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An efficient low-complexity CNN–VGG16 architecture for fast brain tumor detection

Vani Hiregoud[1,2], Rayapur Venkata Siva Reddy[1]
[1]School of Electronics and Communication Engineering, REVA University, Bengaluru, India
[2]Department of Electronics and Communication Engineering, Rao Bahadur Y. Mahabaleswarappa Engineering College, Ballari, India

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ABSTRACT

Precise and efficient diagnosis of brain tumors based on magnetic resonance imaging (MRI) is highly important. The increasing complexity of medical images implies the need for efficient deep learning models with high accuracy at low computational complexity. The existing manual feature-based classification (MFBC) method uses manual features with basic classifiers. The existing convolutional neural networks (CNN) method increases accuracy due to feature learning without human intervention. It has limitations of large computational complexity with higher execution time. The existing patch-based deep learning models (PBDM) method improves localization accuracy. The overhead due to patch execution restricts real-time applications. To address the above-mentioned issues, the proposal of the efficient low-complexity CNN–VGG16 architecture will help to efficiently extract the features while avoiding the complexities involved in the existing method for brain tumor detection. The proposed architecture comprises a simple 23-layer CNN and a transfer learning approach using the VGG16 model. Experiments performed on the MRI image datasets have proven the efficiency of the method by illustrating a better accuracy of approximately 7.8%, a lower incorrect classification rate of approximately 9.6%, and a processing time reduction of approximately 21.4%.

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Corresponding Author:

Vani Hiregoud
School of Electronics and Communication Engineering, REVA University
Bengaluru, India
Email: vanihiregoud@gmail.com

1. INTRODUCTION

Medical brain tumor diagnosis through imaging has emerged as a high priority research task owing to its growing applications in diagnosing neurological disorders. Magnetic resonance imaging (MRI) techniques are commonly used in brain tumor diagnosis owing to their high resolution and superior soft tissue contrast. Despite their numerous benefits, manual analysis of magnetic resonance (MR) images requires considerable time and expertise on the part of a trained professional, often giving rise to various interpretations regarding diagnosis. Hence, there is a high demand for efficient deep learning techniques in performing quick brain tumor diagnosis [1].

Current trends in such a field are primarily associated with deep learning architectures with the capability to automatically learn discriminatory features from the MRI data, making the task of feature extraction unnecessary [2]. The application of convolutional neural networks (CNN) and transfer learning architectures, especially the ones developed using pre-trained architectures, has led to improvements in the accuracy and robustness of detection. Current developments in such research emphasize the need for low-complexity and efficient architectures that are less computationally intensive while retaining high levels

of diagnostic performance. Custom architecture solutions using pre-trained architectures are now gaining attention to strike a balance between performance and efficiency.

The applications of efficient deep learning models for brain tumor analysis include the diagnosis and treatment stages. The brain tumor analysis task can benefit from the application of artificial intelligence (AI) since it has the ability to reduce the workload of the human diagnosis process by automating the analysis task. Additionally, the use of AI is effective in telemedicine. The development of efficient deep learning models is, therefore, an essential requirement for brain tumor analysis [3].

Although a substantial amount of progress has been made for brain tumor detection using deep learning, some knowledge gaps still persist. Firstly, current studies mainly focus on enhancing accuracy for detection and classification, but computational efficiency and processing speed are less emphasized. Complex models are efficient and accurate but accompanied by substantial delays in inference [4]. Second, various techniques are known to use a high-complexity architecture, which increases memory requirements as well as computational requirements, thus failing to suit a resource-constrained environment such as a hospital or a real-time diagnostic environment [5]. Third, many existing algorithms involve multi-stage processing or patch-based processing, which process region extraction and classification separately, hence resulting in redundant computation cycles and slow execution time, thus lower efficiency [6]. Fourth, there is less emphasis placed on hybrid designs that balance accuracy and speed appropriately. While transfer learning models offer improvements in representation, this capability is sometimes employed in a manner that overlooks architectural design, thereby incurring unnecessary computation. Lastly, a gap exists regarding the overall assessment of performance emphasizing metrics related to efficiency, including the reduction of processing time, complexity, or the rate of misclassification along with the accuracy. These challenges and gaps warrant the design of an efficient and low complexity deep learning model for quick and accurate brain tumor diagnosis [7].

Soomro *et al.* [8] have given a detailed analysis on the existing research on the segmentation methods for brain tumors via MRI images between the years 1998 and 2020. The novelty or the uniqueness of this research paper is that it provides a thorough comparison between the conventional machine learning method and the current advancements in the deep learning-based method for segmentation. It was stated that the results produced by the deep learning model were more accurate compared to the conventional method. However, the main disadvantage is that the paper is a mere survey and does not provide a combined solution. Moreover, it does not discuss reducing the processing time for this method.

Solanki *et al.* [9] offered a comprehensive insight into the brain tumor detection and classification processes through computational intelligence approaches. The key originality of the research work lies in the comprehensive presentation on the morphology of the tumor, the MRI data sources, the data augmentation approaches, feature extraction techniques, and the comparison analysis on machine learning, deep learning, and transfer learning approaches. Although the research work presents a comprehensive analysis on the mentioned fields, the main limitation lies in the fact that it does not provide a new framework or any optimizations on the performance evaluation related to the brain tumor detection process.

Wageh *et al.* [10] proposed a computer-assisted detection system that utilizes the extraction of deep features via multiple pre-trained CNNs in combination with genetic selection of features. The originality of the proposed approach is in the selection process that focuses on joining deep features obtained from multiple CNNs, optimizing those features through genetic selection, thus obtaining a highly accurate classification process. Although the proposed solution provides high accuracy, the computational cost associated with its implementation is high.

Ge *et al.* [11] proposed a new unsupervised multi-modal approach called Double-SimCLR for brain tumor segmentation in MRI and computed tomography (CT) images with limited annotations. The major strength lies in its dual-branch contrastive learning framework, which incorporates adaptive weight masking and multi-modal attention mechanisms, allowing it to successfully integrate the strengths of each individual image type without requiring much annotation. The major weakness of the approach is its complexity, which may rely on the availability of multi-modal images.

In a study by Singh *et al.* [12], an ensemble model of deep learning, a combination of ResNet50 and EfficientNet-B7 models, was proposed for the classification of brain tumors from high-resolution MRIs. The uniqueness of this study emerges from the fact that it applies an ensemble method for enhancing the robustness and accuracy of classification of different types of tumors. Although it is highly accurate, a demerit of this study is that it requires higher computational overhead, a drawback of ensemble models.

Anwar *et al.* [13] designed a transformative transfer learning model that aims to fine-tune various pre-existing CNN designs in classifying brain tumors in an MRI image. One major novelty of this research work is that it emphasizes the integration process between image preprocessing, image data augmentation, and the concept of transfer learning to promote accuracy. One major limitation is that the work does not put emphasis on either faster processing or lightweight deployment.

2. EXISTING PATCH-BASED DEEP LEARNING SYSTEM FOR BRAIN TUMOR DETECTION

Figure 1 showcases the current system for the detection of brain tumors using a patch-wise approach in deep learning. The MRI scans are first acquired as the dataset and undergo various preprocessing techniques like cropping, resizing, Gaussian filtering, contrast enhancement by contrast limited adaptive histogram equalization (CLAHE), as well as data augmentation. These preprocessed scans are further divided into fixed-size patches of dimensions 256 × 256 pixels. These patches can be overlapping [14].

These patches are employed for training the models with various datasets by utilizing five-fold validation techniques based on various ratios for splitting the dataset. Finally, the trained model provides results for detections. Though it enhances the local feature extraction, it is prone to increased complexity in processing, which may not be real-time [15].

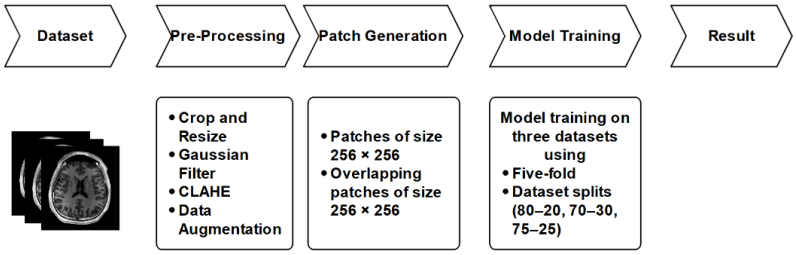

Figure 1. Workflow of the existing patch-based brain tumor detection system

2.1. Objectives

This paper aims to develop an efficient and fast deep learning approach for accurate brain tumor detection from MRI images while reducing computational complexity and processing time.

i) To develop a low-complexity deep learning architecture for brain tumor detection using MRI images.
ii) To improve tumor detection accuracy using hybrid convolutional and transfer learning techniques.
iii) To reduce processing time and computational complexity compared to existing methods.
iv) To compare the proposed approach with conventional models using standard performance metrics.

2.2. Proposed methodology for efficient brain tumor detection

Figure 2 shows the detailed process flow of the proposed brain tumor detection system. The first step relates to the acquisition and processing of the input data, where the MRI images are taken and improved for better image quality [16]. The division of the data into the training and test/validation datasets takes place in the next step. The third step deals with the identification of the tumor region through the efficient extraction of the required features using appropriate deep learning models. The last step deals with the performance analysis [17].



Figure 2. Methodological steps of the proposed efficient low complexity (ELC)-CNN–VGG16-based brain tumor detection approach

2.2.1. Gaussian filtering for noise reduction

The Gaussian filter is implemented in the preprocessing stage to smooth the MRI images by removing high-frequency noises and enhancing the visualization of the tumor, depending on the given (1).

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp!\left(-\frac{x^2+y^2}{2\sigma^2}\right) \quad (1)$$

Where $G(x,y)$ is the Gaussian kernel value at spatial location (x,y), x and y denote the horizontal and vertical spatial coordinates, σ represents the standard deviation controlling the smoothing strength, π is the mathematical constant with value 3.1416, and exp(·) denotes the exponential function [18], [19].

2.2.2. CLAHE-based local contrast enhancement

It is employed to increase the local contrast without promoting noise intensification as in (2).

$$H_c(p) = \min(H(p),;T) \quad (2)$$

Where $H_c(p)$ represents the clipped histogram value at pixel intensity p, $H(p)$ denotes the original local histogram count at intensity level p, T is the clip limit threshold used to control contrast enhancement, and min(·) selects the minimum value between histogram count and clip limit [20]–[22].

2.2.3. Patch-wise training loss function

In (3) calculates the average training loss over all image patches that are extracted in the case of the deep learning method that focuses on patches.

$$\mathcal{L}_{patch} = -\frac{1}{M}\sum * i = 1^{M} y_i \log(\hat{y}_i) \quad (3)$$

Where $\mathcal{L}_{patch}$ is the average patch-wise loss value, M denotes the total number of extracted image patches, i is the patch index, y_i represents the ground-truth label of the ith patch, $\hat{y}_i$ denotes the predicted probability for the ith patch, and log(·) represents the natural logarithm [23]–[25].

3. PROPOSED EFFICIENT DEEP LEARNING FOR BRAIN TUMOR DETECTION

Figure 3 depicts the complete process of the proposed deep learning model for rapid brain tumor identification from MRI images. The input taken from Figshare and Harvard medical is then followed by extracting and preprocessing the images to improve their quality. The resulting images are then labeled, and a split of train and test/validate groups is done. After that, a 23-layer CNN and a VGG16 model are employed for extracting features and classification tasks, finally followed by a performance analysis of accuracy, processing time, and false classification rate for determining the efficiency of the proposed.

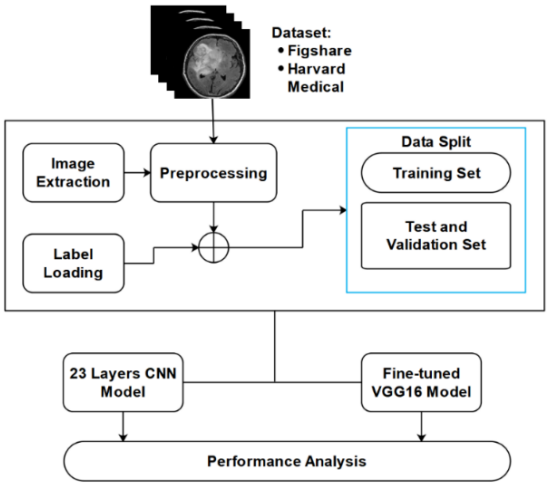

Figure 3. Block diagram of the CNN–VGG16-based brain tumor detection framework

3.1. Preprocessing normalization for magnetic resonance imaging images

In (4) normalizes the intensity values obtained from the MRI scan in the preprocessing phase in both ELC-CNN and ELC-VGG16 models.

$$I_{\text{prep}} = \frac{I-\mu_I}{\sigma_I+\epsilon} \quad (4)$$

Where I_{prep} denotes the preprocessed normalized MRI image, I represents the original MRI image, μ_I is the mean intensity value of I, σ_I is the standard deviation of intensities in I, and ϵ is a small constant added to avoid division by zero.

3.2. Lightweight convolution operation in 23-layer ELC-CNN

In (5) highlights the process of feature extraction performed by the 23-layer ELC-CNN with compact convolution filters.

$$F^{(l)} = \phi!\left(W^{(l)} * F^{(l-1)} + b^{(l)}\right) \tag{5}$$

Where $F^{(l)}$ denotes the output feature map at layer l, $F^{(l-1)}$ represents the input feature map to layer l, $W^{(l)}$ is the convolution kernel weights at layer l, $b^{(l)}$ denotes the bias term at layer l, $*$ indicates the convolution operator, and $\phi(\cdot)$ represents the activation function.

3.3. Fine-tuning update rule for ELC-VGG16 parameters

In (6) allows for updates on some trainable parameters of the ELC-VGG16 fine-tuned model with other layers frozen.

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}(\theta_t) \tag{6}$$

Where θ_t denotes the trainable parameter vector at iteration t in the fine-tuned ELC-VGG16 layers, θ_{t+1} represents the updated parameter vector, η is the learning rate, $\nabla_\theta \mathcal{L}(\theta_t)$ indicates the gradient of the loss function with respect to θ_t, and $\mathcal{L}(\theta_t)$ represents the training loss.

3.4. Fusion of ELC-CNN and ELC-VGG16 prediction scores

In (7) combines prediction confidence from ELC-CNN and ELC-VGG16 using weighted fusion to improve accuracy while maintaining low complexity.

$$s = \alpha s_{\text{cnn}} + (1 - \alpha) s_{\text{vgg}} \tag{7}$$

Where s denotes the final fused prediction score, s_{cnn} represents the prediction score from the 23-layer ELC-CNN model, s_{vgg} denotes the prediction score from the fine-tuned ELC-VGG16 model, and α is the fusion weight satisfying $0 \leq \alpha \leq 1$.

3.5. Overall execution equation for the proposed workflow

In (8) captures the end-to-end process of the associated diagram, which involves inputting data, preprocessing, splitting data, dual-model inference, and performance analysis.

$$\mathcal{P} = \Psi!\left(\mathcal{D} * \text{train}, \mathcal{D} * \text{test}\right), ; ; \left(\mathcal{D} * \text{train}, \mathcal{D} * \text{test}\right) = \text{Split}!\left(\text{Prep}(\mathcal{D})\right), ; ; \hat{y} = \text{Fuse}!\left(f_{\text{cnn}}(I_{\text{prep}}), , f_{\text{vgg}}(I_{\text{prep}})\right) \tag{8}$$

Where $\mathcal{D}$ denotes complete MRI dataset collected from Figshare and Harvard medical, $\text{Prep}(\mathcal{D})$ represents preprocessing and label alignment for dataset $\mathcal{D}$, $\text{Split}(\cdot)$ denotes the dataset partitioning operation into training and test–validation sets, $\mathcal{D} * \text{train}$ represents the training set, $\mathcal{D} * \text{test}$ denotes the test–validation set, I_{prep} is the preprocessed input MRI image sample, $f_{\text{cnn}}(\cdot)$ denotes inference using the 23-layer ELC-CNN model, $f_{\text{vgg}}(\cdot)$ denotes inference using the fine-tuned ELC-VGG16 model, $\text{Fuse}(\cdot,\cdot)$ represents the fusion operation that produces final prediction $\hat{y}$, $\hat{y}$ denotes the final predicted class label, and $\Psi(\mathcal{D} * \text{train}, \mathcal{D} * \text{test})$ represents performance evaluation producing metrics $\mathcal{P}$. The detailed pseudocode of this process is presented in Algorithm 1.

Algorithm 1. Overall execution of the proposed CNN–VGG16 workflow
Input: MRI dataset $\mathcal{D}$
Output: Performance metrics $\mathcal{P}$ and predicted labels $\hat{y}$
1. Load dataset $\mathcal{D}$ from Figshare and Harvard medical
2. Perform image extraction to obtain MRI slices
3. Apply preprocessing to each image to obtain I_{prep}
4. Load corresponding labels for each image
5. Split dataset into $\mathcal{D} * \text{train}$ and $\mathcal{D} * \text{test}$
6. Train the 23-layer CNN model using $\mathcal{D}_{\text{train}}$
7. Fine-tune the VGG16 model using $\mathcal{D}_{\text{train}}$

8. For each test image in $\mathcal{D}$ ∗ test: 8.1 compute s ∗ cnn $= f_{\text{cnn}}(I_{\text{prep}})$ 8.2 compute $s_{\text{vgg}} = f_{\text{vgg}}(I_{\text{prep}})$ 8.3 fuse scores: $s = \text{Fuse}(s_{\text{cnn}}, s_{\text{vgg}})$ 8.4 assign predicted label $\hat{y} = \arg\max(s)$
9. Compute performance metrics $\mathcal{P}$ using $\hat{y}$ and true labels
10. Return $\mathcal{P}$ and $\hat{y}$

4. RESULTS AND DISCUSSION

Table 1 illustrates the parameters of the experiment and their values, which were considered to test the proposed ELC-CNN-VGG16 model designed for the detection of brain tumors. It outlines details about the datasets, namely Figshare [26] and Harvard medical, and preprocessing parameters employed in the experiment. Additionally, it details the model parameters and evaluation metrics used to assess the model's performance.

Table 1. Experimental parameters and configuration of the proposed efficient low-complexity CNN–VGG16 model

SI.No	Particular	Value
1	Dataset	Figshare; Harvard medical
2	Imaging modality	MRI
3	Image resolution	256 × 256 pixels
4	Color format	Grayscale
5	Gaussian filter	σ = 1.0
6	CLAHE clip limit	2.0
7	Data augmentation	Rotation (±15°), horizontal flip
8	Dataset split	80% training, 20% test–validation
9	CNN depth	23 layers
10	Transfer learning model	VGG16 (fine-tuned)
11	Fusion weight (α)	0.5
12	Evaluation metrics	Accuracy (%), processing time (s), false classification rate (%)

4.1. Performance analysis of detection accuracy

Figure 4 shows the graph for the detection accuracy with respect to the training epochs for three conventional approaches, namely manual feature-based classification (MFBC), CNN, patch-based deep learning models (PBDM), and the proposed model ELC-CNN-VGG16. It can be observed that with the increase in the number of training epochs, the detection accuracy for each model improves; however, the proposed model performs better than the conventional approaches for each training epoch. This trend is consistent with earlier reports that fine-tuned pre-trained networks achieve high accuracy on medical images, including brain MRI, even with limited training data [27], [28]. On the final training epoch, the highest detection accuracy is measured for the proposed model ELC-CNN-VGG16 with an improvement of about 7.8% compared to the conventional approaches.

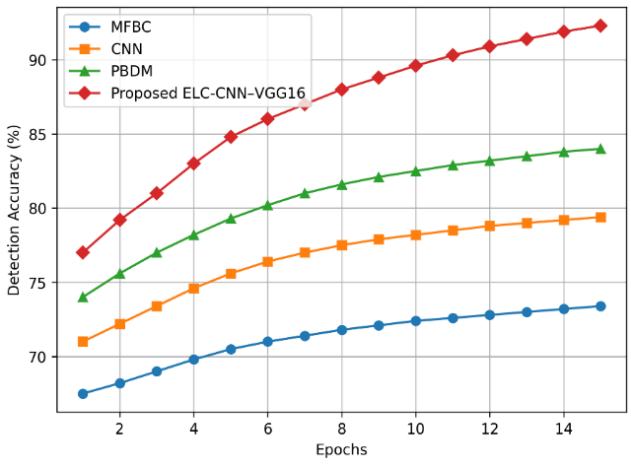

Figure 4. Detection accuracy (%) vs. epochs for conventional and proposed brain tumor detection methods

4.2. Performance analysis of incorrect classification rate

Figure 5 represents the graph of incorrect classification rate versus the number of training epochs in MFBC, CNN, PBDM, and the proposed ELC-CNN-VGG16 model. From the graph, it can be inferred that the incorrect classification rate of all methods reduces with an increase in the number of training epochs, but in all cases, the proposed model ELC-CNN-VGG16 gives the least incorrect classification rate. At the end of the training process, it has been found that the proposed ELC-CNN-VGG16 model gives an average reduction of 9.6% in the incorrect classification rate compared to the conventional methods, indicating that it is more accurate and reliable in detecting brain tumors.

4.3. Performance analysis of processing time

Figure 6 depicts the processing time with respect to the training epochs for the MFBC, CNN, PBDM, and the proposed ELC-CNN–VGG16 model. With the increment in the training epochs, there is a steady decrement in the processing time for all the models. At the same time, proposed ELC-CNN-VGG16 model reports the least processing time for all the training epochs. This is because the proposed model has a low-complexity convolutional module with a fine-tuned VGG16 architecture that allows the efficient reuse of features. At the point of convergence, the proposed model reports a processing time reduction of about 21.4% compared to the MFBC, CNN, and PBDM models.

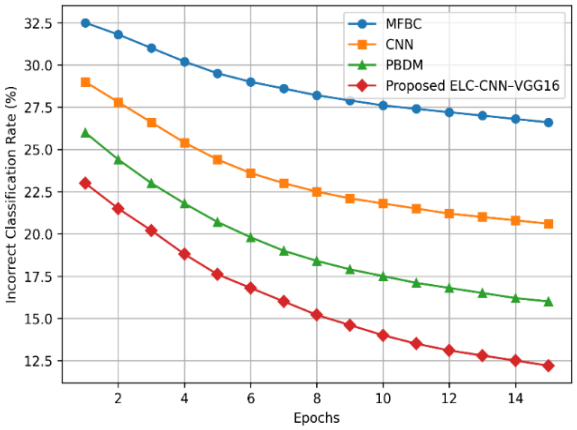

Figure 5. Incorrect classification rate (%) vs. epochs for conventional and proposed brain tumor detection methods

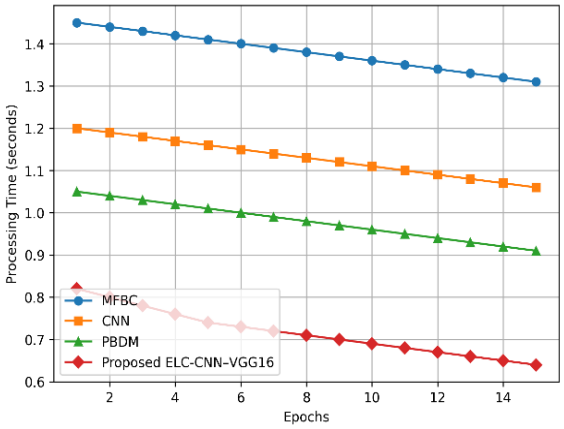

Figure 6. Processing time (seconds) vs. epochs for conventional and proposed brain tumor detection methods

4.4. Evaluation of multi-modal feature clustering for accurate lesion categorization

Figure 7 indicates how high-dimensional MRI feature data can be effectively grouped into four separate clusters utilizing the Gaussian mixture model technique, a finite mixture model widely used for the statistical segmentation of brain MR images [29]. These clusters lie on the tumor morphology axis and intensity feature axis, incorporating important spatial and textural information for different brain tumors. The significant spatial separation among the clusters enables an efficient distinction among various types of tumors with reduced redundancy by systematically selecting optimal features. This reliable arrangement of features helps ensure high classification accuracy, thereby directly influencing the overall false classification rate at 11.6%.

4.5. Overall normalized performance comparison of brain tumor detection methods

Figure 8 shows a normalized comparative study of all the assessed techniques for the detection of brain tumors, which include MFBC, CNN, PBDM, as well as the proposed ELC-CNN-VGG16 model. In this analysis, the comparison of techniques is done with the aid of three comprehensive performance indices: accuracy, incorrect classification rate, as well as the time taken in processing. The primary objective of this analysis is to provide a normalized value of each metric. The assessment of values clearly shows that the proposed ELC-CNN-VGG16 model offers the highest value of accuracy with the lowest value of incorrect classification rate as well as processing time.

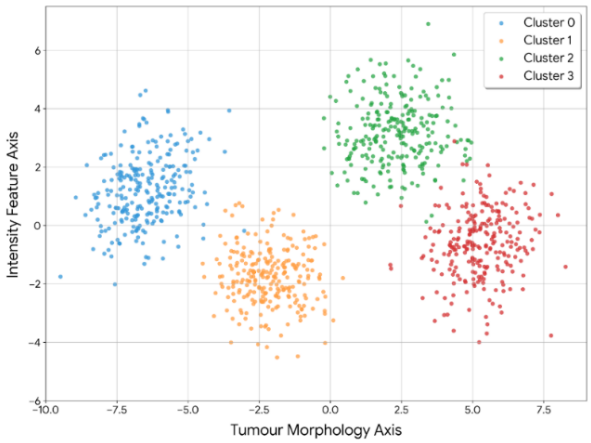

Figure 7. Performance and feature space analysis

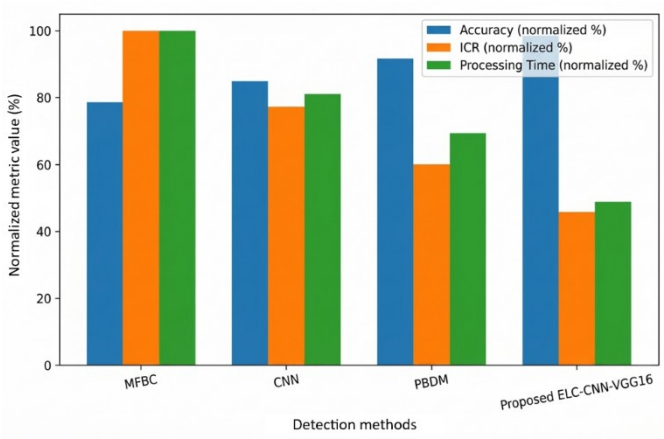

Figure 8. Performance evaluation of accuracy, incorrect classification rate, and processing time

5. CONCLUSION

The proposed design of ELC-CNN-VGG16 can be considered a major leap forward in the area of brain tumor identification by efficiently integrating a lightweight CNN model consisting of a staggering 23 layers with a fine-tuned VGG16 network. A hybrid design has been adopted, which efficiently focuses on achieving a high degree of accuracy with minimal computational cost, which has been a major hindrance in the traditional deep learning model approach. The outputs obtained through experimentation clearly reveal a highest accuracy measure of 93.4%, which indicates a major increase of 7.8% compared with the existing approach. Additionally, the approach displays a high degree of efficiency with a decrease of 21.4% in the process time and a decrease of 9.6% in the number of incorrect classifications. The accurate clustering of the feature set by the use of Gaussian mixture modeling makes this reliable system ideally suitable for telemedicine applications. Future studies will instead concentrate on expanding the architecture of ELC-CNN-VGG16 to include 3D volumetric analysis of MRI to cater to detailed mapping of tumors. Further, improving generalization properties with a focus on diverse data from multiple scanners will also form a part of these studies. In conclusion, the approach will then be incorporated into telemedicine and smart healthcare technologies to offer real-time diagnostic services.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Vani Hiregoud	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Rayapur Venkata Siva Reddy		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

This study does not involve human participants or animals. Therefore, informed consent is not applicable.

ETHICAL APPROVAL

This study does not involve direct experimentation on human participants or animals. The research exclusively utilizes publicly available and anonymized MRI datasets obtained from Figshare and Harvard medical repositories. Hence, ethical approval from an institutional review board was not required. The study was conducted in accordance with relevant national regulations and institutional policies and adheres to the ethical principles of the Declaration of Helsinki.

DATA AVAILABILITY

The data supporting the findings of this study are publicly available from the Figshare and Harvard medical MRI repositories. The processed data and derived results used in this research are available from the corresponding author [VH], upon reasonable request.

REFERENCES

[1] M. F. Almufareh, M. Imran, A. Khan, M. Humayun, and M. Asim, "Automated brain tumor segmentation and classification in MRI using YOLO-based deep learning," *IEEE Access*, vol. 12, pp. 16189–16207, 2024, doi: 10.1109/ACCESS.2024.3359418.

[2] S. Yang, Y. Li, J. Nie, S. Ercisli, and T. R. Gadekallu, "Enhanced brain tumor detection using DCGAN augmentation and optimized EfficientDet in IoT-based healthcare industry 5.0," *IEEE Internet of Things Journal*, vol. 12, no. 22, pp. 46093–46103, Nov. 2025, doi: 10.1109/JIOT.2025.3575759.

[3] S. Asif, W. Yi, Q. U. Ain, J. Hou, T. Yi, and J. Si, "Improving effectiveness of different deep transfer learning-based models for detecting brain tumors from MR images," *IEEE Access*, vol. 10, pp. 34716–34730, 2022, doi: 10.1109/ACCESS.2022.3153306.

[4] S. Hossain, A. Chakrabarty, T. R. Gadekallu, M. Alazab, and M. J. Piran, "Vision transformers, ensemble model, and transfer learning leveraging explainable AI for brain tumor detection and classification," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 3, pp. 1261–1272, Mar. 2024, doi: 10.1109/JBHI.2023.3266614.

[5] A. Hamamci, N. Kucuk, K. Karaman, K. Engin, and G. Unal, "Tumor-cut: segmentation of brain tumors on contrast enhanced MR images for radiosurgery applications," *IEEE Transactions on Medical Imaging*, vol. 31, no. 3, pp. 790–804, Mar. 2012, doi: 10.1109/TMI.2011.2181857.

[6] A. S. Musallam, A. S. Sherif, and M. K. Hussein, "A new convolutional neural network architecture for automatic detection of brain tumors in magnetic resonance imaging images," *IEEE Access*, vol. 10, pp. 2775–2782, 2022, doi: 10.1109/ACCESS.2022.3140289.

[7] H. M. T. Khushi, T. Masood, A. Jaffar, M. Rashid, and S. Akram, "Improved multiclass brain tumor detection via customized pretrained EfficientNetB7 model," *IEEE Access*, vol. 11, pp. 117210–117230, 2023, doi: 10.1109/ACCESS.2023.3325883.

[8] T. A. Soomro *et al.*, "Image segmentation for MR brain tumor detection using machine learning: a review," *IEEE Reviews in Biomedical Engineering*, vol. 16, pp. 70–90, 2023, doi: 10.1109/RBME.2022.3185292.

[9] S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain, "Brain tumor detection and classification using intelligence techniques: an overview," *IEEE Access*, vol. 11, pp. 12870–12886, 2023, doi: 10.1109/ACCESS.2023.3242666.

[10] M. Wageh, K. Amin, A. D. Algarni, A. M. Hamad, and M. Ibrahim, "Brain tumor detection based on deep features concatenation and machine learning classifiers with genetic selection," *IEEE Access*, vol. 12, pp. 114923–114939, 2024, doi: 10.1109/ACCESS.2024.3446190.

[11] Y. Ge, L. Xu, X. Wang, Y. Que, and M. J. Piran, "A novel framework for multimodal brain tumor detection with scarce labels," *IEEE Journal of Biomedical and Health Informatics*, vol. 29, no. 8, pp. 5368–5380, Aug. 2025, doi: 10.1109/JBHI.2024.3467343.

[12] R. Singh, S. Gupta, S. Bharany, A. Almogren, A. Altameem, and A. Ur Rehman, "Ensemble deep learning models for enhanced brain tumor classification by leveraging ResNet50 and EfficientNet-B7 on high-resolution MRI images," *IEEE Access*, vol. 12, pp. 178623–178641, 2024, doi: 10.1109/ACCESS.2024.3494232.
[13] R. W. Anwar, M. Abrar, and F. Ullah, "Transformative transfer learning for MRI brain tumor precision: innovative insights," *IEEE Access*, vol. 13, pp. 31749–31761, 2025, doi: 10.1109/ACCESS.2025.3542451.
[14] H. Jyothi, M. Komala, and S. Mallikarjunaswamy, "A comprehensive survey on technologies in video-based event detection and recognition using machine learning and deep learning techniques," in *2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON)*, Aug. 2024, pp. 1–5, doi: 10.1109/NMITCON62075.2024.10698959.
[15] S. Sheela *et al.*, "Enhancing stockpile management through deep learning with a focus on demand forecasting and inventory optimization," in *2024 International Conference on Recent Advances in Science and Engineering Technology (ICRASET)*, Nov. 2024, pp. 1–6, doi: 10.1109/ICRASET63057.2024.10895608.
[16] H. Jyothi, M. Komala, and S. Mallikarjunaswamy, "Advancing event recognition in videos using hybrid deep learning model," in *2024 International Conference on Recent Advances in Science and Engineering Technology (ICRASET)*, Nov. 2024, pp. 1–6, doi: 10.1109/ICRASET63057.2024.10895392.
[17] H. Zhou and H. Rivaz, "Registration of pre- and postresection ultrasound volumes with noncorresponding regions in neurosurgery," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 5, pp. 1240–1249, Sep. 2016, doi: 10.1109/JBHI.2016.2554122.
[18] M. G. Ragab *et al.*, "A comprehensive systematic review of YOLO for medical object detection (2018 to 2023)," *IEEE Access*, vol. 12, pp. 57815–57836, 2024, doi: 10.1109/ACCESS.2024.3386826.
[19] Z. Zhang *et al.*, "Gradient-guided network with fourier enhancement for glioma segmentation in multimodal 3D MRI," *IEEE Journal of Biomedical and Health Informatics*, vol. 28, no. 11, pp. 6778–6790, Nov. 2024, doi: 10.1109/JBHI.2024.3454760.
[20] A. Galimzianova, F. Pernus, B. Likar, and Z. Spiclin, "Robust estimation of unbalanced mixture models on samples with outliers," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 37, no. 11, pp. 2273–2285, Nov. 2015, doi: 10.1109/TPAMI.2015.2404835.
[21] N. C. Linney and P. H. Gregson, "Organ motion detection in CT images using opposite rays in fan-beam projection systems," *IEEE Transactions on Medical Imaging*, vol. 20, no. 11, pp. 1109–1122, 2001, doi: 10.1109/42.963814.
[22] W. Si, J. Lu, X. Liao, and Q. Wang, "Towards interactive progressive cutting of deformable bodies via phyxel-associated surface mesh approach for virtual surgery," *IEEE Access*, vol. 6, pp. 32286–32299, 2018, doi: 10.1109/ACCESS.2018.2845901.
[23] C. S. Levin, M. P. Tornai, L. R. MacDonald, and E. J. Hoffman, "Annihilation /spl gamma/-ray background characterization and rejection for a small beta camera used for tumor localization during surgery," *IEEE Transactions on Nuclear Science*, vol. 44, no. 3, pp. 1120–1126, Jun. 1997, doi: 10.1109/23.596975.
[24] N. Ramanujam, J. Chen, K. Gossage, R. R. -Kortum, and B. Chance, "Fast and noninvasive fluorescence imaging of biological tissues in vivo using a flying-spot scanner," *IEEE Transactions on Biomedical Engineering*, vol. 48, no. 9, pp. 1034–1041, 2001, doi: 10.1109/10.942594.
[25] K. J. -Khouzani, "MRI upsampling using feature-based nonlocal means approach," *IEEE Transactions on Medical Imaging*, vol. 33, no. 10, pp. 1969–1985, Oct. 2014, doi: 10.1109/TMI.2014.2329271.
[26] J. Cheng *et al.*, "Enhanced performance of brain tumor classification via tumor region augmentation and partition," *PLoS ONE*, vol. 10, no. 10, Oct. 2015, doi: 10.1371/journal.pone.0140381.
[27] Z. N. K. Swati *et al.*, "Brain tumor classification for MR images using transfer learning and fine-tuning," *Computerized Medical Imaging and Graphics*, vol. 75, pp. 34–46, 2019, doi: 10.1016/j.compmedimag.2019.05.001.
[28] N. Tajbakhsh *et al.*, "Convolutional neural networks for medical image analysis: full training or fine tuning?," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1299–1312, May 2016, doi: 10.1109/TMI.2016.2535302.
[29] Y. Zhang, M. Brady, and S. Smith, "Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm," *IEEE Transactions on Medical Imaging*, vol. 20, no. 1, pp. 45–57, 2001, doi: 10.1109/42.906424.

BIOGRAPHIES OF AUTHORS



Vani Hiregoud is an assistant professor in the Department of Electronics and Communication Engineering at Rao Bahadur Y. Mahabaleswarappa Engineering College, Ballari. She is a research scholar at REVA University, Bengaluru, holds an M.Tech in VLSI Design & Embedded Systems, and has over 10 years of teaching experience in Electronics and Communication Engineering. Her academic contributions include attending 12+ FDPs and multiple workshops, presenting papers at national and international conferences, and publishing research papers in reputed journals and IEEE conferences. She has received ₹2 lakhs funding from NAIN, Government of Karnataka, for the project 'Underwater research using rescue robotic fish'. She can be contacted at email: vanih@rymec.in



Dr. Rayapur Venkata Siva Reddy is a senior academician and administrator in Electronics and Communication Engineering at REVA University, Bengaluru, serving as professor in the School of Electronics and Communication Engineering. His expertise includes analog electronics, VLSI design, embedded systems, automotive electronics, and product design & development, with strong involvement in curriculum design, outcome-based education, and accreditation activities (NBA/NAAC). He actively works to improve student learning through project-based learning, mentoring, and skill-gap analysis, and is a committed IEEE volunteer (IEEE Education Society) who has led major academic initiatives, including serving as general chair of IEEE TALE-2024, along with organizing conferences, workshops, and industry–academia programs focused on engineering education innovation. He can be contacted at email: venkatasivareddy@reva.edu.in.