International Journal of advancement in electronics and computer engineering (IJAECE)
Volume 14, Issue 11, Nov. 2025, pp.106-110, ISSN 2278 -1412

A Review on Comparative Analysis of Machine Learning and Deep Learning Models for Brain Tumor Detection

Kajal Gour[1], Prof Swati Khanve[2], Prof Nitya Khare[3]
[1]*M.Tech Scholar, Dept. of CSE, SIRTE, Bhopal, Kajalgour118@gmail.com, India;*
[2]*Asst. Prof., Dept. of CSE, SIRTE, Bhopal, swatikhanve55.sk@gmail.com, India;*
[3]*HOD, Dept. of CSE, SIRTE, Bhopal, India;*

Abstract *– Detecting and classifying brain tumors are some of the most important things to do in medical imaging because they directly affect how doctors plan treatment and how long patients live. People have looked into a lot of different ways to use machine learning (ML), including preprocessing methods like homomorphic filtering, morphological operations, and normalisation. Then, to make classification more accurate, they use feature extraction and feature selection. These methods can work very well, but they often need a lot of work to make the features and hyperparameters work well together. On the other hand, deep learning (DL) models like Convolutional Neural Networks (CNN), DenseNet, and VGG16 have shown that they can automatically learn hierarchical features from raw MRI images. This greatly improves accuracy, robustness, and generalization across different datasets. This review offers a comparative examination of ML and DL methodologies, emphasising their techniques, advantages, and constraints in the classification of brain tumors. The study highlights the significance of preprocessing and feature optimisation in machine learning, while demonstrating that deep learning architectures provide a more dependable and scalable solution for clinical applications.*

Keywords*: Brain Tumor Classification, Machine Learning, Deep Learning, Preprocessing, Feature Selection, CNN, VGG16, DenseNet.*

I. Introduction

Brain tumors are some of the most complicated and potentially fatal neurological conditions. They are brought on by the brain and central nervous system's cells growing abnormally and uncontrollably. If they are not identified in a timely manner, they can cause severe impairment or even death by interfering with essential brain processes including memory, motor coordination, or cognitive processing. The World Health Organization, or WHO, reports that malignancies of the brain along with other central nervous systems (CNS) account for around 3% of all cancers worldwide, but because of their delicate position and biological complexity, they disproportionately contribute to cancer-related death. Because of this, enhancing treatment results and survival rates requires early and precise identification.

Since magnetic resonance imaging (MRI) offers superior soft-tissue contrast and precise viewing of brain structures, it is often considered as the gold standard in brain tumor identification. Clinicians can determine the size, location, and kind of tumors using MRI. However, manual MRI scan interpretation is time-consuming, subjective, & prone to inter-observer variability—particularly when distinguishing between various kinds of tumors. Artificial intelligence (AI) techniques, including Machine Learning (ML) & Deep Learning (DL), have been thoroughly investigated for automated tumor categorization in order to get beyond these restrictions [1].

Four main processes are usually included in traditional ML-based tumor detection: initial processing, feature extraction, feature selection, & classification [2]. By using morphological processes, lighting correction, noise reduction, homomorphic filtering, and pixel normalization, preprocessing enhances the quality of images. Using descriptors like the Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor filters, feature extraction computes texture, shape, and intensity characteristics. Principal Component Analysis (PCA) and other feature selection techniques aid in dimensionality and redundancy reduction, increasing computing efficiency. Lastly, classifiers are used to determine the kind of tumor: support vector machine (SVM), random forest (RF), K-Nearest Neighbor (KNN), Naïve Bayes (NB), XGBoost, CatBoost, and Extra Trees.

Medical imaging has changed as a result of deep learning, particularly convolutional neural networks (CNNs), which do away with the necessity for human feature engineering. CNNs use MRI images to directly learn hierarchical patterns; deeper layers extract more intricate tumor-related structures, while shallower levels record edges and textures [3]. Research indicates that in terms of classification accuracy and resilience, CNN-based models trained on large datasets often perform better than conventional ML approaches. In order to extract and categorize significant characteristics from

DOI Member 211.173.469

International Journal of advancement in electronics and computer engineering (IJAECE)
Volume 14, Issue 11, Nov. 2025, pp.106-110, ISSN 2278 -1412

MRI images, a typical CNN architecture consists of convolutional layers, activation functions, pooling layers, and fully connected layers. Probability ratings are assigned to various tumor classifications by the final output layer.

II. Background & Motivation

Because it directly affects diagnosis, treatment planning, & patient survival, brain tumor categorization using medical imaging has emerged as a crucial field of study. Conventional MRI radiological diagnosis mostly depends on the subjective and time-consuming expertise of radiologists. By extracting manually created characteristics like texture, shape, & intensity from MRI images, machine learning (ML) approaches have been extensively investigated to automate this process [4]. Algorithms like Support Vector Machine (SVM), Random Forest (RF), or k-Nearest Neighbor (KNN) are then used to classify these attributes.

By automatically learning hierarchical features from raw photos and minimizing reliance on human feature engineering, Deep Learning (DL), and in particular Convolutional Neural Networks (CNNs), has revolutionized the discipline [5]. Using pre-trained information from extensive picture datasets, transfer learning models like VGG16, DenseNet, and ResNet50 have attained higher accuracy. Modern hybrid techniques enhance classification performance, particularly in multiclass situations, by combining ML classifiers with DL-based feature extraction.

The goal of this research is to evaluate and contrast ML and DL techniques, pinpoint their advantages and disadvantages, and demonstrate how hybrid frameworks might improve precision, resilience, and clinical relevance. This comparative viewpoint serves as a basis for creating effective diagnostic instruments for early tumor identification.

III. Literature Survey

This study will provide a thorough examination of current deep learning and machine learning methods used in medical imaging to help the precise identification and categorization of brain tumors. By evaluating and comparing preprocessing approaches, the extraction and selection of features strategies, and classification algorithms, this work aims to close knowledge gaps. The paper seeks to determine future research areas by emphasizing the advantages and disadvantages of both sophisticated deep learning systems and conventional machine learning. The ultimate objective is to aid in the development of early brain tumor identification techniques that are more dependable, accurate, and scalable in order to improve clinical judgment and patient outcomes.

Table 1 Literature Reviews

S. No.	Authors	Methods Used	Datasets Used	Accuracy	Key Findings
1	Sharma N. et al. [6]	Transfer Learning (AlexNet, GoogleNet, ResNet 50)	CIFAR-10, CIFAR-100	GoogleNet – 68.95%ResNet50 – 52.55%AlexNet – 13%	GoogleNet outperforms other TL models; ResNet50 and AlexNet perform poorly on small-resolution images.
2	Hana D. et al. [7]	Transfer Learning + Web Data Augmentation (AlexNet, VGG16, ResNet-152)	Flowers102, Dogs, Caltech-101, Event-8, 15-Scene, 67-Indoor Scene	Flowers102 – 92.5%Dogs – 79.8%Caltech101 – 89.3%Event8 – 95.1%15-Scene – 90.6%67-Indoor – 72.1%	Web augmentation significantly boosts TL model performance; ResNet-152 performs strongly on complex datasets.
3	Hussain M. et al. [8]	Transfer Learning with Inception-v3	CIFAR-10, Caltech Face	CIFAR-10 – 70.1%Caltech Face – 65.7%500 epochs – 91%4000 epochs – 96.5%	More training epochs drastically improve performance; TL with Inception-v3 generalizes well with extensive training.
4	Lousaief S. et al. [9]	Deep CNN	Caltech-101	96%	Deep CNN achieves high accuracy showing deep learning's strength

International Journal of advancement in electronics and computer engineering (IJAECE)
Volume 14, Issue 11, Nov. 2025, pp.106-110, ISSN 2278 -1412

					in high-resolution category classification.
5	Ma B. et al. [10]	Genetic DCNN (Autonomous CNN Architecture Generation)	MNIST, CIFAR-10, CIFAR-100	MNIST – 99.72%CIFAR-10 – 89.23%CIFAR-100 – 66.70%	Autonomous CNN architecture search provides near state-of-the-art performance without manual architecture design.
6	Lee S. J. et al. [11]	CNN + AdaBoost	CIFAR-10	88.4%	Boosting improves CNN performance; hybrid methods reduce misclassification in similar classes.
7	Wang et. al. [12]	SVM, CNN	MNIST, COREL-1000	MNIST: SVM 0.88, CNN 0.98COREL-1000: SVM 0.86, CNN 0.83	CNN works better on large datasets (MNIST), while SVM is more effective for small image datasets (COREL-1000).
8	Monika Bansal et. al. [13]	VGG19 + SIFT, SURF, ORB, Shi-Tomasi + ML classifiers	Caltech-101	Random Forest – 93.73%	Hybrid feature extraction (deep + handcrafted) yields higher accuracy than single-feature models.

IV. Machine Learning Approaches

Using a structured pipeline that includes preprocessing, feature extraction, feature selection, and classification, machine learning (ML) has long been used to identify brain tumors. More dependable feature extraction is made possible by preprocessing methods like homomorphic filtering and normalization, which enhance MRI quality. [14] To capture the texture and form properties of tumors, machine learning techniques often include handmade features such as GLCM, LBP, and Gabor filters. Model accuracy is increased, and dimensionality is decreased with the use of feature selection techniques like PCA. When paired with appropriate preprocessing and feature tuning, classifiers such as SVM, Random Forest, and XGBoost often achieve excellent accuracy. But since ML models rely so largely on manually created characteristics, they are less successful for complicated tumor changes and less flexible across datasets.

V. Deep Learning Approaches

By allowing end-to-end learning from raw MRI images without the requirement for human feature engineering, deep learning (DL) has completely changed the categorization of brain tumors. Convolutional Neural Networks (CNNs) are more successful than typical machine learning techniques for capturing complicated tumor patterns because they automatically learn hierarchical features via convolution, activation, pooling, and all connected layers. Through deep feature extraction, dense connectivity, along with residual learning, transfer learning architectures like VGG16, DenseNet, and ResNet50 significantly enhance performance; when optimized on MRI datasets, they often achieve accuracy exceeding 95%. Although DL models need huge, labeled datasets, considerable computing power, and have limited interpretability, they are very scalable and generalize well across many tumor types [15].

VI. Evaluation Metrics

Performance Metrics that guarantee clinical dependability are used to assess the effectiveness of brain tumor classification algorithms. Medical diagnosis depends more on precision, recall, and F1-score, which more accurately represent a model's capacity to identify tumor instances and manage class imbalance, while accuracy shows the percentage of properly categorized cases. A model's discriminative power over a range of thresholds is further measured by metrics like ROC–AUC, and confusion matrices aid in visualizing tumor type misclassifications. To avoid overfitting and guarantee reliable performance, cross-validation and training/validation loss monitoring are often used in both

ML and DL models. [16] When combined, these evaluation techniques provide a thorough analysis of the model's performance in actual tumor categorization situations.

Table 1 Metrics Used in Classification Problems

Metric	Formula	Interpretation
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Overall performance of model
Precision	$\frac{TP}{TP+FP}$	How accurate the positive predictions are
Recall	$\frac{TP}{TP+FN}$	Coverage of actual positive sample
F1 score	$\frac{2TP}{2TP+FP+FN}$	Hybrid metric useful for unbalanced classes

VII. Challenges & Limitations

There are still a number of difficulties in classifying brain tumors using ML and DL, despite tremendous advancements. The availability of large, labeled medical datasets is a major drawback, as the generalizability of deep learning models is restricted by data scarcity [17]. Hospital-specific variations in MRI acquisition procedures also cause domain shift, which weakens the model's resilience. In-depth feature engineering is necessary for machine learning techniques, which necessitates domain knowledge and may not generalize well across datasets [18]. Although DL reduces manual labor, its high computing requirements limit its use in healthcare settings with limited resources. Furthermore, DL models are sometimes criticized for being "black boxes" with little interpretability, which limits their use in clinical processes. Class imbalance, in which uncommon tumor types lack representation and result in skewed forecasts, is another problem. Although they increase pipeline complexity, hybrid ML-DL techniques try to lessen this. Furthermore, several studies show great accuracy on publicly available datasets; yet, real-world implementation necessitates managing clinical data that is noisy, diverse, and incomplete. Resolving these issues is essential to converting research prototypes into clinically applicable technologies that improve radiologists' productivity and diagnostic precision.

VIII. Trends & Future Directions

The goal of brain tumor categorization in the future is to develop research models that are really applicable in medical settings. Since the majority of existing systems still struggle with insufficient and non-diverse data, which affects their real-world dependability, creating bigger, multi-institutional datasets is a crucial necessity. The use of Explainable AI (XAI) techniques, such Grad-CAM, which assist physicians in comprehending the reasons behind a model's prediction and boost clinical adoption, is another significant avenue. [19] As the discipline develops, the objective is to create models that are clear, reliable, and prepared for incorporation into actual clinical processes in addition to increasing accuracy.

IX. Conclusion

Conventional machine learning methods for classifying brain tumors mostly depend on manually created characteristics from MRI image processing. The quality of manually constructed features still limits the effectiveness of machine learning models like SVM, Random Forest, and XGBoost, even when preprocessing & feature selection may attain high accuracy. On the other hand, contemporary deep learning architectures, including CNNs, DenseNet, and VGG16, are able to enhance classification performance and lessen reliance on feature engineering by automatically learning deep hierarchical representations from raw MRI images [20]. Despite these developments, clinical application is hampered by a number of issues, such as restricted availability of big, annotated datasets, high computing needs, and poor interpretability. To improve model robustness and scalability, future research must concentrate on explainable AI, cross-institutional dataset validation, and effective transfer learning techniques. In conclusion, this study offers a thorough comparison of deep learning and machine learning techniques for classifying brain tumors, showing how well each method works in different scenarios and emphasizing the potential of DL models for more precise and clinically significant diagnosis.

References

[1]. Mohsen, H. M., El-Dahshan, E. S. A., El-Horbaty, E. S. M., & Salem, A. B. M. (2018). Classification using deep learning neural networks for brain tumors. Future Computing and Informatics Journal, 3(1), 68–71.

[2]. Tandel, G. S., Biswas, S., Kakde, O. G., Tiwari, A., Suri, H. S., Turk, M., … & Suri, J. S. (2019). A review on a deep learning perspective in brain cancer classification. Cancers, 11(1), 111.

[3]. Deepak, S., & Ameer, P. M. (2019). Brain tumor classification using deep CNN features via transfer learning. Computers in Biology and Medicine, 111, 103–112.

[4]. Tandel, G. S., Biswas, S., Kakde, O. G., Tiwari, A., Suri, H. S., Turk, M., … & Suri, J. S. (2019). A review on a deep learning perspective in brain cancer classification. Cancers, 11(1), 111. https://doi.org/10.3390/cancers11010111

[5]. Deepak, S., & Ameer, P. M. (2019). Brain tumor classification using deep CNN features via transfer learning. Computers in Biology and Medicine, 111, 103–112.

[6]. Sharma, Neha, Vibhor Jain, and Anju Mishra. "An analysis of convolutional neural networks for image classification." Procedia computer science 132 (2018): 377-384.

[7]. Han, Dongmei, Qigang Liu, and Weiguo Fan. "A new image classification method using CNN transfer learning and web data augmentation." Expert systems with applications 95 (2018): 43-56.

[8]. Hussain, Mahbub, Jordan J. Bird, and Diego R. Faria. "A study on CNN transfer learning for image classification." UK Workshop on computational Intelligence. Cham: Springer International Publishing, 2018.

[9]. Loussaief, Sehla, and Afef Abdelkrim. "Deep learning vs. bag of features in machine learning for image classification." 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET). IEEE, 2018.

[10]. Ma, Benteng, et al. "Autonomous deep learning: A genetic DCNN designer for image classification." Neurocomputing 379 (2020): 152-161.

[11]. Lee, Shin-Jye, et al. "Image classification based on the boost convolutional neural network." Ieee Access 6 (2018): 12755-12768.

[12]. Wang, Pin, En Fan, and Peng Wang. "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning." Pattern recognition letters 141 (2021): 61-67.

[13]. Bansal, Monika, et al. "Transfer learning for image classification using VGG19: Caltech-101 image data set." Journal of ambient intelligence and humanized computing 14.4 (2023): 3609-3620.

[14]. Jiang, Song, Yuan Gu, and Ela Kumar. "Magnetic resonance imaging (mri) brain tumor image classification based on five machine learning algorithms." Cloud Computing and Data Science 4.2 (2023): 122-33.

[15]. Jia, Zheshu, and Deyun Chen. "Brain tumor identification and classification of MRI images using deep learning techniques." IEEE Access (2020).

[16]. Deepak, S., and P. M. Ameer. "Brain tumor classification using deep CNN features via transfer learning." Computers in biology and medicine 111 (2019): 103345.

[17]. Baid, Ujjwal, et al. "The rsna-asnr-miccai brats 2021 benchmark on brain tumor segmentation and radiogenomic classification." arXiv preprint arXiv:2107.02314 (2021).

[18]. Alam, Md Ashraful, et al. "Advancing Brain Tumor Detection Using Machine Learning And Artificial Intelligence: A Systematic Literature Review Of Predictive Models And Diagnostic Accuracy." Strategic Data Management and Innovation 1.01 (2024): 37-55.

[19]. Selvaraju, Ramprasaath R., et al. "Grad-cam: Visual explanations from deep networks via gradient-based localization." Proceedings of the IEEE international conference on computer vision. 2017.

[20]. Swati, Zar Nawab Khan, et al. "Brain tumor classification for MR images using transfer learning and fine-tuning." Computerized Medical Imaging and Graphics 75 (2019): 34-46.