Table 3.

Table 3: Different evaluation metrics in terms of TP, TN, FP, FN

Class	TP	TN	FP	FN	Total
Glioma	287	1010	1	13	1311
Meningioma	304	990	15	2	1311
No tumor	405	905	1	0	1311
Pituitary	297	1010	1	3	1311

4.2. Confusion Matrix

The proposed ensemble learning approach achieved an outstanding accuracy of 99.33%, surpassing several state-of-the-art studies in brain tumor classification. This high accuracy shows the effectiveness of the proposed approach in classifying brain tumors into the mentioned different tumor classes.

The proposed approach also achieved an impressive result of 98.6% in precision evaluation metric. This evaluation metric measures the proportion of correctly predicted positive cases out of all cases predicted as positive. This value reflects the superiority of the proposed approach and its efficiency in identifying brain tumor types accurately and reducing false positives.

Furthermore, the proposed ensemble model achieved remarkable specificity with a value equals to 99.54 %. The capability of the model to correctly identify true negatives (the cases that actually belong to the non-tumor class) is known as specificity. The achieved high specificity provides a low rate of false positives among the non-tumor cases, surpassing the performance of previous state-of-the-art studies.

The recall is defined as the ability of the model to correctly identify positive cases across all tumor classes. The proposed ensemble model achieved result of 98.5% in the recall evaluation metric. This high value demonstrates the superiority of the proposed approach and its efficiency to identify brain tumor type accurately and shows ability of the model in reducing false negatives.

The combination of precision and recall into a single metric is called a F1 score. The proposed approach achieved of F1 score 99.52%. This high F1 score value confirms that the proposed approach has a superiority on several state-of-the-art studies in brain tumor classification and an excellent ability to achieve a balanced trade-off between precision and recall. Figure 4 presents the confusion matrix of the proposed approach.

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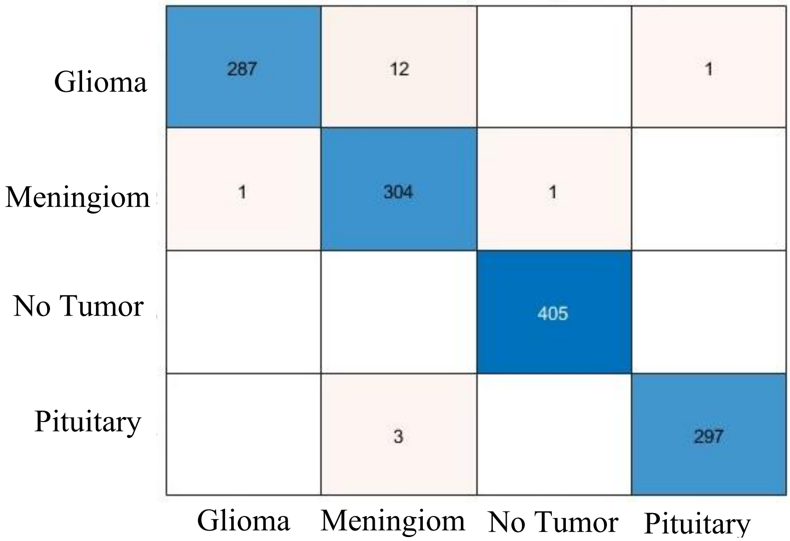

Figure 4: The confusion matrix of the proposed approach: The X-axis of the matrix represents the predicted class, whereas the Y-axis represents the output class

The experimental results show that the proposed ensemble learning approach based on voting technique surpass several state-of-the-art studies in this field. The achieved high accuracy, precision, specificity, recall, and F1 score reflect the superiority of the proposed approach in identifying the existence and specific type of brain tumors. The different evaluation metrics are calculated based on the mentioned equations and the results are shown in Table 4. These promising results will contribute in the development of accurate diagnostic systems based on artificial intelligence, and support the efforts of translation these systems to clinical applications. It also will support the doctors to take the correct medicine decision in the field of neurology.

Table 4: Different evaluation metrics in terms of accuracy, specificity, sensitivity and precision

Class	Accuracy %	Precision %	Specificity %	Recall %	F1 score %
Glioma	99.00	99.65	99.90	95.67	97.62
Meningioma	98.70	95.30	98.50	99.34	97.28
No tumor	99.92	99.75	99.89	100.00	99.87
Pituitary	99.70	99.67	99.90	99.00	99.33
Average	99.33	98.60	99.54	98.50	98.52

4.3. Comparison with State-of-the-Art Methods

In this section, the performance of the proposed approach is compared with several state-of-the-art methods for brain tumor classification. This comparison is done using the evaluation metrics performance which are discussed in the previous section. The comparison shows that the proposed ensemble learning approach based on voting technique surpass state-of-the-art studies in the field of brain tumor classification.

Table 5: Comparison of the proposed approach with individual models and several state-of-the-art methods

Model/Study	Year	Accuracy (%)	Precision (%)	Recall (%)	F1
VGG19 A	-	98.17	98.17	99.39	99.17
VGG19 B	-	98.40	98.39	98.39	98.39
VGG19 C	-	98.40	98.39	98.39	98.39
Özkaraca et al. [40]	2023	-	96.00	96.50	96.00
Kibriya et al. [42]	2022	97.20	97.00	96.00	-
Rasool et al. [43]	2022	98.10	98.20	98.17	98.15
Gómez et.al. [44]	2023	97.12	97.97	-	97.28
Priya et al. [45]	2024	97.00	97.63	96.78	97.25
Saeed et al. [49]	2025	99.06	99.05	99.05	99.06
Proposed	2025	99.33	98.60	98.50	98.52

As can be seen from Table 5, the proposed ensemble model has achieved the highest accuracy, precision, specificity, recall, and F1 score among the compared methods. This comparison confirms that the proposed approach is effective and reliable for brain tumor classification tasks.

5. Discussion

There are several factors behind the high performance which is achieved by the proposed ensemble model. Firstly, overfitting is minimized due to applying of multiple models with varying parameters, this also led to improve generalization performance. Secondly, the voting ensemble technique can combine the predictions of the individual models in one prediction has more accuracy and efficiency.

The proposed approach has several advantages over other brain tumor classification techniques. Firstly, it is computationally efficient, as the individual models can be trained independently and then combined. Secondly, it is

https://doi.org/10.59222/ustjet.4.1.4

interpretable, as the contributions of each model to the final prediction can be analyzed. Thirdly, it is generalizable, as it can be applied to other medical imaging tasks.

In conclusion, the proposed ensemble learning approach provides a promising solution for accurate and reliable brain tumor classification. The high performance achieved suggests that this approach has the potential to improve patient care by aiding in the diagnosis and prognosis of brain tumors. Table 5 shows the accuracy metrics that are extracted from the confusion matrices. The highest performance of precision, sensitivity, specificity and accuracy are bolded in the Table.

6. Conclusion

In this study, an ensemble learning based on voting technique is successfully implemented to improve the performance of brain tumor classification. Three VGG19 models with varying parameters are trained individually on a dataset of 7041 MRI brain images. The voting ensemble technique is applied to combine these models into one model has better accuracy and reliability.

The ensemble model achieved an impressive accuracy of 99.33%, with a precision of 98.6%, a specificity of 99.54%, a recall of 98.5%, and a F1 score of 98.52%, surpassing the state-of-the-art studies in this field. These results demonstrate the effectiveness of the proposed ensemble learning for improving the performance of brain tumor classification models.

There are several advantages which the proposed approach achieved. Firstly, it minimized the overfitting effect and enhancing generalization, which led to improve the efficiency of multiple models' performance. Secondly, it is computationally efficient, as the individual models can be trained independently and then combined. Thirdly, it is interpretable, as the contributions of each model to the final prediction can be analyzed.

In conclusion, the proposed approach introduced a promising, accurate and reliable solution for brain tumor classification. These promising results will contribute in the development of accurate diagnostic systems based on artificial intelligence, and support the efforts of translation these systems to clinical applications. It also will support the doctors to take the correct medicine decision in the field of neurology.

References

[1] V. K. Dhakshnamurthy, M. Govindan, K. Sreerangan, M. D. Nagarajan, and A. Thomas, "Brain Tumor Detection and Classification Using Transfer Learning Models," Engineering Proceedings, vol. 62, no. 1, p. 1, 2024.

[2] M. A. Hamid and N. A. Khan, "Investigation and classification of MRI brain tumors using feature extraction technique," Journal of Medical and Biological Engineering, vol. 40, pp. 307-317, 2020.

[3] E. Dandıl, M. Çakıroğlu, and Z. Ekşi, "Computer-aided diagnosis of malign and benign brain tumors on MR images," in ICT Innovations 2014: World of Data, 2015: Springer, pp. 157-166.

[4] H. Kibriya, M. Masood, M. Nawaz, and T. Nazir, "Multiclass classification of brain tumors using a novel CNN architecture," Multimedia Tools and Applications, vol. 81, no. 21, pp. 29847-29863, 2022.

[5] A. A. Asiri et al., "Brain tumor detection and classification using fine-tuned CNN with ResNet50 and U-Net model: A study on TCGA-LGG and TCIA dataset for MRI applications," Life, vol. 13, no. 7, p. 1449, 2023.

[6] N. A. Samee et al., "Classification framework for medical diagnosis of brain tumor with an effective hybrid transfer learning model," Diagnostics, vol. 12, no. 10, p. 2541, 2022.

[7] S. K. Mathivanan, S. Sonaimuthu, S. Murugesan, H. Rajadurai, B. D. Shivahare, and M. A. Shah, "Employing deep learning and transfer learning for accurate brain tumor detection," Scientific Reports, vol. 14, no. 1, p. 7232, 2024.

[8] "Body MRI." https://www.radiologyinfo.org/en/info/bodymr (accessed.

[9] N. Yamanakkanavar, J. Y. Choi, and B. Lee, "MRI segmentation and classification of human brain using deep learning for diagnosis of Alzheimer's disease: a survey," Sensors, vol. 20, no. 11, p. 3243, 2020.

[10] L. Chen, S. Li, Q. Bai, J. Yang, S. Jiang, and Y. Miao, "Review of image classification algorithms based on convolutional neural networks," Remote Sensing, vol. 13, no. 22, p. 4712, 2021.

[11] K. Omer, L. Caucci, and M. Kupinski, "Limitations of CNNs for Approximating the Ideal Observer Despite Quantity of Training Data or Depth of Network," The Journal of imaging science and technology, vol. 64, no. 6, pp. 60408-1, 2020.

[12] A. Mohammed and R. Kora, "A comprehensive review on ensemble deep learning: Opportunities and challenges," Journal of King Saud University-Computer and Information Sciences, vol. 35, no. 2, pp. 757-774, 2023.

[13] B. Naderalvojoud and T. Hernandez-Boussard, "Improving machine learning with ensemble learning on observational healthcare data," in AMIA Annual Symposium Proceedings, 2023, vol. 2023: American Medical Informatics Association, p. 521.

[14] H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-classification of brain tumor images using deep neural network," IEEE access, vol. 7, pp. 69215-69225, 2019.

[15] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches," Applied Sciences, vol. 12, no. 14, p. 7282, 2022.

[16] M. Rasool et al., "A hybrid deep learning model for brain tumour classification," Entropy, vol. 24, no. 6, p. 799, 2022.

[17] O. Özkaraca et al., "Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images," Life, vol. 13, no. 2, p. 349, 2023.

[18] "Brain Tumor MRI Dataset." https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset (accessed.

[19] M. Bansal, M. Kumar, M. Sachdeva, and A. Mittal, "Transfer learning for image classification using VGG19: Caltech-101 image data set," Journal of ambient intelligence and humanized computing, pp. 1-12, 2023.

[20] T.-H. Nguyen, T.-N. Nguyen, and B.-V. Ngo, "A VGG-19 model with transfer learning and image segmentation for classification of tomato leaf disease," AgriEngineering, vol. 4, no. 4, pp. 871-887, 2022.

[21] B. Han, J. Du, Y. Jia, and H. Zhu, "Zero-watermarking algorithm for medical image based on VGG19 deep convolution neural network," Journal of Healthcare Engineering, vol. 2021, 2021.

[22] "VGG-Net Architecture Explained."https://medium.com/@siddheshb008/vgg-net-architecture-explained-71179310050f (accessed.

[23] W. Li, K. Liu, L. Zhang, and F. Cheng, "Object detection based on an adaptive attention mechanism," Scientific Reports, vol. 10, no. 1, p. 11307, 2020.

[24] H. Wang, F. Zhang, and L. Wang, "Fruit classification model based on improved Darknet53 convolutional neural network," in 2020 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), 2020: IEEE, pp. 881-884.

[25] "Darknet53."https://github.com/developer0hye/PyTorch-Darknet53?tab=readme-ov-file (accessed).

[26] T. Magadza and S. Viriri, "Deep learning for brain tumor segmentation: a survey of state-of- the-art," Journal of Imaging, vol. 7, no. 2, p. 19, 2021.

[27] W. Zhao, D. Zhou, X. Qiu, and W. Jiang, "Compare the performance of the models in art classification," PLOS ONE, vol. 16, no. 3, p. e0248414, Mar. 2021.

[28] B. Naderalvojoud and T. Hernandez-Boussard, "Improving machine learning with ensemble learning on observational healthcare data," AMIA ... Annual Symposium proceedings. AMIA Symposium, vol. 2023, pp. 521–529, 2024, Accessed: May 03, 2024.

[29] S. Bian and W. Wang, "On diversity and accuracy of homogeneous and heterogeneous ensembles," International Journal of Hybrid Intelligent Systems, vol. 4, no. 2, pp. 103–128, Jun. 2007.

[30] S. Mascarenhas and M. Agarwal, "A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for Image Classification," IEEE Xplore, Nov. 01, 2021.

[31] Akmalbek Bobomirzaevich Abdusalomov, Mukhriddin Mukhiddinov, and Taeg Keun Whangbo, "Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging," Cancers, vol. 15, no. 16, pp. 4172–4172, Aug. 2023.

[32] N. Habib, Md. M. Hasan, Md. M. Reza, and M. M. Rahman, "Ensemble of CheXNet and VGG-19 Feature Extractor with Random Forest Classifier for Pediatric Pneumonia Detection," SN Computer Science, vol. 1, no. 6, Oct. 2020

[33] A. Raza et al., " A hybrid deep learning-based approach for brain tumor classification, " Electronics, vol. 11, no. 7, p. 1146, 2022.

[34] Abida, "A Deep Dive into Pretrained Models: VGG-16, VGG-19, ResNet, AlexNet, and Inception," Medium, Nov. 04, 2023. https://medium.com/@abidaubaid229/a-deep-dive-into-pretrained-models-vgg-16-vgg-19-resnet-alexnet-and-inception-40df8cfa38c1

[35] M. Bansal, M. Kumar, M. Sachdeva, and A. Mittal, "Transfer learning for image classification using VGG19: Caltech-101 image data set," Journal of Ambient Intelligence and Humanized Computing, Sep. 2021

https://doi.org/10.59222/ustjet.4.1.4

[36] L. Yanli, G. Yuan, and Y. Wotao, "An Improved Analysis of Stochastic Gradient Descent with Momentum," Advances in Neural Information Processing Systems, vol. 33, 2020

[37] M. Al-Jabbar, E. Al-Mansor, S. Abdel-Khalek, and S. Alkhalaf, "Ebola optimization with modified DarkNet-53 model for scene classification and security on Internet of Things in smart cities," Alexandria Engineering Journal, vol. 75, pp. 29–40, Jul. 2023

[38] K. Raza, "Chapter 8 - Improving the prediction accuracy of heart disease with ensemble learning and majority voting rule," ScienceDirect, Jan. 01, 2019.

[39] M. A. Ganaie, M. Hu, A. K. Malik, M. Tanveer, and P. N. Suganthan, "Ensemble deep learning: A review," Engineering Applications of Artificial Intelligence, vol. 115, p. 105151, Oct. 2022.

[40] O. Özkaraca et al., "Multiple Brain Tumor Classification with Dense CNN Architecture Using Brain MRI Images," Life, vol. 13, no. 2, p. 349, 2023.

[41] F. Uysal and M. Erkan, "Multiclass Classification of Brain Tumors with Various Deep Learning Models," Engineering Proceedings, vol. 27, no. 1, p. 30, 2022.

[42] H. Kibriya, M. Masood, M. Nawaz, and T. Nazir, "Multiclass classification of brain tumors using a novel CNN architecture," Multimedia Tools and Applications, vol. 81, no. 21, pp. 29847-29863, 2022.

[43] M. Rasool et al., "A hybrid deep learning model for brain tumour classification," Entropy, vol. 24, no. 6, p. 799, 2022.

[44] M. A. Gómez-Guzmán et al., "Classifying Brain Tumors on Magnetic Resonance Imaging by Using Convolutional Neural Networks," Electronics, vol. 12, no. 4, p. 955, Jan. 2023.

[45] A. Priya and V. Vasudevan, "Brain tumor classification and detection via hybrid alexnet-gru based on deep learning," Biomedical Signal Processing and Control, vol. 89, pp. 105716–105716, Mar. 2024.

[46] G. Boesch, "Ensemble Learning: A Combined Prediction Model (2024 Guide)," viso.ai, Mar. 07, 2024. https://viso.ai/deep-learning/ensemble-learning.

[47] Md. Nahiduzzaman et al., "A hybrid explainable model based on advanced machine learning and deep learning models for classifying brain tumors using MRI images," Scientific Reports, vol. 15, no. 1, Jan. 2025.

[48] Md. Mamun Hossain, Md. Moazzem Hossain, Most. Binoee Arefin, F. Akhtar, and J. Blake, “Combining State-of-the-Art Pre-Trained Deep Learning Models: A Noble Approach for Skin Cancer Detection Using Max Voting Ensemble,” Diagnostics, vol. 14, no. 1, pp. 89–89, Dec. 2023.

[49] A. Saeed, Khurram Shehzad, S. S. Bhatti, S. Ahmed, and A. T. Azar, “GGLA-NeXtE2NET: A Dual-Branch Ensemble Network with Gated Global-Local Attention for Enhanced Brain Tumor Recognition,” IEEE Access, pp. 1–1, Jan. 2025.

[50] R. Maurya and S. Wadhwani, “An Efficient Method for Brain Image Preprocessing with Anisotropic Diffusion Filter & Tumor Segmentation,” Optik, vol. 265, p. 169474, Sep. 2022.

[51] N. Nobel et al., “A Novel Mixed Convolution Transformer Model for the Fast and Accurate Diagnosis of Glioma Subtypes,” Advanced Intelligent Systems, Nov. 2024.

[52] M. Alsamawi, W. H. Al-Arashi, M. M. Alkhawlani, and F. A. A. J. Almahri, “A Class-Wise Deep Ensemble Framework Using ResNet101 and DenseNet201 for Brain Tumor Classification,” Journal of Imaging Informatics in Medicine, Dec. 2025, doi: https://doi.org/10.1007/s10278-025-01762-6.