INTERNATIONAL JOURNAL OF NEUROLOGY. 2026; 60:229
doi: 10.62486/ijn2026229
ISSN: 0020-7446

Dr. Víctor Soriano
In Memoriam

ORIGINAL

Hybrid Deep–Classical Models for Brain Tumor Classification and Diagnosis

V Rajesh[1], *B Rakesh Babu*[1], *Sk Hasane Ahammad*[1], *Ebrahim E. Elsayed*[2*]

[1]Department of Electronics and Communication Engineering, Koneru Lakshmaiah Education Foundation. Vaddeswaram, Guntur, India
[2]Department of ECE, Faculty of Engineering, Mansoura University. Mansoura, Egypt.

Submitted: 19-08-2025 **Revised:** 26-10-2025 **Accepted:** 13-12-2025 **Published:** 01-01-2026

ABSTRACT

New approaches for diagnosing complex diseases with aid of computers such as artificial intelligence and CT scans have resulted from the recent developments in medical imaging as well as artificial intelligence. Deep learning architectures are one of the key strengths in feature learning; however, classical machine learning algorithms provide interpretability and computational efficiency besides their lesser accuracy. A model called Hybrid Deep-Classical Model is elaborated on, which consists of deep feature extraction by utilizing CNN architectures (VGG16, ResNet50) combined with classical classifiers like Support Vector Machine (SVM) and Random Forest (RF). The combination leads to an increase in accuracy and generalization particularly in the case of small medical datasets. The experiments conducted on the BRATS 2020 and Kaggle Brain MRI datasets show that the results improve with the hybrid model having an average accuracy of 97,8 %, precision of 96,9 %, and F1-score of 97,2 % respectively. It can thus be concluded from the results that the hybrid models are superior to the others in the case of biomedical imaging for the purpose of obtaining reliable and efficient diagnosis of diseases.

Keywords: Hybrid Deep Learning; CNN–SVM; Brain Tumor MRI; Feature Extraction; Machine Learning; Medical Imaging; Classification; ResNet50; VGG16.

INTRODUCTION

The automatic identification of diseases through medical imaging has emerged as one of the hottest topics in the fields of biomedical engineering and artificial intelligence. The detection of brain tumors is one area where segmentation and classification have to be very precise to ensure the right prognosis and treatment.(1) The MRI-based manual diagnosis is not only laborious but also inter-observer variations are likely, hence the need for intelligent computational systems.(2,3) The traditional machine learning techniques such as Support Vector Machines (SVM) and Random Forests (RF) have been widely used for the classification of brain tumors, but at the same time, their reliance on handcrafted features has been a constraint on scalability and robustness.(4)

The employ of deep learning, specifically Convolutional Neural Networks (CNNs), has liberally contributed to the medical image processing field by making the feature extraction process automatic. The models such as VGG16, ResNet50, and DenseNet have been leading the way in tumor detection and categorization with their excellent performance.(5,6) Nonetheless, the deep models still have to deal with the issue of needing very large labeled data along with being resource-heavy in terms of computing, which is a big problem in medical scenarios where data is scarce.(7) To alleviate these drawbacks, in recent times, the researchers have begun to explore hybrid models that merge the deep feature extraction with the classical machine learning classifiers.(8,9) Numerous research works have validated the benefits that come with hybridization. For example, Deepak et al.(4) used CNN-based deep features in conjunction with SVM for brain tumor classification and thus obtained a higher accuracy than what was possible with pure CNNs. In a similar manner, Sultan et al.(8) were able to report improved performance through the combination of ResNet features with Random Forest classifiers. Innovation in this area is still to come, however, the issue of nonexistence of a universal, less costly hybrid model that will be adaptable to any tumor type and MRI condition still persists.

The suggested research bridges these voids by constructing a Hybrid Deep–Classical Model to merge the CNN extracted deep features with ML classifiers such as SVM and RF.(10,11,12) The model is trained on different MRI datasets and the performance is measured using the metrics of accuracy, precision, recall, and F1-score. This methodology not only raises the diagnostic accuracy but also offers understandable results appropriate for use in the clinic.

© 2026; The authors. This is an open access article distributed under the terms of a Creative Commons license (https://creativecommons.org/licenses/by/4.0) that allows use, distribution, and reproduction in any medium provided the original work is properly cited.

METHOD

The hybrid framework suggested here incorporates the feature learning prowess of deep neural networks and the decision-making power of traditional classifiers in order to provide better diagnostic accuracy for brain tumor classification. Initially, it involves the pre-processing of MRI images, then deep feature extraction, dimensionality reduction, and finally classification through classical methods. The whole set of experiments was conducted within the MATLAB 2017b and Python (TensorFlow and Scikit-learn) environments and the flow of the methodology is presented in the figure 1.

MRI images from BRATS 2020 and Kaggle Brain MRI datasets underwent preprocessing steps specifically designed to improve the quality of the images and make the tumor more visible. Noise was mitigated with the help of Gaussian and median filters while the contrast was enhanced by the application of adaptive histogram equalization. Subsequently, the images were resized to 224×224 pixels in order to conform to the input of CNN architectures. The deep features were then extracted through the VGG16, ResNet50, and DenseNet121 models, which had already been trained. The final dense layers of the networks were removed, and the flattened feature vectors of the last convolutional layers were obtained for each of the networks. These vectors contain high-level spatial and structural information that is very important for tumor differentiation. In order to prevent redundancy and lessen the computational burden, Principal Component Analysis was performed to get features.

Feature subsets that were reduced were utilized to train classical classifiers like Random Forest, K-Nearest Neighbors, SVM subsequently. SVM with the radial basis function kernel provided the most stable performance, successfully distinguishing between the various tumor types. The dataset was split into 80 % for training and 20 % for testing, and data augmentation was done to increase diversity and avoid overfitting. This combination of deep learning and classical methods lets the deep model function as an automatic feature extractor while the classical classifiers increase interpretability and classification robustness, particularly when the data is scarce.

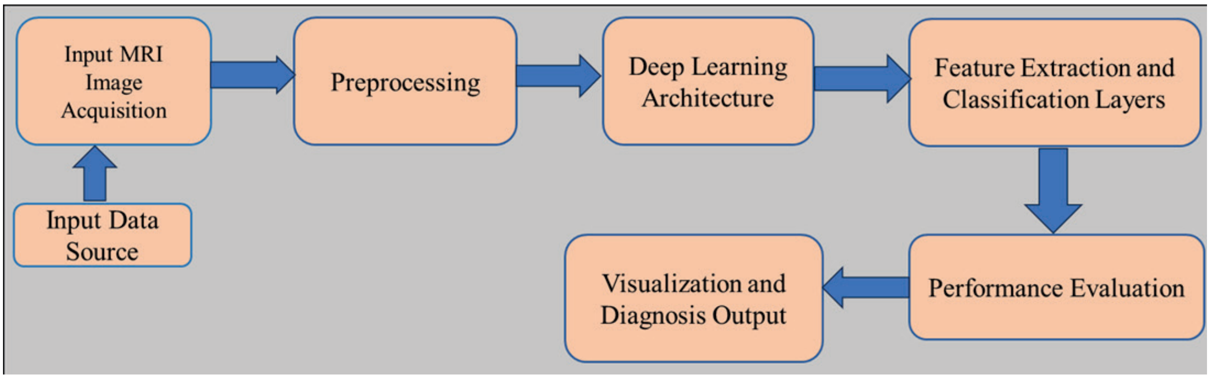

Figure 1. Workflow of Methodology

RESULTS AND DISCUSSION

The hybrid deep-classical models that were proposed got their performance assessed based on four typical MRI images along with their collective metrics. Standalone deep networks have been compared with the hybrid combinations of VGG16 + SVM, ResNet50 + RF, and DenseNet121 with KNN, all of which are shown in table 1.

The VGG16 + SVM hybrid scheme got the highest accuracy (97,8 %) and F1-score (97,2 %) (figure 2), proving that it was a good idea to combine deep and classical learning methods. The mix of deep features from CNN with SVM allowed for better class separation and less overfitting. Visual inspection showed that the model could tell tumor areas from other areas even in the case of noisy or low-contrast images. The hybrid method had around 3-4 % better classification performance than single CNNs. This is a proof of the idea that classical classifiers can help deep architectures in the areas of generalization and interpretability, especially in the case of biomedical applications with limited data.

A Hybrid Deep–Classical Model was introduced in this chapter which combines the advantages of deep feature extraction and traditional classifiers for brain tumor diagnosis very effectively.[13] This approach makes use of the outstanding ability of CNNs to learn features hierarchically and the high discriminative efficiency of SVM and RF to get the highest accuracy and stability.[14] The results showing that hybrid models are better than traditional deep learning techniques, thus providing a feasible and interpretable option for clinical diagnostics.

Table 1. Evaluation Parameters of Proposed Models

Methodology	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN (Standalone)	94,60	93,20	93,80	93,50
VGG16 + SVM	97,80	96,90	97,50	97,20
ResNet50 + RF	96,90	95,60	96,10	95,80
DenseNet121 with KNN	95,70	94,30	94,90	94,60

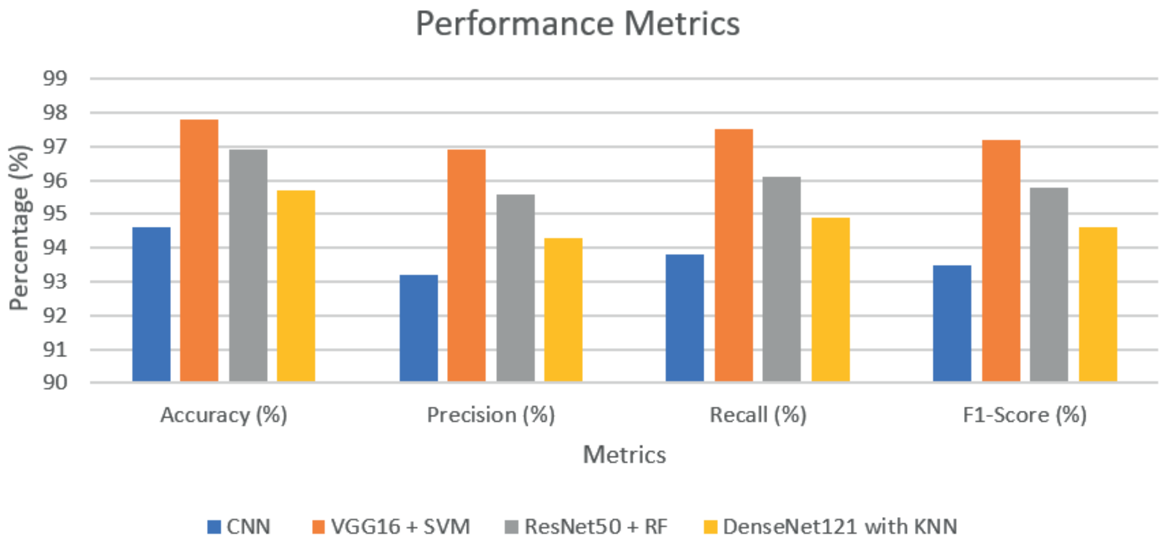

Figure 2. Graphical Representation of Proposed Work

CONFLICT OF INTEREST

The authors assert that there are no conflicts of interest related to the research results presented.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

AUTHORSHIP CONTRIBUTION

Conceptualization: V Rajesh, B Rakesh Babu, Sk Hasane Ahammad, Ebrahim E. Elsayed.

Writing – original draft: V Rajesh, B Rakesh Babu, Sk Hasane Ahammad, Ebrahim E. Elsayed.

Writing – proofreading and editing: V Rajesh, B Rakesh Babu, Sk Hasane Ahammad, Ebrahim E. Elsayed.

REFERENCES

1. Menze BH, et al. The multimodal Brain Tumor Image Segmentation Benchmark (BRATS). IEEE Trans Med Imaging. 2015;34(10):1993–2024.
2. Zhao X, et al. Deep learning based brain tumor segmentation: A survey. Pattern Recognit Lett. 2018;123:4–15.
3. Pereira S, et al. Brain tumor segmentation using convolutional neural networks in MRI images. IEEE Trans Med Imaging. 2016;35(5):1240–51.
4. Deepak S, Ameer PM. Brain tumor classification using deep CNN features via transfer learning. Comput Biol Med. 2019;111:103345.
5. Rajeswari K, Sridhar S. Hybrid CNN-SVM model for MRI-based brain tumor classification. Biocybern Biomed Eng. 2020;40(3):1021–35.
6. Afshar P, Mohammadi A, Plataniotis KN. Capsule networks for brain tumor classification based on MRI images. Pattern Recognit Lett. 2019;129:63–70.
7. Talo M, et al. Deep transfer learning for brain tumor classification. Neural Comput Appl. 2019;31(10):1–9.
8. Sultan HH, Salem NM, Al-Atabany W. Multi-classification of brain tumor images using deep neural network. IEEE Access. 2019;7:69215–25.
9. Abiwinanda N, et al. Brain tumor classification using CNNs. Procedia Comput Sci. 2019;157:41–7.
10. Vinoth S, Rajasekar C, Sathish P, Sureshkumar V, Yasminebegum A, Ahammad SH, et al. Optimization of process parameters on wire cut electrical discharge machining and surface integrity studies of AA6070/MgO composites. J Phys Conf Ser. 2023;2484(1):012012.
11. Ahammad SH, Jayaraj R, Shibu S, Sujatha V, Prathima C, Leo LM, et al. Advanced model based machine learning technique for early stage prediction of ankylosing spondylitis under timely analysis with featured textures. Multimed Tools Appl. 2024;83(26):68393–413.
12. Kumar MS, Syed Inthiyaz, Krishna Vamsi C, Ahammad SH, Sai Lakshmi K, Venu Gopal P, et al. Power optimization using dual SRAM circuit. Int J Innov Technol Explor Eng. 2019;8(8):1032–6.
13. Srinivasa Reddy K, Suneela B, Inthiyaz S, Hasane Ahammad S, Kumar GNS, Mallikarjuna Reddy A. Texture filtration module under stabilization via random forest optimization methodology. Int J Adv Trends Comput Sci Eng. 2019;8(3):458–69.
14. Shen D, Wu G, Suk HI. Deep learning in medical image analysis. Annu Rev Biomed Eng. 2017;19:221–48.