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Advanced Machine Learning for Brain Tumor and Alzheimer's Disease Detection: A Comprehensive Review of Neuroimaging-based Classification Techniques

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Abstract

Alzheimer's disease with progressive neurodegeneration and brain tumors notably characterized by rapid, not limited cell proliferation poses significant health risks unless timely diagnosed and treated. Tumors have a diverse feature and characteristics, added to subtle changes in the brain whose hallmark is Alzheimer's, making accurate segmentation and classification quite challenging. Indeed, while there have been research in the last decade or so that have proven promising results, challenges still linger on. The present work discusses various approaches for image classification and staging of Alzheimer's disease and brain tumors by exploiting techniques in statistical image processing and computational intelligence. This paper includes discussion on morphology of brain tumors along with neuroimaging changes caused by Alzheimer's disease, existing datasets, data augmentation techniques, and methods for component extraction and classification within the DL, TL, and ML framework. Such specific systems have been given the metrics using the datasets; the descriptions of the implementations, however may vary with the case at hand.

Keywords: *Alzheimer Detection, Convolutional Neural Networks, Brain Tumor Detection*.

1. Introduction

AD and brain tumors are but two examples of the most common neurological diseases worldwide [1]. This disease might affect millions around the globe every year, yet in both conditions there is a problem relating to significant difficulties in diagnosis and treatment due to large, complexly interconnected networks of neurons (and other supporting cells). More than that, these diseases do not affect only the single patient but also affect their caregivers, families, and enormous healthcare systems. Lastly, a very high economic cost comes with brain tumors and Alzheimer's: direct medical costs, lost productivity, and long-term care. Although these issues are utterly overwhelming, plans to enhance knowledge and treatment better are underway.

Brain tumors are collections of abnormal cell growth in the brain, interfere with normal brain function, and can be lethal [2]. There are various forms of brain tumors including gliomas, meningiomas, and pituitary tumors, which vary in their characteristic features and require a specific mode of treatment to control the tumor. The brain tumors will be treated only if they are diagnosed early in the course of the disease, so that a basic treatment approach may be adopted that will allow the disease course in the patient to become enhanced. According to their location as well as their size, symptoms of brain tumors vary and may present manifestations ranging from headaches and seizures to alteration in personality and cognitive functions. It comes as no surprise that heterogeneity of symptoms leads to misdiagnosis, since they are initially attributed to other much more common conditions. A second critical role the blood-brain barrier plays is its role in the exclusion of neurotoxins from entry into the brain; on the other hand, it would also severely compromise access of therapeutic agents to tumors growing in the brain.

Alzheimer's is a neurodegenerative disease primarily linked to old age. The two hallmarks of Alzheimer's include the tau tangles and beta-amyloid plaques in the brain that progressively lead to degeneration of cognitive functions, loss of memory, and ultimately dependence [3]. The course of the illness is characterized by three progressive stages one after the other: EMCI followed by LMCI then full-blown AD [4]. Though making a diagnosis may be challenging at the early stages of the disease, intervention still appears to be warranted insofar as it may retard the process of this disease and likely enhance the quality of life for the patient as well as his or her caregiver. Researchers are trying to disentangle very complicated relationships among a wide variety of genetic, environmental, and lifestyle factors that may influence the bases of this disease. Current studies are also investigating different contributions of inflammation, vascular health, and the gut microbiome towards the initiation and development of AD. Because AD research requires multifaceted studies for diagnoses and treatments.

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Advances in medical imaging technologies and, particularly in MRI have nearly revolutionized the diagnosis and monitoring capabilities for brain tumors and Alzheimer's disease. It provides very anatomical insight into the brain; hence, helps identify tumors, patterns of atrophy, and other abnormalities related to these conditions [5]. However, such images require much experience and time-consuming processing that would result in some delay in diagnosis and treatment. Besides structural MRI, functional MRI and diffusion tensor imaging proved to be very effective techniques for a better study of connectivity and patterns of functionality in the brain. These modalities shed further new light on the impact that tumors and neurodegenerative diseases have on the networks of the brain. In this respect, PET imaging is also important when it contains tracers that selectively target tau and amyloid proteins specifically; these became very relevant for diagnosis and study of Alzheimer's disease and also for in vivo visualization of pathological protein aggregates.

Convolutional neural networks are the signature, most recently, which gained extreme popularity as an extremely powerful tool in this area, with the additional benefit of very high precision for tasks of image classification. Deep learning models automatically extract features from medical images and identify complex patterns that could not be easily detected by the human eye. CNNs one of the good application processing huge amount of imaging data due to its power parallel processing, and speed reliability.

Researchers used the AI and machine learning technique, that is, deep learning in computer-based systems, and came up with devising them to classify brain tumors and Alzheimer's disease [6]. Further, training on other datasets could be done to include subtle differences within the presentation of disease among populations in an effort to increase the generalization of the algorithms toward diagnosis.

In many ways, one develops deep models for classification of neurological disorders. Among all the above strategies, two have been considerably considered as the most effective ones: those are multi-model approaches that aggregate different architectures towards acquiring a wide range of features and transfer learning that fine-tunes the pre-trained models towards an image-based medical task.

Recently, work has also been done in feature extraction technique with PCA and GLCM techniques in enhancement of the discriminative potential of such models. Thus, integration of structural MRI with PET or DTI looks quite promising in enhancing diagnostic accuracy and comprehensive evaluation of the health of the brain. Besides, other research work is being carried out to combine non-imaging data while developing high accuracy and personalized diagnostic tools within models of AI, such as genetic details, cognitive tests' results, and clinical history.

Classification for brain tumor and Alzheimer's disease has also been pretty promising with deep learning models. Many challenging areas are still there that require a solution. It runs the gamut from explainable AI systems where it would be possible for doctors to understand the reasoning behind their decisions, working through natural clinical workflows with these technologies to data sets with higher diversity in order to get increased model generalization [11]. In this domain, interpretability of model is of great value. This domain will not only give point why the patient has been diagnosed with some particular ailment but also show the importance of those features-a computer itself can be equally important or even more important than the diagnosis. Techniques such as relevance propagation layer-wise and attention mapping are used to "highlight to the researcher what features and regions of the brain an AI model thinks will be most important for classification." Thus, robust validation methodologies, performance indicators therefore have to be developed, so that the results can be reliable and comparable among different AI approaches within research and institutions.

2. Literature Review

Recently, deep learning has revolutionized medical imaging and especially in the detection and classification of complex conditions like Alzheimer's disease and brain tumor. Thus, for example, Santos Bringas et al. used data from accelerometers of smartphone devices for designing a deep learning architecture, employing CNNs, to enable distinguishing among various stages of Alzheimer's disease [12]. The network demonstrates that CNNs can be notably superior to other mainstream classifiers like SVM and Decision Trees when average hits 90.91%. Several limitations about generalisability have been pointed out for the model since it is only developed with the database of 35 subjects participating in the study. In addition, the inability of the model to be explained in its decision process also gives way to the need for developing more transparent AI methods that underpin clinical utility [12]. Similarly, (Santos and Santos 2024) applied the lightweight CNN model MobileNetV2 architecture in the identification process of the presence of brain tumors using MRI images [13]. This was achieved after training the model on a dataset of 3,762 MRI images with an accuracy of 89%, thus showing that MobileNetV2 is indeed effective for tasks involving medical imaging. The research in this subject has a limitation tied to the problems associated with the minimal number of samples used in the dataset, which may limit the strength of the model and its generalizability. In future work, the size of the dataset should be enhanced using more diverse deep architectures to build up further the performance as well as the reliability of the model [13].

Nayak et al. in 2024 later proposed the dense EfficientNet architecture for the classification of the subtypes of brain cancers, such as pituitary, meningioma, and glioma [14]. The training dataset consisted of 3,260 artificially augmented T1-weighted MRI images using advance data augmentation techniques. Although such a dense EfficientNet model would be much more difficult to use in real-time clinical environments, it reaches great values of accuracy-on the training set at 99.97% and on the testing set at 98.78%. In short, it is emphasized that model simplification is relevant for the reduction of overhead computations while maintaining high-accuracy results. In addition, since the size of the dataset was not large, further research studies should focus on increasing the size of the dataset and testing the model in further clinical environments to confirm its generalization capability [14]. In the same direction, Nassar et al. (2024) proposed a hybrid deep learning approach that utilizes the power of different CNN architectures by adopting a majority vote method [15]. The above system obtained an accuracy of 99. 31% in terms of classification. This outperformed the performances obtained by other separate CNN-based classifiers. The authors highly recommend a larger and diverse dataset for the improvement of the model in terms of robustness, along with adding other deep learning techniques in order to exploit classification improvements further [15].

Helaly et al. (2024) utilized MRI images of the ADNI dataset to classify the stages of Alzheimer's disease by using the most minimalistic CNN architectures and transfer learning on a pre-trained VGG19 model [16]. Optimized for the task, the VGG19 model proved with accuracy the prospects of transfer learning in medical imaging with an accuracy rate of 97%. Although these results are promising, the study sheds light on pretty much a thin dataset applied and encourages more advanced data augmentation techniques which may get the robustness of the model high [16]. Also, Odusami et al. (2024) proposed an explainable deep learning model to facilitate the diagnosis of Alzheimer's disease, which is developed by fusing multimodal input into PET and MRI images. At the same time, with structural adjustments to the architecture of ResNet18 in order to include the merged data, the model correctly classified it to be either EMCI or LMCI with 73. 9% accuracy. Along with several applications of explainable AI methods, excellent interpretability of the model was achieved-the all-important requirement for clinical applications. Despite all this, it identified a host of challenges related to the complexity of the model and thus recommended future work relate to the capabilities of XAI and refining the model for real-time applications [17].

Besides that, Küstner et al. (2024) presented the development of AI application for MRI and MRS [18]. In this research, they used deep learning in discussing the phases of MRI which includes planning, acquisition, and reconstruction. The study showed that applying the above techniques, the diagnosis and reconstruction of MRI and MRS can be extended without the requirement of fully labeled data. Besides that, new architectures for neural networks must be further researched to strengthen trust and usability of models for various clinical settings. Problems related to instability of the model, hallucinations, and shifts in the domain have indeed occurred within clinical practice of natural language models [18]. The last, Sharif et al. (2024) proposed a decision support system which utilised advanced feature selection techniques and an enhanced version of model densenet201 for the classification of multimodal brain tumors [19]. Their model reported success in the strategy formulated by their model by achieving above 95% accuracy upon testing on datasets of multimodal MRI: BRATS2018 and BRATS2019. It was based on this consideration that this study identified that high-dimensional feature spaces present challenges to the effectiveness and generalizability of the model and therefore recommended further research to develop feature selection techniques and extend the method to other medical imaging scenarios [19].

2.1. Deep Learning Techniques

Deep learning algorithms have also dramatically revolutionized the process of medical image processing, including review brain MRIs to classify different neurological conditions. Among all architectures, CNNs have emerged as the most popular due to widely reported success in many applications, including notably image segmentation, tumor detection, and disease classification. According to Xie et al., CNNs have outperformed other approaches in machine learning based on efficiency and accuracy for the detection of MRI brain imagery using even limited datasets [5]. Indeed, several recognitions have been presented based on the success of CNN in attaining a capability to acquire, automatically from images, features without human involvement and bypass complications involved with feature engineering techniques. It demonstrated its effectiveness on the more modest datasets typical to medical imaging when applied.

Singh et al. transferred pre-trained models, such as VGG16 and InceptionV3, to win in the task of pneumonia detection from chest X-rays [6]. The proposed approach was successfully applied for analysis of brain MRIs without failure. Mehmood et al. [4] employed transfer learning employing a modified version of VGG-19 architecture to achieve high classification accuracy in the possibility of several stages of cognitive impairment and ease of detection at an early Alzheimer's disease. With these findings, the authors concluded that freezing down some of the layers of the pre-trained network while fine-tuning others brings enormous improvement in the model combined with the data augmentation techniques. With the newest techniques of multitask learning, it has been promising to solve a suite of classification problems all at once, which subsequently can make the model more effective and performative. Liu et al. proposed a multitask deep learning architecture with 3D DenseNet for feature extraction and a multitask CNN for hippocampus segmentation and disease classification [11]. This is one example of how a large set of related tasks might be applicable toward improvement of the model, such as high classification accuracy in the case of Alzheimer's. 3D CNNs would capture volumetric MRI information much better in terms of spatial information than their 2D counterparts and may lead eventually to more precise diagnoses.

Moreover, other techniques for concatenation of features and ensemble methods for improving the classification accuracy have been explored as well. Noreen et al. achieved 99. 34% and 99. 51% accuracy for a system to identify brain tumors with features from various levels of Inception-v3 and DenseNet201 models, respectively, by using a concatenation-based technique [8]. The method further enhances the classification model by utilizing various levels of feature extraction as well as different architectures of the network. Similarly, Irmak developed CNN models based on automatically learned hyperparameters to assist in multi-classification of the brain tumors [2]. The classifying accuracy for tumor grading was 98. 14%, tumor detection results showed 99. 33% accuracy, and the type of the tumor with an accuracy of 92. 66%. An optimization technique via grid search for the adjustment of the hyperparameter reveals how an automatic model optimization actually enhances the accuracy of the classification.

2.2. Machine Learning Methods

1. Preparatory stage: Applying preprocessing techniques, such as picture normalization and data augmentation in the case of usability, and noise reduction in the case of high-quality data is of great importance for medical image analysis using machine learning. Among the most applied techniques for improving the performance of the next stages and improving the quality of the image, the following are utilized: Gaussian filtering and histogram equalization. These preprocessing techniques help in normalizing input data, reduce heterogeneity, and therefore, make machine-learning models stronger for MRI brain imaging [1, 3].

2. Segmentation: This is the important part of the process of medical image analysis, where segmentation focuses on splitting up an image into sections which need more inspection. Many machine learning techniques have been used for segmentation of medical imaging challenges, especially CNNs and U-Nets models. These models are trained to identify and discriminate between objects like tumors or organs from an MRI picture. CNNs show great promise in accurately detecting brain tumors from MRI images, which is crucial for both diagnosis and therapy planning [2, 7].

3. Feature Extraction: This stage is where the prominent features or patterns that may be present in the image can be extracted and may later be used to classify images. Inasmuch as deep learning models, such as CNNs, directly identify and extract the characteristics from the raw picture data, this process is usually taken over for automating this stage of medical image analysis. But with these advanced models other approaches like PCA and Gabor filters are developed further in order to achieve better feature extraction techniques. Studies on brain MRI which compare the features of the extracted tissue, like texture, shape, and intensity are compared against healthy and ill tissue, these techniques have been proven [4, 6].

4. Classification: In the last stage of classification, the features that are extracted from an image get classified into more than one class. For example, brain tumor classification and Alzheimer's disease diagnosis also falls in the category of classifications. SVMs and DNNs are two of the most famous machine learning models with regard to this. As an example, such a high degree of specificity in subclassification of brain tumors into such categories as pituitary tumors, gliomas, and meningiomas can be nothing but admired. Using the approach of transfer learning algorithms, pre-trained models may be re-used for specific domains in medical images to enhance the classification performance [4, 8].

3. Results and Findings

These researches collectively show how profoundly deep learning models may aid in improving the precision and efficiency of medical images, like classifying brain tumors and detecting Alzheimer's. This can apparently be achieved with Convolutional Neural Networks when processing mobility data from an accelerometer in classifying the stages of Alzheimer's disease with a mean accuracy of 90.91% as supplied by Santos Bringas et al. (2024) [12]. This translates to complex patterns regarding neurological conditions subjected to complex processing and analysis by deep learning models. Santos and Santos, in 2024, capitalized on this need for MRI images and the MobileNetV2 architecture to successfully realize the detection of brain tumors with an accuracy rate of 89% [13]. From their study, they indicate that lightweight CNNs are feasible in clinical applications, particularly for cases where processing capabilities are limited [13]. Meanwhile, Nayak et al. (2024) said it was actually the Dense EfficientNet model that was employed in the classification of brain tumors and achieved an amazing accuracy of 99.97% by using the training set and 98.78% by using the testing set [14]. This research work also underscores that not only complex neural network architectures can result in achieving near-perfect results in classification but, most importantly, data augmentation techniques also play a significant role in achieving better performance of the model [14]. Likewise, the hybrid deep learning approach adopted by Nassar et al., (2024) was also able to attain high classification accuracy of 99.31% and proved that multi-CNN architectures combining using majority voting techniques improve the reliability of the diagnoses [15].

Apart from presenting some important conclusions with respect to issues and future tracks for deep learning in medical imaging, some of the reviews presented high accuracy levels. Helaly et al. (2024) proved that transfer learning is applicable in medicine by reporting a 97% accuracy classification concerning the stages of Alzheimer's disease using an optimized version of the VGG19 model [16]. As in other research studies, they further also pointed out the limitation of the small data-sets used that could influence the ability of deep learning-based models to generalize well. In the diagnosis of AD, Odusami et al. (2024) suggested using XAI methods within a tailored ResNet18 architecture to classify between EMCI and LMCI achieved 73. 9% classification accuracy [17]. Their study gives testimony to the interpretability of AI models; in a medical setting as much lies behind the right diagnosis as does the reason behind the result obtained. Küstner et al.'s work with AI for MRI and MRS in 2024 proves that indeed deep breakthrough had been achieved in the reconstruction of imaging and in the actual diagnosis [18]. Model instability was also mentioned, and indeed the need for more than just a validation in limits was discussed [18]. Lastly, Shamir et al. developed DSS reached an accuracy over 95%. (2024) Applied the state-of-the-art densenet201 model along with innovative feature selection methods, and is the most concrete demonstration of ability of deep learning to enhance algorithms of clinical decision-making [19]. Table 1 shows the methodology and accuracy of all the deep learning and CNN models along with the datasets on which they have been trained on.

Table 1. *Analysis of Deep Learning Models).*

Paper Title	Methodology	Algorithm	Accuracy	Dataset Used
Image Classification of MRI Brain Image based on Deep Learning	Review of traditional and deep learning methods for MRI image classification	CNN, DNN, Transfer Learning, SVM	CNN: 96.97%, Transfer Learning: 92.8%	Various MRI datasets for Alzheimer’s and brain tumors
Identification of Brain Diseases Using Image Classification: A Deep Learning Approach	Deep learning techniques for classifying brain diseases from MRI images	CNN	Not specified	MRI scans for Alzheimer's, glioma, meningioma, pituitary tumor
Medical Image Classification for Disease Diagnosis based on Deep Convolutional Neural Network	Multiple methods for pneumonia detection from X-rays	SVM, Transfer Learning (VGG16, InceptionV3), CapsNet	VGG16: 94.7%, CapsNet: 93.6%	Chest X-ray images, 5,232 training images and 624 testing images
CNN and SVM-Based Brain Tumor Image Classification Performance Analysis	CNN and SVM models for brain tumor classification	CNN, SVM	CNN: 98.85% (Pituitary)	3,064 MRI images (Meningioma, Glioma, Pituitary)
Using a Neural Network Model Enhanced with PCA and SWLDA, improving Alzheimer’s Disease Classification in Brain MRI images	PCA and SWLDA combined with ANN for AD classification	PCA, SWLDA, ANN	99.35% (Weighted Avg.)	Not specified
Convolutional Neural Networks for Classification of Alzheimer's Disease:	Systematic review and CNN evaluation for AD classification	CNN	Similar to SVM: 76%-89%	Data from ADNI, AIBL, OASIS datasets
Method of Transfer Learning for AI-Powered Brain Tumor Classification	Transfer Learning using pre-trained CNN models	AlexNet, GoogLeNet, ResNet18, ResNet50, VGG16	99.04%	696 T1-weighted MRI images
A practical Deep Learning-Based Brain Imaging Classifier for Alzheimer's Disease on 85,721 Samples	Transfer Learning and CNN for AD classification	Inception-Resnet-V2	94.5% (AIBL dataset)	85,721 MRI scans from 50,876 participants
Medical Image Analysis Using Machine Learning and Deep Learning: Diagnosis to Detection	Literature review and experimental comparison of ML and DL models	PCA, LDA, CNN, SVM	CNN outperformed ML models	MRI datasets for various medical conditions
A Review of Brain MRI Image Classification Methods for Neurological Disorders	Review of classification techniques for neurological disorders	KNN, SVM, CNN, Decision Trees, Neural Networks	CNN: up to 98%	MRI images, including 6 normal and 4 abnormal brain images

A Multi-Model Deep Convolutional Neural Network for Automatic Hippocampus Segmentation and Classification in Alzheimer's Disease	Multi-task learning combining hippocampus segmentation and disease classification	3D DenseNet, Multi-task CNN	AD vs. NC: 88.9%, MCI vs. NC: 76.2%	Baseline T1-weighted MRI from ADNI (97 AD, 233 MCI, 119 NC subjects)
Classification of Autoimmune Disease and Brain Tumors via Ensemble Learning	Using ensemble learning to categorize autoimmune disorders and brain tumors	SVM, Majority Voting	Accuracy: 98.719%, Sensitivity: 97.5%	2,399 MRI images (Glioma, Meningioma, Pituitary Adenoma, Multiple Sclerosis)
MRI Brain Image Classification and Abnormality Detection Using Convolutional Neural Networks	CNN classification using feature extraction in Curvelet domain	AlexNet (25 layers), K-Means (segmentation)	Not specified	Public MRI brain image databases
Multi-Classification of Brain Tumor MRI Images via a Fully Optimized Deep	CNN with grid search optimization for multi-class brain tumor classification	Custom CNN models	Tumor detection: 99.33%, Multi-class: 92.66%, Tumor	RIDER, REMBRANDT, TCGA-LGG, Cheng datasets

3.1. DL Models

Some of the state-of-the-art front models of Deep Learning applied to medical image analysis include Convolutional Neural Networks, especially for automated feature extraction besides outstanding accuracy. Among some of the state-of-the-art architectures for CNN are ResNet, VGG, and Inception models that were achieved for outstanding results besides being very deep indeed for brain tumor identification. As such models are trained on larger datasets, they could be capable of dealing with complex patterns found in medical images. In addition, various studies have recently noted the utilization of transfer learning-that is, fine-tuning of pre-trained models on large datasets about specific medical image datasets to optimize efficiency and curtail consumption of processing power [4, 8].

3.2. Parameters

These three hyperparameters decide the efficiency of the deep learning model in detecting tumors in the brain include, Layer Count, Learning Rate, and Batch Size. These three hyperparameters are highly sensitive in terms of changing the performance of the model by changing them. Dropout is also often used to avoid overfitting and in addition to enhancing the robustness of the model. Some examples include layers that may most likely impact the capacity of the model to learn complex features, while the right choice of learning rates will impact not only the precision but also the convergence time of the model [10].

3.3. Drawback of ML Over DL Approaches

ML methods for medical image analysis are useful but have many disadvantages compared to deep learning methods. In ML features are always manually extracted. The method is time-consuming and prone to human error. Perhaps this very approach does influence the general performance of the model, which considers suboptimal feature presentation. Second, DL models outperform the ML models, especially when they need to handle high-dimensional data such as images of the medical picture as it allows for the direct extraction of hierarchical features directly from raw data. This is why DL models are generally superior to ML models in tasks, such as identification and classification of tumors, hence excellent for generalization and accuracy [2, 5].

3. Future Research Directions

As presented below are some of the salient points regarding which future research in deep learning models for brain tumor detection is likely to focus. Such precision in diagnosis and classification calls for integration of data from various imaging modalities such as CT, MRI, and PET scans. Another area of interest would be the development of more robust and interpretable AI models, which in turn leads further to the enhancement of capabilities of deep learning models in decision making and greater reliance on the model in clinical applications. Further, two relevant research areas include applications of DL in real-time diagnostics and federated learning, during which the model gets trained across decentralized sources of data. Accordingly, thanks to new features in this sphere, patients may note the better performance of such cases by using deep learning models within clinical practice [6, 11].

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