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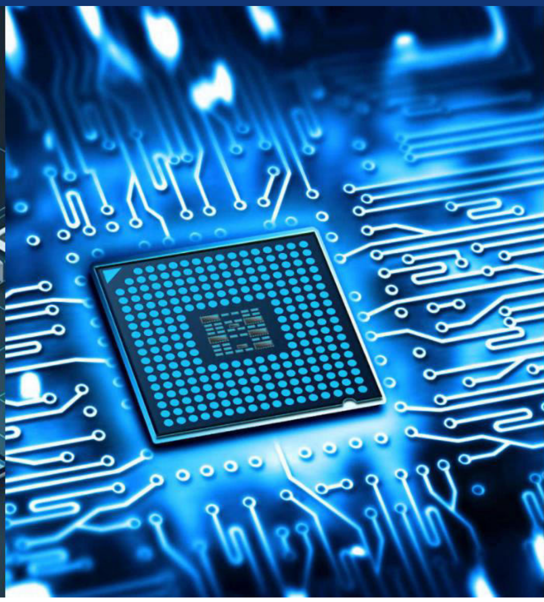


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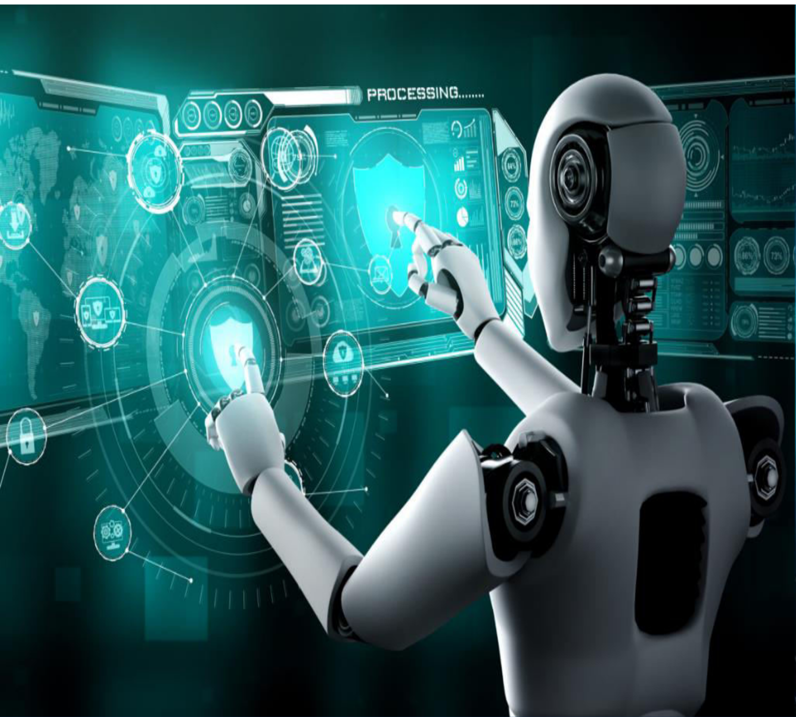

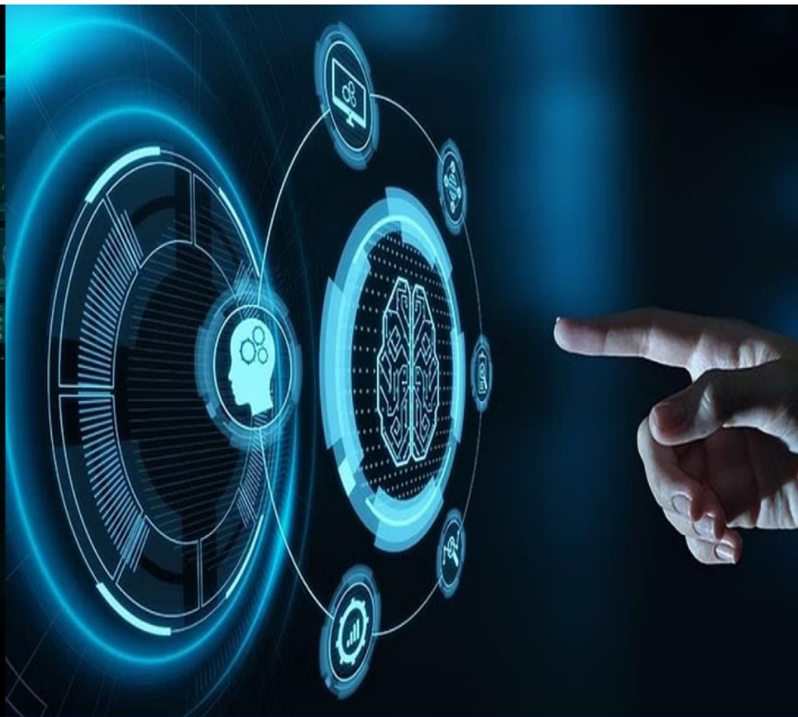

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Deep Learning Techniques for Brain Tumor Classification: A Review of CNNs and Ensemble Models

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ABSTRACT: The complicated the brain's anatomy and the variety of tumour kinds, sizes, shapes and locations may brain tumour diagnosis difficult. By enabling the automatic extraction of attributes from MRI images recent advances have significantly advanced in DL the classification of brain tumors. Neural network algorithms and convolution transfer learning can accurately learn complex spatial and textural features. However, overfitting sensitivity to data changes and limited generalization are common issues that individual CNN mortals encounter when trained on small and unbalanced medical data sets. Ensemble DL techniques have garnered attention as a potential solution to these issues by combining multiple CNN architectures to enhance resilience and predictive performance. In particular by combining probabilistic outcomes from several model's ensemble models based on soft voting improve classification reliability. Additionally, data augmentation using generative adversarial networks has been utilized to address class disparities and data shortages. This study offers a thorough examination of CNN-based models transfer learning and ensemble learning approaches for brain tumour classification, highlighting current breakthroughs, limits, and possible directions for future research.

KEYWORDS: Brain Tumor, CNN, Ensemble model, Deep Learning Technique

I. INTRODUCTION

The quantity of brain tumors instances has dramatically climbed within the past few decades, making the diagnosis extremely difficult for scientific communities due to its complexity and need for extreme precision. According to Alanazi et al. (2022) [5], the brain is the most complex organ within the human body, functioning through billions of cells and synaptic connections. The human neural system that governs all of the body's organs is the brain (Mewada et al., 2020; Rizwan et al., 2022a) [9] [12]. Therefore, a person's health suffers greatly when they have an atypical brain. According to the World Health Organization, brain cancer is the second most frequent cause of death globally, making up approximately 10 million fatalities in 2020 (Can, 2022) [6].

The primary obstacle in identifying brain tumors is the variety in tumor location, type, size, and shape (Amin et al., 2021) [10]. The identification of a brain cancer is dependent upon the kind and location of the tumor such that forecast the patients' chances of survival and make treatment selections that range from surgery to radiation and chemotherapy (Kumar et al., 2022) [7]. Thus, Brain tumor early detection aids in treatment planning and patient condition monitoring. It is necessary to increase the length of treatment and guaranteeing higher rates of survival.

As of right now, brain tumours may be categorised as either benign or malignant, each of which requires a different course of therapy. Most of today's traditional diagnostic techniques rely on radiological imaging, which is often shown to be inadequate for early tumour type detection in addition to differential diagnosis. Due to these drawbacks, there's a legitimate need for the creation of more advanced diagnostic instruments that would enable accurate and dependable tumour categorisation in order to support therapeutic benefits [2].

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CNN and DL Approaches have demonstrated impressive results in medical image processing including the classification of brain tumors. Due to their strong future extraction capabilities and improved convergence through transfer learning pre-trained architectures such as ResNet Snake and efficient the internet has been widely used. Even though individual CNN models show promise they frequently experience problems common to medical imaging like decreased generalization as instructed on short or unbalanced datasets and overfitting sensitivity to data changes. Combining several deep learning models to take advantage of their complimentary feature's ensemble learning has become a successful strategy to get around these restrictions. In contrast to single-model architectures group approaches especially those based on soft voting mechanisms have been shown to increase classification precision and resilience. Ensemble models reduce prediction variance and increase reliability by combining the probabilistic results of multiple CNNs this qualifies them for important medical uses such as the identification of brain tumors. By combining several DL models to take advantage of their complementing strength's ensemble learning has become as a successful way to get around these restrictions. When compared to single-model architectures group approaches especially those based on soft voting mechanisms have been shown to increase classification precision and robustness. Ensemble models can be used for critical medical applications such as the identification of brain tumors because they combine probabilistic outputs from several CNNs to lower prediction variance and boost reliability. The absence of MRI data with labels and the existence of class imbalance among tumor types present another significant obstacle to the classification of brain tumors. GANs are becoming more and more common as a potent method for data argumentation that can produce realistic artificial medical images. GAN-based augmentation enhances model generalization balances class distributions and increases training datasets without the need for more annotated data. Deep learning's classifiers performance can be considerably improved by incorporating GAN-generated images into training pipelines as several recent studies have shown.

With an emphasis on individual CNN models and ensemble learning techniques this review paper offers a thorough examination of D L techniques for classifying brain tumors. To highlight recent developments constraints and research gaps a comparative assessment of current approaches is executed with usual performance metrics. The assessment's objective is to offer insightful information and upcoming paths for creating reliable accurate and robust brain tumor classification systems.

II. RELATED WORK

Markchom et al. (2025carried out a comparison study of brain tumour deep learning models MRI classification using standardized evaluation metrics. The research offered insightful information on the relative strengths and weaknesses of various CNN architectures, emphasizing the importance of systematic performance comparison. However, the proposed analysis did not incorporate GAN-based data augmentation or ensemble voting strategies, which could improve classification robustness and accuracy [1].

Kumar et al. (2024) investigated the use of advanced CNN architectures, specifically EfficientNet and DenseNet, for classifying brain tumours into multiple classes using MRI images. In comparison to conventional CNN models, the study showed that these designs offer better feature extraction capabilities and increased classification accuracy. Despite these advancements, possible performance enhancements were not investigated because the paper assessed the models separately and didn't investigate ensemble learning or using GAN to enhance data. [3].

Swati et al. (2023) suggested method for categorising brain tumours using CNN architectures and transfer learning. Applying DL models that have previously received training, despite having little training data, the research was able to improve precision of classification. The outcomes validated transfer learning's efficacy in assignments involving medical imaging with little labelled data. Nevertheless, the approach relied with just one CNN model and did not incorporate ensemble techniques or explicit imbalance-handling mechanisms, which may affect performance stability across diverse datasets [4].

Zhou et al. (2021) investigated group Deep learning methods in medicine pictures classification, demonstrating that ensemble CNN models outperform individual networks. While the results confirmed the advantages of group learning, the research did not include GAN-based data augmentation & provided limited evaluation specific to brain tumor MRI datasets [11].

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Khan et al. (2022) presented a comprehensive study on deep learning–based MRI image-based categorisation of brain tumours. The authors evaluated multiple CNN architectures to analyze their efficiency in categorisation across several tumor classes. According to study, categorization accuracy varies significantly depending on network depth and architectural design, demonstrating the significance of model selection in the medical imagery. However, the work focused solely on individual CNN models and did not investigate ensemble learning strategies or address class imbalance, which limits robustness and generalization in real clinical scenarios [8].

Rehman et al. (2020) combined GAN-based data augmentation with 3D CNN architectures for microscopic brain tumor classification. The incorporation of synthetic data improved precision of classification and robustness. Despite these advantages, the approach involves high computational complexity and excludes comparative comparison with techniques for ensemble learning [13].

Table1: summary of the related work

Authors	Year	Title	Contribution	Limitations
Markchom et al.	2025	Comparative Analysis of DL Brain Tumor MRI models Classification	Conducts a comparative study of CNN architectures using standardized evaluation metrics.	Does not integrate GAN-based augmentation / ensemble voting strategies.
Kumar et al.	2024	Brain Tumor Classification Using EfficientNet and DenseNet	Investigates advanced CNN architectures for multi-class brain tumor classification; reports improved feature extraction capability.	Uses standalone models; lacks ensemble learning and GAN-based augmentation.
Swati et al.	2023	Brain Tumor Classification Using Transfer Learning and CNN	Applies transfer learning-based CNN models for classification of brain cancers using MRI pictures, achieving improved accuracy with limited data.	Relies on a single CNN architecture; robustness under data imbalance not fully addressed.
Khan et al.	2022	A Comprehensive Study on Deep Learning-Based Classification of brain tumors	Presents an extensive evaluation of multiple CNN designs for brain tumor MRI classification; highlights performance variations across models.	Uses individual CNN models only; does not investigate group learning or data imbalance handling.
Zhou et al.	2021	Ensemble Deep Learning for Medical Image Classification	Explores ensemble CNN strategies for medical image classification, showing improved accuracy over individual models.	Does not incorporate GAN-based data augmentation; limited brain tumor-specific evaluation.
Rehman et al.	2020	Microscopic Brain Tumor Classification Using 3D CNN and GAN	Combines GAN-based data augmentation with 3D CNNs for improved brain tumor classification accuracy.	High computational complexity; lacks ensemble learning comparison.

III. DEEP LEARNING TECHNIQUES FOR BRAIN TUMOR CLASSIFICATION

Analysis of medical images has changed significantly as a result of deep learning's ability to identify powerful patterns and retrieve features automatically. System for deep learning learn complex spatial and textural characteristics of MRI scans, eliminating the necessity of manually produced characteristics in the brain tumors. Due to their exceptional accuracy and efficiency, CNN and transfer learning algorithms are the most frequently utilized deep learning methods.

A. Convolutional Neural Networks (CNNs)

The DL models that are most widely used for activities that requires the classification of brain tumors are CNN. Convolutional pooling models for activities that require the classification of numerous layers that comprise a CNN. Three crucial CNN parameters are pitch padding and the filter's size. Every layer makes use of numerous filters for detailed feature extraction. According to stride the filters change within the pictures. CNNs performance decreases when the size of the stride exceeds two. There is no cushioning required to maintain the structural evaluation when the filter fails to fully screen each and every input picture in the convolutional layer. For instance, the initial layer highlights the borders of the lesions the second layer retrieves complex geometric details and the third layer highlights the forms and shades of the lesions. Each convolutional layer seeks to achieve a specific goal.

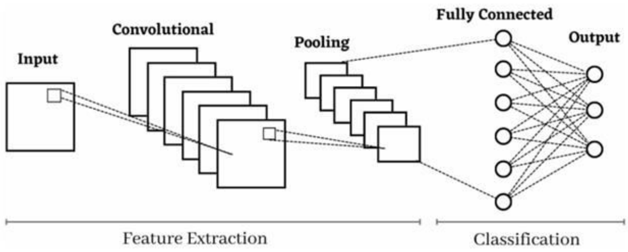

Figure 1: Architecture of Convolutional Neural Network

The feature map's ReLU layer suppresses negative values, making them zero, while passing positive values (Senan et al., 2022). To down sample or lessen the size of the retrieved features, the layer of maximum pooling is employed. The two most popular methods are the maximum and average for the max-pooling layer. According to Goyal et al. (2019) and Kang et al. (2021), the picture is categorized into various classes utilising the layer that is entirely connected with the 512 unit. Regarding the batch normalization layer of the feature map is employed for normalizing. These layers speed up network control and training. The dropout layer is used in some situations and is very useful for addressing over-fitting issues with networks (Balaha et al., 2021). In Figure 1, the CNN architecture is shown.

B. Transfer Learning in Medical Imaging

Transfer education has been used in medical picture analysis gained popularity as a solution to the problem of sparse labelled data. In transfer learning, medical imaging datasets are used to refine models that have been pre-trained on huge datasets such as ImageNet, enabling them to take use of previously learned characteristics. This method greatly speeds up training and enhances classification performance, particularly when available medical data are scarce. Below figure 2, shows that Medical imaging through transfer learning.

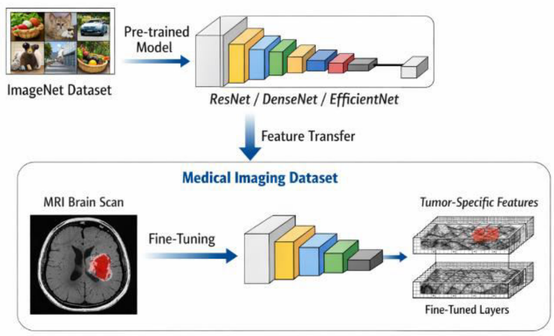

Figure 2: Medical imaging through transfer learning

CNN models can efficiently learn relevant MRI characteristics images with fewer training samples thanks to brain tumor categorization using transfer learning. Tumor-specific patterns are identified by fine-tuning deeper layers of pre-trained architectures like ResNet DenseNet and EfficientNet where the initial layers capture generic image features. When compared to training CNNs from scratch transfer learning increases accuracy stability and convergence speed according to numerous studies. However, feature transferability may occasionally be limited by the differences between natural and medical images requiring careful fine-tuning and optimization.

C. Methods of Ensemble Deep Learning

When contrast to individual models' ensemble deep learning techniques improve predictive performance by combining several models. Ensemble approaches reduce prediction errors increase robustness and improve generalization by merging the outcomes of several DL models rather than depending on a single classifier. Because of its capacity to intricate tumor patterns and lower model prediction uncertainty collective learning has drawn interest in the examination of medical pictures specifically in the categorisation of brain tumours.

D. Concepts of ensemble learning

A method for ML called ensemble learning combines the forecasts of multiple models that have received training to solve the same problem to create a final output. The fundamental tenet of ensemble learning is that various models may extract distinct patterns or characteristics from the data and combining them improves overall performance. When working with noisy or small datasets ensemble methods can help minimize bias increase stability and reduce variance. Voting-based techniques bagging and boosting are common ensemble strategies. Because each model learns complementary feature representations ensemble learning in deep learning is especially useful when combining models with different architectures. Because of this diversity ensemble learning is a good fit for applications involving medical imaging where data complexity and variability are high.

E. Ensemble Models with Soft Voting

Among the simplest and efficient ensemble methods is voting-based ensembles. In soft voting the group with the greatest combined probability is chosen as the ultimate forecast using the anticipated class probabilities from each individual model are averaged. Soft voting generates more reliable and dependable predictions by taking into account each models confidence level in contrast to hard voting which only takes into account the anticipated class labels. Because of their usability and efficiency soft voting-based ensembles are frequently employed in medical image classification. Soft voting improves overall classification accuracy by combining probabilistic outputs which lessens the impact of inaccurate predictions from any one model. This method is particularly helpful for categorizing brain tumors as incorrect classification can have major clinical repercussions.

F. CNNs in an ensemble for classifying brain tumors

By making use of the relative strengths of ensemble CNN models have been demonstrated to surpass unique CNN architectures in the identification of brain tumors. To increase robustness and accuracy of classification studies have combined several pre-trained CNN models including ResNet DenseNet EfficientNet and VGG. By extracting distinct feature representations from MRI images each CNN architecture allows the ensemble to obtain a more thorough understanding of tumor characteristics. Because they enhance the generality of the model ensemble CNN frameworks work particularly well when combined with data augmentation methods like GAN-generated images. CNN ensembles based on soft voting have consistently improved precision recall accuracy and F1-score on a variety of brain tumors datasets. These results show how effective ensemble DL methods can be as dependable and strong methods for categorizing brain tumors automatically.

IV. COMPARATIVE ANALYSIS

An analysis of the current methods for brain tumour classification is necessary to comprehend the strengths and weaknesses of various deep learning techniques. In this segment, we use commonly used assessment metrics like as accuracy precision recall F1-score and the AUC, or area under the curve to compare ensemble-based techniques with individual CNN models. The inquiry shows that as tactics become more complex, model performance rises.

Table2: A Comparison using DL methods for Classifying Brain Tumours

Approach Type	Models Used	Key Advantages	Limitations	Performance Trend
Individual CNN Models	ResNet, DenseNet, EfficientNet	Strong feature extraction, easy implementation, effective with transfer learning	Overfitting on small datasets, sensitive to class imbalance, limited generalization	High accuracy on large datasets; performance drops with limited data
Traditional Augmented CNN Models	CNNs with rotation, flipping, scaling	Simple and computationally efficient, reduces overfitting to some extent	Limited diversity, unable to represent complex tumor variations	Moderate improvement over baseline CNNs
Ensemble CNN Models	ResNet + DenseNet + EfficientNet	Reduced variance, improved robustness, better generalization	Higher computational complexity, increased training time	Higher accuracy than single CNN models

V. CONCLUSION

This review examined significant developments in DL methods for classifying brain tumors emphasizing CNN-based models transfer learning and group education techniques. When labeled medical data is scarce CNNs have shown a remarkable capacity to automatically extract complex characteristics from MRI pictures and transfer learning has been successful in enhancing performance. Individual models still have serious shortcomings though such as restricted generalization data imbalance and overfitting. Ensemble deep learning algorithms particularly soft voting-based ensembles address these issues by combining several CNN architectures to improve resilience precision and reliability. Further research is also required to bettering the model interpretability in clinical validation and real-world application. In order to enable precise and trustworthy brain tumour diagnosis and treatment planning, future research should concentrate on creating scalable, data-efficient, and explainable deep learning frameworks. To enable precise and trustworthy brain tumour diagnosis and treatment planning, future studies need to concentrate on developing scalable, data-efficient, and explicable deep learning frameworks.

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