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Chronological Review of various Machine Learning Techniques and Convolutional Neural Network (CNN)-based deep learning models for Brain Tumor Detection

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Abstract

This paper involves a chronological review of various Machine Learning Algorithms and Convolutional Neural Network (CNN)-based deep learning models to evaluate their effectiveness in brain tumor detection. The performance of these techniques is analyzed based on accuracy, reliability, and computational efficiency. This comparative study evaluates various research works based on performance metrics such as accuracy, precision, recall, F1-score, dataset size, and train–test ratio. The study provides a clear understanding of how deep learning models outperform traditional machine learning techniques and establishes CNN-based approaches as the most promising solution for brain tumor detection.

Keywords: Brain tumor detection; Machine Learning Algorithms; Convolutional Neural Network (CNN)-based deep learning models;accuracy

1. Introduction

Brain tumors occur due to the abnormal growth of cells within the brain and can severely affect normal brain functions. Depending on their type, size, and location, brain tumors may cause symptoms such as headaches, seizures, vision problems, and cognitive impairment. Early detection plays a vital role in reducing mortality rates and improving treatment planning. Table 1 shows details of Brain Tumors considered in this study and Figure 1 shows the percentage of occurrence of these different brain tumors as depicted in the studies.

Table 1: Details of Types of Brain Tumors considered in this study

Attributes	Pituitary Tumor	Meningioma Tumor	Glioma Tumor
Category	Primary brain tumor	Primary brain tumor	Primary brain tumor
Nature	Usually benign	Mostly benign (some can be malignant)	Often malignant
Origin	Pituitary gland (base of the brain)	Meninges (protective layers of the brain)	Glial cells
WHO Grade	Mostly Grade I or II	Commonly Grade I	Grade II to Grade IV

Type of Spread	Affects hormone production rather than spreading aggressively	Slow-growing and well-defined	Includes aggressive types like Glioblastoma (Grade IV)
Worldwide Incidence	10–15% of all primary brain tumors [1]	37–38% of all primary brain tumors [2]	42–43% of all primary brain tumors [3]

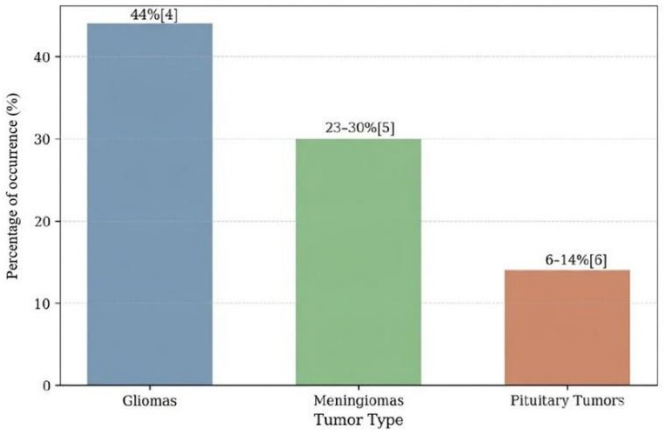

Figure 1: Occurrence of different types of Brain Tumors as depicted in several studies

Magnetic Resonance Imaging (MRI) is the most commonly used imaging technique for detecting brain tumors because it provides high-resolution images of brain tissues without exposing patients to ionizing radiation. Despite advancements in imaging technology, manual analysis of MRI scans remains challenging. Radiologists must carefully examine hundreds of slices for each patient, which is time-consuming and prone to human error. Furthermore, tumor boundaries are often irregular and may closely resemble healthy tissues, making diagnosis difficult. These challenges have motivated researchers to explore automated and intelligent diagnostic systems using machine learning and artificial intelligence techniques.

Traditional machine learning methods have been widely applied for brain tumor detection. These methods typically involve multiple steps, including image preprocessing, manual feature extraction, feature selection, and classification using algorithms such as SVM or KNN. Although these approaches provide reasonable performance, their accuracy largely depends on the quality of handcrafted features and expert knowledge.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized medical image analysis. CNNs are capable of automatically learning hierarchical features from images, eliminating the need for manual feature extraction. Advanced CNN architectures and transfer learning models such as VGG, ResNet, Inception, and EfficientNet have demonstrated remarkable performance in brain tumor classification tasks. In traditional machine learning approaches, image features such as texture, intensity, and shape are manually extracted using methods like GLCM, LBP, and Gabor filters. These features are then classified using ML algorithms such as SVM, KNN, Random Forest, or Naive Bayes. While these approaches are computationally less complex, they suffer from limited generalization and dependency on handcrafted features. Deep learning methods, especially CNNs, follow an end-to-end learning approach where feature extraction and classification are performed simultaneously. CNNs consist of convolutional layers, pooling layers, and fully connected layers that learn spatial patterns such as edges, textures, and tumor

boundaries automatically. Transfer learning models further enhance performance by utilizing pretrained networks trained on large-scale datasets.

The study is a literature-based comparative analysis focusing on brain tumor detection techniques using MRI images. The overall workflow followed in most of the reviewed research works includes MRI image acquisition, preprocessing, feature extraction, classification, and performance evaluation. This work focuses on understanding the impact of image preprocessing, feature extraction methods, and classification strategies on detection performance. By incorporating advanced CNN architectures and transfer learning techniques, the objective is to improve detection accuracy even with limited medical datasets.

2. Chronological Review

Several studies have been conducted using traditional machine learning and deep learning techniques to improve the accuracy and efficiency of brain tumor detection from MRI images. These works explore different preprocessing methods, feature extraction techniques, classification algorithms, and advanced CNN architectures. A detailed review of these studies helps in understanding the strengths and limitations of existing approaches and provides valuable insights for selecting appropriate techniques for the proposed comparative study. The following section presents a chronological review of relevant research contributions in this field.

Gujral *et al (2014).* proposed an automated brain tumor detection system using machine learning techniques to reduce the dependency on manual MRI image analysis. The study focused on detecting brain tumors from MRI images collected from standard medical image databases. The proposed method involved preprocessing to remove noise, followed by texture feature extraction using the Gray Level Co-occurrence Matrix (GLCM). Supervised machine learning classifiers were used for analysis and classification. The results showed that the system could successfully distinguish between normal and abnormal brain MRI images with acceptable accuracy. However, the approach depended on hand-crafted features and a limited dataset. The authors concluded that machine learning-based systems can assist radiologists but require larger datasets and improved robustness for clinical use. [7]

Kasban *et al. (2015)* presented a comparative analysis of different medical imaging modalities such as MRI, CT, PET, and X-ray for brain tumor detection. The study aimed to identify the most suitable imaging technique for accurate tumor diagnosis. The data for this analysis was collected from clinical imaging standards and previously published medical studies. The authors performed qualitative and analytical comparisons based on image resolution, tissue contrast, radiation exposure, and diagnostic effectiveness. One major drawback of this study was the lack of automated image analysis and classification methods. This limitation was later addressed by integrating artificial intelligence-based techniques in subsequent research. The result analysis confirmed that MRI provides superior soft tissue contrast and is the most effective imaging modality for brain tumor detection. The authors concluded that MRI should be used as the primary input for automated tumor detection systems. [8]

Yasmin *et al. (2018)* proposed a feature fusion-based brain tumor detection approach to improve classification accuracy. The study addressed the problem of complex tumor structures in MRI images. Multimodal MRI datasets were collected from publicly available sources. The proposed analysis included unsupervised clustering for tumor segmentation, followed by feature extraction using Gabor Wavelet Features, Local Binary Pattern (LBP), Histogram of Oriented Gradients (HOG), and SFTA. A Random Forest

classifier was applied for classification. The result analysis showed improved accuracy compared to single-feature methods. However, the method increased computational complexity and faced challenges in precise segmentation. The authors concluded that feature fusion enhances performance but segmentation accuracy remains a limitation. [9]

Anjum *et al. (2019)* proposed a statistical and machine learning-based brain tumor detection system aimed at early diagnosis. MRI images were collected from BRATS benchmark datasets and local medical sources. The proposed method used Wiener filtering for image enhancement and Potential Field clustering for tumor segmentation. Texture features were extracted and fused for classification. The analysis demonstrated high accuracy, sensitivity, and Dice similarity coefficient. However, the multi-stage processing increased computational cost and reduced real-time applicability. The authors concluded that the proposed system improves detection accuracy but requires optimization for practical clinical deployment. [10]

Chippakatti *et al. (2019)* proposed a machine learning-based computer-aided diagnosis system for brain tumor detection using MRI images. The study focused on overcoming the limitations of manual diagnosis for large MRI datasets. MRI brain images were collected from clinical and standard datasets. The proposed analysis involved preprocessing, GLCM-based texture feature extraction, and classification using machine learning algorithms such as SVM and neural networks. The results showed satisfactory detection accuracy. However, the method was sensitive to noise and lacked deep feature representation. The authors concluded that automated detection systems are effective but need better generalization capability. [11]

Shah *et al. (2020)* proposed a hybrid brain tumor detection system combining traditional machine learning and deep learning techniques. The study addressed the low accuracy of conventional classifiers. Real-time MRI brain image datasets were used for data collection. The proposed method applied Fuzzy C-Means clustering for tumor segmentation and a Convolutional Neural Network (CNN) for classification. The result analysis showed that CNN achieved higher accuracy than traditional methods. However, the approach required high computational resources and lacked explainability. The authors concluded that deep learning-based methods provide superior performance but face challenges in real-time clinical implementation. [12]

Sharma *et al. (2021)* presented a CNN-based model for brain tumour detection and segmentation using MRI images. The study emphasized the importance of early detection to improve patient survival rates. MRI datasets were collected from publicly available sources such as Kaggle and Figshare, containing healthy and tumor-affected brain images. The proposed system included image resizing, augmentation, segmentation, and CNN-based feature extraction and classification. The model achieved an accuracy of 97.79%, outperforming traditional machine learning techniques. Despite its high accuracy, the study identified limitations such as high computational requirements and long training time. The authors concluded that CNN-based approaches provide superior performance but require optimization for practical healthcare implementation. [13]

Chattopadhyay *et al. (2022)* proposed a comprehensive machine learning and deep learning-based brain tumor detection system using MRI images. The dataset used in the study was sourced from publicly available medical image repositories and consisted of both tumor and non-tumor images. The authors performed extensive preprocessing, followed by feature extraction for classical ML models and automated feature learning using convolutional neural networks. A key drawback of earlier approaches was limited accuracy due to manual feature extraction and small datasets. This was overcome by adopting deep learning techniques and data augmentation methods. Result analysis showed that CNN-based models achieved significantly higher accuracy compared to traditional classifiers. The authors concluded that deep learning-driven approaches

offer a powerful and reliable solution for early and accurate brain tumor detection. [14]

Ghade et al. (2022) presented in the project, a brain tumor detection system using Convolutional Neural Networks (CNN) and transfer learning with pre-trained Keras models such as VGG16, ResNet50, and InceptionV3. The system performs preprocessing, feature extraction, and classification of MRI images to detect and classify tumors. Both binary and multi-class classifications were analyzed. Experimental results show that transfer learning improves accuracy, reduces computation time by nearly 50%, and minimizes overfitting compared to training from scratch. Among the models tested, ResNet50 achieved the best overall performance. The system also includes a user-friendly web interface to assist doctors in uploading MRI images and obtaining classification results efficiently. The study highlights that transfer learning is highly beneficial when working with limited datasets, as it leverages previously learned image features. Proper data augmentation and regularization techniques further enhance model generalization. Overall, the proposed system provides a reliable, non-invasive, and efficient solution for brain tumor detection. With further improvements such as 3D image analysis and enhanced model optimization, the system can become a valuable clinical support tool in hospitals and diagnostic centers. [15]

Joseph *et al. (2023)* proposed a machine learning framework for brain tumor detection and classification using MRI scans. The study explored both supervised and unsupervised learning techniques, with convolutional neural networks playing a key role in feature extraction and classification. MRI datasets containing tumor and non-tumor images, including glioma, meningioma, and pituitary tumors, were used. Preprocessing steps such as resizing, normalization, labeling, and batching were applied before training the CNN models. The results demonstrated improved detection accuracy and reduced dependency on manual diagnosis. However, the approach required high computational power and long training time. The authors concluded that machine learning-based systems can effectively assist radiologists but require further improvements for scalability and deployment in clinical environments. [16]

Saeedi *et al. (2023)* suggested a comparative study of machine learning and deep learning techniques for automated brain tumor detection using MRI images. The study focused on analyzing how different classifiers perform in identifying tumor and non-tumor regions. MRI data was collected from publicly available datasets, including benchmark medical imaging repositories. The authors applied preprocessing techniques such as normalization and noise removal, followed by feature extraction and classification using traditional machine learning classifiers and deep learning models. One major drawback identified was that traditional machine learning techniques relied heavily on handcrafted features, which limited their ability to generalize across diverse MRI datasets. This limitation was overcome by introducing deep learning models that automatically learn discriminative features. The result analysis showed that CNN-based models significantly outperformed classical methods in terms of accuracy and robustness. The authors concluded that deep learning techniques provide a more reliable and scalable solution for brain tumor detection. [17]

Shekar et al. (2023) presents a machine learning-based approach for detecting brain tumors using MRI images. The system incorporates image preprocessing, feature extraction, and classification techniques. Random Forest and K-Nearest Neighbors (KNN) algorithms are implemented to classify tumor regions efficiently. Automated detection reduces the time and effort required for manual analysis while improving diagnostic accuracy. The proposed method demonstrates effective performance in identifying abnormal brain regions, highlighting the potential of machine learning in medical image analysis. The hybrid approach enhances detection accuracy and reduces the need for manual intervention. The system requires fewer training samples and provides faster processing, making it suitable for medical applications. Overall, this

method offers a reliable and efficient solution for early brain tumor diagnosis and supports improved clinical decision-making. [18]

Reddy *et al. (2024)* proposed a deep learning–based approach for automated brain tumor detection from MRI scans. The study aimed to overcome the limitations of traditional image processing techniques by utilizing advanced convolutional neural network architectures. A dataset consisting of 7,770 MRI images was used, covering glioma, meningioma, pituitary tumors, and non-tumor cases. Preprocessing techniques such as normalization, resizing, data augmentation, and segmentation were applied to improve image quality and learning efficiency. The study evaluated CNN, MobileNet, and Xception architectures using the Adam optimizer and categorical cross-entropy loss function. Experimental results showed that the Xception model achieved the highest accuracy of 98%. However, the study highlighted limitations such as dataset dependency and the need for broader clinical validation. The authors concluded that deep learning significantly improves brain tumor detection accuracy and has strong potential for real-world medical applications. [19]

Koushik *et al (2024).* suggested in their paper an automated approach for brain tumor detection using deep learning techniques, specifically Convolutional Neural Networks (CNNs), to overcome the limitations of manual MRI scan analysis. The study focuses on improving diagnostic accuracy and reducing human error in medical image interpretation.

The data used in this study consists of MRI brain images collected from medical institutions and public repositories, containing both tumor-affected and healthy brain scans. The dataset was divided into training, validation, and testing sets to ensure proper model evaluation and generalization.

The authors performed deep learning–based image analysis, where preprocessing techniques such as resizing, normalization, noise reduction, and data augmentation were applied. A CNN architecture with convolutional, pooling, dropout, and fully connected layers was designed to automatically extract features and classify MRI images into tumor and non-tumor categories.

One major drawback identified in this study is the limited availability of high-quality and diverse medical datasets, which can affect model generalization. Additionally, CNN models suffer from lack of interpretability, making it difficult for clinicians to understand decision-making processes.

To overcome these drawbacks, the authors employed data augmentation techniques to increase dataset diversity and used regularization methods such as dropout and early stopping to reduce overfitting. Validation using independent test datasets helped ensure robustness.The result analysis showed that the proposed CNN-based system achieved high accuracy and robustness, outperforming traditional machine learning methods such as SVM and KNN. Performance metrics including accuracy, sensitivity, specificity, and AUC-ROC demonstrated reliable tumor detection capability. The authors concluded that CNN-based deep learning models are highly effective for automated brain tumor detection, offering improved accuracy, reduced diagnosis time, and strong potential for future clinical deployment, provided further validation and interpretability improvements are addressed. [20]

Khaliki *et al.(2024)* presented a study focusing on brain tumor detection using traditional machine learning techniques applied to MRI brain images. The primary objective of the study was to assist radiologists by providing an automated decision-support system that improves diagnostic efficiency.

The dataset used in this research was obtained from publicly available MRI repositories and hospital-collected brain scans, consisting of labeled tumor and non-tumor images. The dataset size was relatively limited, and images were categorized for supervised learning.

The analysis involved image preprocessing, manual feature extraction, and classification. Texture-based features were extracted using statistical methods such as Gray Level Co-occurrence Matrix (GLCM) and

intensity-based measures. Machine learning classifiers such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naïve Bayes were used for tumor classification.

A key drawback of this approach was the dependency on handcrafted feature extraction, which requires expert knowledge and may fail to capture complex tumor patterns. Additionally, performance degradation was observed due to small dataset size and high feature dimensionality.

To mitigate these issues, the authors applied feature selection techniques to reduce redundancy and improve classifier efficiency. Cross-validation was used to improve reliability and prevent overfitting. The result analysis indicated that machine learning classifiers achieved moderate to good accuracy, with SVM outperforming other algorithms. However, the accuracy was still lower compared to deep learning-based methods reported in later studies. The authors concluded that traditional machine learning techniques are effective for basic brain tumor detection, but their performance is limited by manual feature engineering. The study highlighted the need for deep learning models capable of automatic feature learning, paving the way for CNN-based approaches in future research. [21]

Aamir et al. (2024) introduced a hyperparameter-optimized convolutional neural network (CNN) model for automated brain tumor classification using MRI images. Critical hyperparameters such as learning rate, batch size, filter size, activation functions, padding, and pooling strategies are fine-tuned to enhance performance. The model is evaluated on three publicly available Kaggle MRI datasets comprising glioma, meningioma, pituitary, and no-tumor classes. Experimental results demonstrate approximately 97% accuracy along with high precision, F1 score, and F1-score values. Comparative analysis confirms the superiority of the optimized CNN over existing approaches. The hyperparameter-tuned CNN significantly improves classification accuracy and generalization across multiple datasets. The model demonstrates strong robustness and clinical applicability. Future research will focus on multimodal imaging integration, larger multi-center datasets, and explainable AI for improved diagnostic transparency. [22]

Ummaneni et al. (2024) explored the use of a customized EfficientNetV2B3 deep learning model for brain tumor prediction using MRI images. The research evaluates whether the proposed model outperforms existing methods, examines the impact of different optimizers (Adagrad, Adam, and SGD), and analyzes the effect of dropout regularization on model generalization. The model achieved 99% accuracy, surpassing previously reported approaches. Among the optimizers, Adam produced the best performance, and the inclusion of dropout improved generalization by reducing overfitting. The results demonstrate that EfficientNetV2B3 is highly effective for accurate brain tumor classification. The customized EfficientNetV2B3 model proved to be highly accurate and efficient for brain tumor prediction, achieving 99% accuracy. The Adam optimizer provided the best results compared to Adagrad and SGD. Additionally, dropout regularization enhanced the model's generalization and reduced overfitting. Overall, the study confirms that advanced deep learning techniques can significantly improve brain tumor detection and support medical diagnosis. [23]

Oh et al. (2024) proposes a Convolutional Neural Network (CNN)-based approach for detecting brain tumors from MRI images. The system involves preprocessing techniques such as image resizing, normalization, and segmentation, followed by deep feature extraction using CNN layers. The model is trained to classify MRI scans into tumor and non-tumor categories. Experimental results show that the CNN-based model achieves high accuracy and performs better than traditional machine learning methods, demonstrating the effectiveness of deep learning in automated brain tumor detection. The study confirms that Convolutional Neural Networks provide an efficient and accurate method for brain tumor detection using MRI images. The proposed CNN model successfully extracts important features and improves classification performance compared to conventional techniques. Automated detection reduces human effort and supports early

diagnosis. Overall, the approach highlights the potential of deep learning models in enhancing medical image analysis and assisting healthcare professionals in decision-making. [24]

Ahire *et al. (2025)* proposed a machine learning–based framework for detecting brain tumors using MRI images, with a strong emphasis on convolutional neural networks. The study addressed limitations of manual diagnosis, including time consumption and human error. The proposed methodology involved image preprocessing, segmentation using Otsu thresholding, feature extraction, and CNN-based classification. The paper also included a comparative review of deep learning approaches published between 2019 and 2022. Experimental analysis showed that CNN-based systems achieved high accuracy in tumor detection. However, the study noted challenges such as the requirement for large datasets and high computational resources. The authors concluded that machine learning and deep learning techniques provide effective solutions for automated brain tumor detection, though further optimization is required for real-time clinical use. [25]

Han et al. (2026) presented an automated deep learning-based framework for effective brain tumor detection and classification using MRI images. By combining optimized preprocessing and advanced CNN architectures, the proposed model significantly improves diagnostic accuracy and computational efficiency. The experimental results confirm the robustness and reliability of the framework, achieving high performance across multiple evaluation metrics. The system demonstrates strong potential for real-world clinical implementation, enabling early diagnosis and improved treatment planning. Future work will focus on expanding dataset diversity, integrating explainable AI techniques, and deploying the model in real-time diagnostic environments. [26]

Uniyal et al. (2026) introduced an intelligent deep learning-based framework for automated brain tumor classification using MRI images. The proposed model employs optimized convolutional neural networks and data augmentation techniques to enhance feature extraction and classification performance. Extensive experimental evaluations demonstrate that the system achieves superior accuracy, sensitivity, and specificity compared to traditional machine learning and baseline deep learning models. The proposed framework ensures high robustness and efficiency, making it suitable for real-time clinical diagnostic systems. The proposed intelligent deep learning framework effectively addresses the challenges associated with accurate brain tumor classification. The integration of optimized CNN architectures and robust preprocessing techniques significantly enhances diagnostic reliability and computational efficiency. Experimental results validate the superiority of the proposed system over conventional methods. This approach holds strong clinical potential for early tumor detection and diagnosis. Future research will explore hybrid deep learning models, multi-modal medical data integration, and explainable AI mechanisms to improve model transparency and clinical trust. [27]

Mehrdad et al. (2026) proposed an optimized ResNet50-based deep learning framework incorporating dynamic precision optimization and architectural enhancements to improve computational efficiency and diagnostic accuracy. The proposed model achieves a remarkable accuracy of 99.69%, while significantly reducing training time and computational overhead. Transfer learning, fine-tuning strategies, and hybrid integration with Random Forest classifiers further enhance model interpretability and performance. The system demonstrates high robustness and clinical applicability for automated brain tumor diagnosis. The hybrid integration with Random Forest classifiers enhanced decision interpretability, increasing clinical trust. Experimental validation confirms the robustness and reliability of the system. Future research will focus on real-time clinical implementation, expansion to larger multi-center datasets, and integration of explainable AI tools to further enhance diagnostic transparency and clinical adoption. [28]

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The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

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