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ADVANCEMENTS IN TRANSFER LEARNING: A COMPREHENSIVE REVIEW OF NOVEL APPROACHES FOR MRI BRAIN IMAGE DIAGNOSIS

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ABSTRACT:

Magnetic Resonance Imaging (MRI) has rapidly advanced and established itself as an indispensable tool in both the detection and diagnosis of several diseases, most notably brain tumors. The interpretation of MRI scans still largely relies on expert radiologists, which can be time-consuming and potentially subject to variability. Transfer learning (henceforth, TL) approaches show potential for improving diagnostic precision in medical imaging analysis. In this literature review, the potential of MRI scans in classifying and detecting various medical conditions, such as glioma and Alzheimer's, is discussed alongside current algorithmic limitations. Current research indicates potential challenges in adapting existing supervised deep learning algorithms that process MRI images to more efficient approaches. The findings suggest a notable increase in the quality of detecting sub-pathologies, even with a scarcity of well-annotated images. This can potentially reduce the training cycle duration. When transfer learning is applied to diagnostic approaches, it may act as supplemental support for decision-making processes for tumorous growth detection, potentially reducing the time period for treatment and increasing effectiveness according to preliminary research. This review examines the expansion in transfer learning in MRI for the assessment and treatment of brain disorders through recent algorithms from the current literature.
KEYWORDS: Transfer Learning, Machine Learning, MRI Image, Diagnose Diseases, Training Algorithm, Deep Learning.

1. INTRODUCTION

The use of MRI has helped expand the scope of identifying and diagnosing conditions in brain tumor patients but the interpretation of such images still requires high levels of skill and expertise to appropriately analyze the data (Azeez & Abdulazeez, 2024). It is also important to note that the traditional methods involve manual analysis, which even though works, probably leading to potential errors due to being time consuming. In relation to these issues, artificial intelligence (AI), alongside with machine learning, is being extensively researched and implemented. Transfer learning has emerged as a promising approach among machine learning methods. Transfer learning *reduces the need for* the resource heavy pre-trained models by leveraging knowledge from existing datasets, so it *can* accurate and efficient in regards to analyzing and detecting tumors that lie within the brain (Rebar & Abdulazeez, 2024).

According to Alla and Athota (2022), transfer learning utilizes the knowledge acquired through the use of extensive datasets to improve the model's performance on tasks where the amount of training data available is comparatively lesser. For medical imaging tasks, pre-trained models on huge image databases can be fine-tuned to identify MRI scan features (Alla & Athota, 2022). This methodology allows the training of models with a limited quantity of labelled data while increasing the speed of the training process so that actionable results can be obtained by the medical specialists in less time. Consequently, transfer learning may help address the imbalance in demand for accurate diagnostic devices and the issues pertaining to lack of availability of appropriate data in medical imaging (Disci *et al*., 2025).

Besides, the use of transfer deep learning in MRI scans goes beyond tumor detection and includes a number of other brain diseases such as Alzheimer's and other neurodegenerative diseases (Sorour, 2024). With the help of deep learning methods, models are constructed that aim to reliably distinguish healthy brain tissue from diseased ones, potentially adding in timely diagnosis and treatment. The application of transfer learning into clinical settings could potentially help radiologists and neurologists to further improve the patient's clinical outcomes in such areas as healthcare delivery. As the discipline develops, it is likely that AI algorithms integrated with medical images will help in improving diagnosis and management of various brain disorders (Kittani & Abdulazeez, 2024).

This study is organized into several sections to provide a comprehensive review of transfer learning. Section Two delves into the complexities of transfer learning, highlighting its significance and implications, while also examining various techniques associated with it. Section Three offers the applications of transfer learning on medical image. Section Four addresses limitation or challenges faced transfer learning using medical images Section Five offers a thorough literature review that succinctly summarizes key findings from prior research published in the recent year with algorithms that considered to be novel. Section Six is dedicated to discussions and the presentation of results. Finally, Section Seven concludes the study and outlines future directions for research.

Transfer Learning:

Transfer learning is one of the most important aspects of artificial intelligence and machine learning as it enables the transfer of knowledge from one domain to another which is related. It helps in dealing with the issue of lack of data by utilizing already trained models, which means that features have been trained on a source data set to perform well on a target task with few labeled data (Ali & Abdulazeez, 2024).

Transfer learning helps the user to be able to apply the knowledge gained in one domain and be able to apply it in a

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completely different context which is useful in cases such as when it is expensive or impossible to obtain a lot of labeled data. For example, with regard to computer vision, a model trained on large scale images can be utilized to help train on recognizing a different but related type of images which may lead to a faster training and better accuracy (Khaliki & Başarslan, 2024).

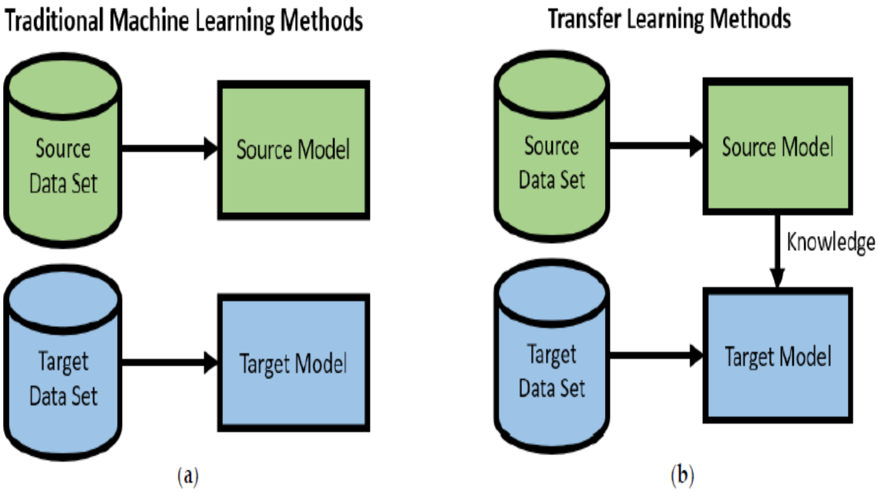

Figure 1: Traditional ML vs. Transfer Learning Methods

The difference between traditional and transfer learning methods can be described in Figure 1-a. (The traditional machine learning). Separate models are trained for the source and target datasets, and these models do not interact. In the same (i.e., 1-b), the model is first trained on the source dataset, and the knowledge gained from this training is then used to inform and improve the model for the target dataset (Combs *et al*., 2023).

Figure 2: Traditional ML vs. Transfer Learning Methods

According to transfer learning, the prerequisite of transfer is that there needs to be a connection between two learning activities. In practice, a system that has learned training from scratch can take a fair amount of time to generate output. However, a system that has gained a knowledge based on pre-trained system can produce output much faster, as shown in the example mentioned in Figure 2 (Zhuang *et al*., 2020).

Because of the growing need of adaptive learning systems, transfer learning has become an overreaching concept crucial for technological advancements in various fields including natural language processing and autonomous systems. By utilizing the concept of transfer learning, researchers may be able to create robust models that can help AI to address increasingly complex tasks. As a result, advancements in the efficiency and optimization of AI may take place (Sedeeq & Abdulazeez, 2024).

According to survey conducted by Ali and Abdulazeez (2024), transfer learning can be categorized into four primary methods. They can help in understanding the different strategies and methodologies used in transfer learning to enhance model performance across various applications:

1. Instance-Based Transfer Learning: This method involves training a model for the target domain using weighted combinations or resampled data from the source domain. It focuses on selecting the most informative instances from the source domain to improve learning in the target domain.
2. Feature-Based Transfer Learning: This approach maps data from both the source and target domains into a shared feature

space. It utilizes specific feature representations to facilitate the transfer of knowledge between domains.

3. Model-Based Transfer Learning: This method refers to transferring models or model parameters across the source and target domains. It includes algorithms that adapt pre-trained models to new tasks or domains.

4. Relation-Based Transfer Learning: This approach emphasizes identifying relationships between the source and target domains and transferring information based on these connections. It often employs techniques like Markov logic networks to facilitate the transfer. (Zhou *et al*., 2021; Ali & Abdulazeez, 2024).

Applications of Transfer Learning:

Transfer learning potentially enhances the performance of medical imaging tasks by allowing models to leverage previously learned features, especially when dealing with limited data. This approach may not only improve accuracy but can also potentially reduce the time and resources required for training models from scratch, making it a valuable tool in the medical field (Matsoukas *et al*., 2022; Meena *et al*., 2024; Mohammed *et al*., 2024).

1. Disease Classification: Transfer learning helps classify diseases (like diabetic retinopathy and skin lesions) by fine-tuning models pre-trained on large datasets (such as ImageNet) to work with smaller, domain-specific datasets (Shamshad *et al*., 2024).
2. Anomaly Detection: Transfer learning aids in detecting anomalies, such as masses or calcifications in mammograms, using datasets like CBIS-DDSM (Murugesan *et al*., 2024).
3. Segmentation Tasks: Transfer learning is used in segmentation tasks, like tumor detection in MRI scans or organ delineation in CT images, by adapting models to smaller datasets (Shchetinin, 2024).
4. Radiology: Transfer learning improves diagnostic accuracy in chest X-ray analysis by classifying conditions with datasets like CHEXPERT (Rustom *et al.*, 2024).
5. Histopathology: It also enhances the classification of histopathological images, such as detecting cancerous tissues, using datasets like PATCHCAMELYON (Vajiram & Senthil, 2024).
6. Multi-modal Imaging: Transfer learning can integrate information from different imaging modalities (e.g., MRI and CT scans), improving diagnosis by combining knowledge from diverse datasets (Gottipati & Thumbur, 2024).
7. Real-time Applications: In time-sensitive scenarios like emergency medicine, transfer learning enables faster training and deployment of models, aiding quick decision-making (Dhakshnamurthy *et al*., 2024).
8. Personalized Medicine: By adapting models to individual patient data, transfer learning can personalize diagnostic and treatment plans based on unique medical image characteristics (Matsoukas *et al*., 2022; Shamshad *et al*., 2024; Al-Azzwi, 2024) .

Challenges of TL on Medical Images:

Transfer learning in medical imaging also faces notable challenges that include:

1- Challenges of Data: Large volumes of data are necessary if transfer learning models are to reach their optimal performance. There are however many instances where enough data is not provided, thus, having an effect on the performance of such models (Gu, 2024).

2- Retroactive Images: Enabling the usage of retroactive images in MRI may prove to be difficult to ML and DL models due to interference noise that these images may carry. Attempts to minimize such noise interference and improve image quality through the use of pre data processing steps lacks uniformity thus resulting in differing image quality standards (Muthuraj, 2024).

3- Feature Demand: Although features may be automatically extracted by deep learning models, feature selection may remain an area lacking understanding. This could have an impact on the model performance due to attributing inclusion of many parameters and exclusion of a few (Salehi *et al*., 2023).

4- Adequate Computing Resources: Ownership of high memory GPU based systems and large bandwidths has remained an obstacle to the masses. These provisions are not amenable to every researcher which in turn dampens the quality of their research (Al-Azzwi, 2024).

5- Generation Problems: Possessing advanced data augmentation techniques that assist in improving smaller data sets in a bid to make generalized models is essential.

Nonetheless, several approaches in the literature emphasize only on increasing the amount of images, neglecting any relationships of space or texture, which may present issues during analysis (Kaifi, 2023). Such issues would make it apparent that transfer learning as a solution to classifying brain tumors is complex and these issues do require a research based approach to be solved.

Literature Review:

Machine learning methods typically require a significant quantity of labeled data for training, rendering them less feasible in situations where data is scarce or costly to get. Transfer learning overcomes this difficulty by enabling models to apply information acquired from a source domain with ample data to a target domain with little data, consequently improving performance and generalization. The following table presents a comprehensive analysis of novel transfer learning algorithms applied to medical MRI images for brain disease or tumor detection from recent literature. These studies were identified through systematic searches of major research platforms including Springer Nature, MDPI, ResearchGate, and Google Scholar.

Table 1: Summary of the work performed by most of the research reviewed in this paper

References	Algorithm	Database	Advantage	Limitation
Z. Ullah *et al*. (2024)	CNN, VGG-16, VGG-19, LeNet-5	MRI images, synthetic data augmentation	High accuracy (99.24%), effective feature learning, CAD system support	Limited real patient data, reliance on synthetic datasets
Nag *et al*. (2024)	TumorGANet (Transfer Learning with GANs)	7023 MRI images (gliomas, meningiomas, non-tumorous cases, pituitary tumors)	High accuracy (99.53%), precision and recall (100%), robust data augmentation	May not generalize well across all data types, potential for synthetic artifacts, high resource demand
Bibi *et al*. (2024)	Inception v4 model (Transfer Learning)	figshare, SARTAJ dataset, and Br35H	High accuracy (98.7%), effective feature extraction	Limited dataset size (253 images), potential misclassification risks
Zubair Rahman *et al*. (2024)	EfficientNetB2	BD-BrainTumor	High accuracy, robust performance 99.83%	Needs real-world validation

Gopinadhan (2024)	AD-TL method, MLP, CNN, DCNN, ResNet50, AlexNet	Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset	High accuracy (98.99%), early detection, non-invasive	Requires extensive training data, potential overfitting
Pal *et al*. (2024)	Convolutional Neural Networks (CNN), Inception V3, VGG-19, Ensemble Learning	Brain Tumor Image Segmentation Challenge dataset (3000 MRI images)	High accuracy, improved performance with limited data, 98% accuracy achieved	Requires extensive training data, potential overfitting on small datasets
Mahmud *et al*. (2024)	VGG16, VGG19, DenseNet169, DenseNet201 (transfer learning)	MRI OASIS scans	High accuracy (96%), enhanced interpretability with XAI techniques	Requires large datasets for training, and potential overfitting issues
Ren *et al*. (2024)	3D U-Net, Compound Loss Function	BraTS 2023	Improved accuracy, lesion-wise evaluation, Average Dice score: 79%, 72%, 74%	False positives in small connected components
Ashraf *et al*. (2024)	CNN, Transfer Learning	ABIDE I, ABIDE II, ABIDE I+II	Improved accuracy, less data required, 79.09% accuracy, 80.71% sensitivity, 78.71% specificity	Limited dataset size, data collection challenges
Panigrahi *et al*. (2024)	Modified DenseNet121, Transfer Learning	Br35H: Brain Tumor Detection 2020	High accuracy, computational efficiency, 99.14%	Limited dataset size, potential overfitting
Srikrishna *et al*. (2024)	Deep learning models (U-Net)	Gothenburg H70 Birth Cohort, Uppsala University Hospital datasets	Automated extraction of volumetric metrics, reduced manual analysis time, high accuracy (93% pre-shunt, 92% post-shunt)	Reliance on initial manual and automated labelling, potential variability in training data
Natha *et al*. (2024)	SETL_BMRI (ensemble of AlexNet and VGG19)	Kaggle Brain Tumor MRI Dataset	High accuracy, improved generalization, reduced overfitting, 97.02% accuracy, 97.30% recall, 95.70% precision, 97.20 F1-Score	Requires significant computational power, may not generalize well to unseen data
Vajiram and Senthil (2024)	VGG-16, ResNet50, ResU-net	TCIA Archives (MRI images)	Effective feature extraction, high accuracy, ResNet50: 95.06%	Requires large datasets, sensitive to noise
M. S. Ullah *et al*. (2024)	Hybrid deep learning model, Bayesian optimization, Quantum Theory-based Marine Predator Algorithm	Figshare dataset	High accuracy, improved feature selection, addresses class imbalance, achieved accuracy of 99.67%	Complexity of model, potential overfitting, reliance on data augmentation
Raza *et al*. (2024)	Deep Convolutional Neural Networks (CNNs), Principal Component Analysis (PCA), Stacking	BTS (small dataset), BTL (large dataset)	Enhanced classification accuracy, robust feature extraction, reduced dimensionality, accuracy of 94.34% on the BTS dataset and 99.89% on the BTL dataset.	Difficulty in acquiring large datasets, potential overfitting on small datasets
Reddy *et al*. (2024)	Convolutional Neural Networks (CNN), Transfer Learning (VGG16, ResNet-50)	Kaggle (MRI images dataset)	Improved detection speed, accuracy, and efficiency in diagnosis, precision of 93.3%,	Limited dataset size, potential bias in the testing set
Dhakshnamurthy *et al*. (2024)	Hybrid VGG16–ResNet50, AlexNet, VGG16, ResNet-50	Kaggle (3264 MRI images)	High accuracy (99.98%), improved early detection, effective classification.	Lack of empirical investigations, absence of elucidation tools
Wageh *et al*. (2024)	SVM, Random Forest, Decision Tree, XGB, Genetic Algorithm	MRI brain images dataset	Enhanced feature representation, improved accuracy, effective detection, achieved accuracy rates up to 98.12%	Requires extensive training data, computational complexity
Nayak *et al*. (2024)	EfficientNetB0, CNN	3264 2-D MRI scans (4 classes: no tumor, glioma, meningioma, pituitary)	High accuracy (97.61%), effective tumor classification	Potential information loss in deeper networks (e.g., VGG16)

PANDIYAN *et al*. (2024)	Deep Transfer Learning (CNN)	3000 MRI scan images	High accuracy, detailed tumor visualization, Overall accuracy: 96%, Precision: 99%, Recall: 99%	False negatives in some cases
Mehmood and Bajwa (2024)	ConvNext architecture	BraTS 2019 dataset	High accuracy, effective feature extraction, 99.5%	Limited to MRI sequences, requires pre-training
Hsu *et al*. (2024)	Transfer learning with MobileNetV2	OCT volumes from patients diagnosed with glioma	Fast classification, improved diagnostic accuracy, user-friendly interface, and the accuracy reported to be 86.4%	Limited dataset size, exclusion of certain image frames, and the need for model generalization
Shchetinin (2024)	TL-U-Net (DenseNet121 as encoder)	Brain Tumor Segmentation (BraTS) dataset	High accuracy, flexibility, low computational cost, Mean IoU: 91.14%, Mean Dice: 94.26%, Accuracy: 94.22%	Unbalanced classes in image sets may affect accuracy metrics.
Zia-ur-Rehman *et al*. (2024)	DenseNet-201	AD5C dataset	High accuracy, improved classification, 98.24%	Requires large, high-quality data; overfitting risk; lack of interpretability
Sorour *et al*. (2024)	CNNs, LSTM, SVM, Transfer Learning (VGG16-SVM)	MRI datasets for Alzheimer's Disease classification	High accuracy (99.92%), precision (100%), recall (99.50%)	Relatively small data size; requires high accuracy in medical data
Raina *et al*. (2024)	VGG-16 (CNN)	Brain MRIs for Tumor Classification	High accuracy, efficient transfer learning, Validation accuracy ~96.92%	Requires large datasets, may not generalize well
Rustom *et al*. (2024)	Convolutional Neural Networks (CNNs)	The Cancer Imaging Archive (TCIA)	High accuracy in tumor detection; mimics radiologist analysis. The accuracy output was reported as 86.14%	Limited demographic data; reliance on available MRI datasets
Zhou (2024)	Multi-scale CNN, U-Net, Cascaded CNN, Heuristic methods, k-Space deep learning, ML-KCNN	BraTS (Brain Tumor Segmentation) dataset	Improved accuracy (e.g., 97.3%), tailored treatment plans, enhanced diagnostic precision.	Computational complexity (high), potential for false positives (variable), challenges with missing modalities (variable)
Shedbalkar and Prabhushetty (2024)	UNet, Chopped VGGNet	MRI images of Glioma, Meningioma, Pituitary tumors (3064 images total)	High accuracy, non-invasive classification aids radiologists. Overall accuracy: 98.4%, highest accuracy for Pituitary: 99.45%	Dependency on the quality of input images, potential overfitting
Bhardwaj *et al*. (2024)	Fine-tuned VGG16	Publicly available brain MRI dataset	Automated diagnosis, high accuracy, 97%	Requires large datasets for training
Ravikumar *et al*. (2024)	Convolutional Neural Network (CNN)	TCGA-LGG and TCIA Datasets	Early detection, high accuracy (over 95%)	Time-consuming preprocessing, potential for human error in manual analysis
Murugesan *et al*. (2024)	Ensemble deep learning models (e.g., BTGC, InceptionResNetV2)	Six clinical datasets for brain tumor detection and classification	High accuracy, improved diagnostic precision, user-friendly integration, Up to 99.92% for tumor classification	Potential overfitting, need for extensive clinical validation
Kumar *et al*. (2024)	AlexNet, VGG19, ResNet152, DenseNet169, MobileNetv3	Dataset of 3604 MRI images (meningiomas, gliomas, pituitary tumors)	High accuracy, efficient with limited labelled data, improved diagnostic speed, up to 99.75% with MobileNetv3	Potential biases in training data, generalization issues to external datasets
Ali *et al*. (2024)	26-layer CNN model with transfer learning	Alzheimer's dataset, ADNI_Extracted_Axial	High accuracy, automatic feature extraction, minimal training time, 99.70% for dementia sub-classification, 97.45% for MRI classification	Potential confounding variables, reliance on dataset quality

Naveen and Nagaraj (2024)	VGG-19, ResNet-50, Inception V3 (transfer learning)	ADNI (Alzheimer's Disease Neuroimaging Initiative)	Improved classification accuracy, effective early detection, Inception V3: 97.54%, VGG-19: 7.16% ResNet-50: 98.70%	Class imbalance, potential overfitting, dependency on the quality of MRI data
Shah (2024)	CNN-based DenseNet with PCA	Kaggle Brain Tumor Detection Dataset	Reduces dimensionality, improves accuracy up to 97%	Limited dataset size may require larger datasets
Albalawi *et al*. (2024)	Convolutional Neural Networks (CNNs)	Kaggle Brain Tumor MRI Dataset	High precision and recall; effective tumor type classification; generalization capability, Accuracy 98%	Data privacy concerns, limited annotated datasets, and challenges in generalization
Khaw and Abdullah (2024)	Convolutional Neural Networks (CNN), VGG16	Open Access Series of Imaging Studies (OASIS)	Quick and accurate diagnosis; 98.56% accuracy	Challenges in classifying MCI; need for multimodal approaches
Rao *et al*. (2024)	ResNet50v2, InceptionResNetV2	3256 MRI images from various sources	High accuracy, automated detection, minimizes human error, 92.15% training accuracy, 91.25% testing accuracy.	Potential overfitting, reliance on the quality of input data
Kako *et al*. (2024)	U-Net and transfer learning	High-Resolution Fundus (HRF) Image Database	Enhanced segmentation accuracy; interpretable saliency maps, 97.90% on DRIVE dataset	Small dataset, generalizability concerns, complexity in clinical use
Gottipati and Thumbur (2024)	VGG16, Inception V3, ResNet 50	Meme-CEUS dataset	Improved accuracy, enhanced feature extraction, effective tumor classification, 98.80% accuracy, 92.96% sensitivity, 93.60% precision	Potential dependency on data quality and complexity, need for further optimization
Alotaibi *et al*. (2024)	CVG-Net (2D-CNN, VGG16)	Multi-class MRI image dataset (21,672 images)	Enhanced diagnostic accuracy, automated feature extraction, High accuracy of 96%	Computationally expensive, requires hyperparameter tuning
Kilani *et al*. (2024)	Convolutional Neural Network, Discriminative Restricted Boltzmann Machine	BCI Competition III Dataset II, RSVP Dataset	Reduces training samples needed, efficient transfer learning, Achieved 97% average accuracy	Calibration time-consuming, subject-specific ERP variability
Neamah *et al*. (2024)	Improved ResNet50 with Spatial Pyramid Pooling (SPP)	MRI images for brain tumor classification	High accuracy, effective feature extraction, enhanced generalization, 99.02% accuracy, precision 0.996, recall 0.991	Dependency on quality of training data, potential overfitting

2. DISCUSSION

The analysis of the reviewed research papers indicates patterns in the deployment of deep learning algorithms for biomarker identification for brain disorders with the help of medical MRI images. There is a notable emphasis on the convolutional neural networks and their accuracy in feature extraction. Moreover, transfer learning has become an essential strategy to improve performance metrics while working with a limited number of samples by allowing customization of multiple pre-trained models with extensive datasets. The most frequently reported algorithms include VGG-16, ResNet-50, DenseNet and Inception, models with accuracy exceeding 95% in controlled research setting, While several studies reported extremely high accuracy values. It is important to note that these results are often achieved in specific research contexts and may not directly translate to clinical performance

There are also other noteworthy results including CNNs with transfer learning, for Alzheimer's disease 99.92% of the 99% was attributed to the classification, while ResNet-50 99.93% of the accuracy for brain tumor percent was attributed to its inception.

A recurring theme across the studies is that the primary infrastructure of these algorithms is high accuracy and their ability to robustly learn relevant features and augment data. In distinguishing between healthy and diseased tissues many models demonstrate strong performance in research settings, implying that they may be effective tools to support clinical decision-making, through further validation is needed. The strength of CNNs is the ability to eliminate the necessity for manual feature engineering by learning relevant features from MRI images, autonomously augmenting the diagnostic process.

Synthetic data generation can boost the training datasets and thus potentially increase the robustness and generalization of a model. However, several important restrictions still exist such as the issue of small size datasets which can contribute to overfitting and generalizing problems. Inception v4 was constrained in its use by such a limited number of images, 253 to be exact. Moreover, while synthetic datasets can act as compensatory data, there is danger of including outliers that do not fit well in practical situations. The cost of training very sophisticated models is also significant, especially in the clinical area with relatively low computational resources.

Transfer learning is a promising method as it allows researchers to use models that have been trained on large datasets. This may not only speed up the training processes but also potentially improve the accuracy in instances where there are limited large annotated datasets available. The combined use of transfer learning with DenseNet and EfficientNet models has shown improvements in the accuracy of functional MRI image diagnosis of the brain making them popular in modern research. Recent research demonstrates that transfer learning approaches can enable more efficient algorithm development for brain disease detection compared to training models from scratch.

Preliminary work in medicine is quite encouraging so far with respect to algorithmic performance. However, it will be important to deal with the bottlenecks associated with the availability of datasets as well as computing facilities for these technologies to be operational in clinical settings. Additionally, more robust clinical validation studies are needed to bridge the gap between research performance throughout theoretical and computational studies when compared to real-world clinical utilities.

CONCLUSION

This review has examined how transfer learning approaches can potentially enhance the diagnosis of neurological conditions through MRI image analysis. Due to the fact that MRI images are utilized for diagnosing various ailments, transfer learning can aid in tackling the shortage of labeled data. It appears that this approach can help meet future needs of the medical diagnosis field, given the constant shortage of medical data availability due to fragmented healthcare systems.

Additionally, transfer learning does not restrict itself to tumor detection, but it is equally adaptable in diagnosing various types of Alzheimer's and other neurological conditions as well. Several applications have already been developed that can compare tissues of healthy individuals against those of patients developing differential models aimed towards assisting in accurate diagnosis alongside timely treatment.

Finally, the novel algorithms reviewed in this paper demonstrate potential for supporting medical practitioners in their diagnostic word, where clinical validation remains a crucial next stage. Nonetheless, the review also recognizes the drawbacks and difficulties of transfer learning such as dependence on simulated datasets, and a shortage of data on real patients.

As AI continues to develop in conjunction with the realm of medical imaging, the partnership between these two sectors will be critical in furthering the goal of understanding and treating disorders affecting the brain. In the future, studies ought to take up the challenge of overcoming those barriers while also looking into the possibility of transfer learning models on medical images without losing out on the potential advantages, where this technology holds in a clinical setting. This will require interdisciplinary collaboration between AI researchers, medical imaging specialists, clinicians, and ethicists to ensure that technological advancements translate to improved patient care.

Declaration:

I declare that this research manuscript was prepared by me and the work displayed herein is my own, and that this work was not submitted previously for any other degree or professional qualification. The collaborative contributions have been illustrated clearly and acknowledged.

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Author Contribution:

The research paper framework is carried out by the main author from the work field to data analysis and manuscript writing, whereas the coauthor supervised and contributed to the revision of the manuscript

REFERENCES

Abdulqadir, M., & Abdulazeez, A. M. (2024). A Review on Alzheimer's Disease Classification Using Deep Learning. *Indonesian Journal of Computer Science*, *13*. https://doi.org/10.33022/ijcs.v13i3.4031

Al-Azzwi, Z. (2024). Medical image Classification using Transfer Learning: Convolutional Neural Network Models approach. *Journal of Electrical Systems*, *20*, 2561–2569. https://doi.org/10.52783/jes.3243

Ali, A. H., & Abdulazeez, A. M. (2024). Transfer Learning in Machine Learning: A Review of Methods and Applications. *Indonesian Journal of Computer Science*. https://api.semanticscholar.org/CorpusID:271605825

Alla, S., & Athota, K. (2022). Brain Tumor Detection Using Transfer Learning in Deep Learning. *Indian Journal Of Science And Technology*, *15*, 2093–2102. https://doi.org/10.17485/IJST/v15i40.1307

Ashraf, A., Qingjie, Z., Bangyal, W. H. K., & Iqbal, M. (2024). Analysis of Brain Imaging Data for the Detection of Early Age Autism Spectrum Disorder Using Transfer Learning Approaches for Internet of Things. *IEEE Transactions on Consumer Electronics*, *70*(1), 4478–4489. https://doi.org/10.1109/TCE.2023.3328479

Azeez, O., & Abdulazeez, A. (2024). Classification of Brain Tumor based on Machine Learning Algorithms: A Review. *Journal of Applied Science and Technology Trends*, *6*, 01–15. https://doi.org/10.38094/jastt61188

Bibi, N., Wahid, F., Ma, Y., Ali, S., Abbasi, I. A., Alkhayyat, A., & Khyber. (2024). A Transfer Learning-Based Approach for Brain Tumor Classification. *IEEE Access*, *12*, 111218–111238. https://doi.org/10.1109/ACCESS.2024.3425469

Combs, K., Lu, H., & Bihl, T. J. (2023). Transfer Learning and Analogical Inference: A Critical Comparison of Algorithms, Methods, and Applications. *Algorithms*, *16*(3). https://doi.org/10.3390/a16030146

Dhakshnamurthy, V. K., Govindan, M., Sreerangan, K., Nagarajan, M. D., & Thomas, A. (2024). Brain Tumor Detection and Classification Using Transfer Learning Models. *Engineering Proceedings*, *62*(1). https://doi.org/10.3390/engproc2024062001

Disci, R., Gurcan, F., & Soylu, A. (2025). Advanced Brain Tumor Classification in MR Images Using Transfer Learning and Pre-Trained Deep CNN Models. *Cancers*, *17*(1). https://doi.org/10.3390/cancers17010121

Gopinadhan, A. (2024). Ad-Tl: Alzheimer's Disease Prediction Using Transfer Learning. *Journal of Electrical Systems*, *20*, 1132–1147. https://doi.org/10.52783/jes.2845

Gu, C. (2024). Enhancing medical image classification with convolutional neural networks through transfer learning: A comprehensive review. *Applied and Computational Engineering*, *35*, 280–284. https://doi.org/10.54254/2755-2721/35/20230407

Kaifi, R. (2023). A Review of Recent Advances in Brain Tumor Diagnosis Based on AI-Based Classification. *Diagnostics*, *13*, 3007. https://doi.org/10.3390/diagnostics13183007

Khaliki, M. Z., & Başarslan, M. S. (2024). Brain tumor detection from images and comparison with transfer learning methods and 3-layer CNN. *Scientific Reports*, *14*(1), 2664. https://doi.org/10.1038/s41598-024-52823-9

Kittani, T., & Abdulazeez, A. (2024). Deep Learning Classification Algorithms Applications: A Review. *Indonesian Journal of Computer Science*, *13*. https://doi.org/10.33022/ijcs.v13i3.4064

Mahmud, T., Barua, K., Habiba, S. U., Sharmen, N., Hossain, M. S., & Andersson, K. (2024). An Explainable AI Paradigm for Alzheimer's Diagnosis Using Deep Transfer Learning. *Diagnostics*, *14*(3). https://doi.org/10.3390/diagnostics14030345

Matsoukas, C., Haslum, J. F., Sorkhei, M., Soderberg, M. P., & Smith, K. (2022). What Makes Transfer Learning Work for Medical Images: Feature Reuse & Other Factors. *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 9215–9224. https://doi.org/10.1109/CVPR52688.2022.00901

Meena, M., Balaswetha, U., & Harini, M. (2024). Brain Tumor Classification Using Pretained Deep Convolutional Neural Networks. *International Journal of Health Sciences and Research*. https://api.semanticscholar.org/CorpusID:269688172

Mohammed, A.-Z., Ansarullah, S., Al-Eissa, M., Dar, G., Alqahtani, R., & Alkahtani, S. (2024). Exploring the Efficacy of Deep Learning Techniques in Detecting and Diagnosing Alzheimer's Disease: A Comparative Study. *Journal of Disability Research*, *3*. https://doi.org/10.57197/JDR-2024-0064

Muthuraj, S. (2024). Neural Networks in Neuroimaging: A Critical Analysis of Deep Learning Techniques for Brain Tumor Prediction. *Journal of Electrical Systems*, *20*, 1617–1636. https://doi.org/10.52783/jes.1468

Nag, A., Mondal, H., Mehedi Hassan, M., Al-Shehari, T., Kadrie, M., Al-Razgan, M., Alfakih, T., Biswas, S., & Kumar Bairagi, A. (2024). TumorGANet: A Transfer Learning and Generative Adversarial Network- Based Data Augmentation Model for Brain Tumor Classification. *IEEE Access*, *12*, 103060–103081. https://doi.org/10.1109/ACCESS.2024.3429633

Natha, S., Laila, U., Gashim, I. A., Mahboob, K., Saeed, M. N., & Noaman, K. M. (2024). Automated Brain Tumor Identification in Biomedical Radiology Images: A Multi-Model Ensemble Deep Learning Approach. *Applied Sciences*, *14*(5). https://doi.org/10.3390/app14052210

Nayak, R., Rao, S., Jayakar Shetty, S., S, V., & Shashikala. (2024). Brain Tumor Detection Using Deep Learning Technique. *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, *12*(V). https://doi.org/10.22214/ijraset.2024.61745

Pal, A., Seth, J., Tyagi, A., Haider, A., & Mishra, A. (2024). An Efficient Brain Tumor Detection Using Ensemble Learning. *Educational Administration Theory and Practices*, *30*. https://doi.org/10.53555/kuey.v30i5.4686

Panigrahi, S., Adhikary, D., & Pattanayak, B. (2024). Analyzing Activation Functions With Transfer Learning-Based Layer Customization for Improved Brain Tumor Classification. *IEEE Access*, *PP*, 1–1. https://doi.org/10.1109/ACCESS.2024.3497346

Raza, S., Gul, N., Khattak, H., Rehan, A., Farid, M., Kamal, A., Rajput, D., Mukhtiar, S., & Ullah, A. (2024). BRAIN TUMOR DETECTION AND CLASSIFICATION USING DEEP FEATURE FUSION AND STACKING CONCEPTS. *Journal of Population Therapeutics and Clinical Pharmacology*, 1339–1356. https://doi.org/10.53555/jptcp.v31i1.4179

Rebar, Z., & Abdulazeez, A. (2024). Deep and Machine Learning Algorithms for Diagnosing Brain Cancer and Tumors. *Indonesian Journal of Computer Science*, *13*, 3932–3960. https://doi.org/10.33022/ijcs.v13i3.4028

Reddy, L., Muniyandy, E., Vamsikrishna, M., & Ravindra, C. (2024). Brain Tumor Detection and Classification Using Deep Learning Models on MRI Scans. *EAI Endorsed Transactions on Pervasive Health and Technology*, *10*. https://doi.org/10.4108/eetpht.10.5553

Ren, T., Honey, E., Rebala, H., Sharma, A., Chopra, A., & Kurt, M. (2024). An Optimization Framework for Processing and Transfer Learning for the Brain Tumor Segmentation. *ArXiv*, *abs/2402.07008*. https://api.semanticscholar.org/CorpusID:267626912

Salehi, A. W., Khan, S., Gupta, G., Alabduallah, B. I., Almjally, A., Alsolai, H., Siddiqui, T., & Mellit, A. (2023). A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope. *Sustainability*, *15*(7). https://doi.org/10.3390/su15075930

Sedeeq, N., & Abdulazeez, A. M. (2024). CNN-Based Segmentation and Detection of Brain Tumors MRI Images: A Review. *Indonesian Journal of Computer Science*, *13*. https://doi.org/10.33022/ijcs.v13i3.4029

Shamshad, N., Sarwr, D., Almogren, A., Saleem, K., Munawar, A., Rehman, A., & Bharany, S. (2024). Enhancing Brain Tumor Classification by a Comprehensive Study on Transfer Learning Techniques and Model Efficiency Using MRI Datasets. *IEEE Access*, *PP*, 1–1. https://doi.org/10.1109/ACCESS.2024.3430109

Srikrishna, M., Seo, W., Zettergren, A., Kern, S., Cantré, D., Gessler, F., Sotoudeh, H., Seidlitz, J., Bernstock, J. D., Wahlund, L.-O., Westman, E., Skoog, I., Virhammar, J., Fällmar, D., & Schöll, M. (2024). Assessing CT-based Volumetric Analysis via Transfer Learning with MRI and Manual Labels for Idiopathic Normal Pressure Hydrocephalus. *medRxiv*. https://doi.org/10.1101/2024.06.23.24309144

Ullah, M. S., Khan, M. A., Masood, A., Mzoughi, O., Saidani, O., & Alturki, N. (2024). Brain tumor classification from MRI scans: A framework of hybrid deep learning model with Bayesian optimization and quantum theory-based marine predator algorithm. *Frontiers in Oncology*, *14*. https://doi.org/10.3389/fonc.2024.1335740

Ullah, Z., Jamjoom, M., Thirumalaisamy, M., Alajmani, S., Saleem, F., Sheikh Akbari, A., & Khan, U. (2024). A Deep Learning Based Intelligent Decision Support System for Automatic Detection of Brain Tumor. *Biomedical Engineering and Computational Biology*, *15*. https://doi.org/10.1177/11795972241277322

Sorour, E. S, Amr A. A., Khalied M. A., Abdulrahman K. A., and Abeer A. W. (2024). Deep Learning Classification using MRI for Alzheimer's Disease Detection. *International Scientific Journal of Engineering and Management*. https://api.semanticscholar.org/CorpusID:269453742

Vajiram, J., & Senthil, A. (2024). *Brain MRI detection by Sematic Segmentation models- Transfer Learning approach*. https://arxiv.org/abs/2405.14886

Wageh, M., Amin, K., Algarni, A., & Hamad, A. (2024). Brain Tumor Detection Based on Deep Features Concatenation and Machine Learning Classifiers With Genetic Selection. *IEEE Access*, *12*, 114923–114939. https://doi.org/10.1109/ACCESS.2024.3446190

Zhou, Y., Zhang, X., Wang, Y., & Zhang, B. (2021). Transfer learning and its application research. *Journal of Physics: Conference Series*, *1920*, 012058. https://doi.org/10.1088/1742-6596/1920/1/012058

Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., Xiong, H., & He, Q. (2020). A Comprehensive Survey on Transfer Learning. *Proceedings of the IEEE*, *PP*, 1–34. https://doi.org/10.1109/JPROC.2020.3004555

Zubair Rahman, A. M. J., Gupta, M., Aarathi, S., Mahesh, T. R., Vinoth Kumar, V., Yogesh Kumaran, S., & Guluwadi, S. (2024). Advanced AI-driven approach for enhanced brain tumor detection from MRI images utilizing

EfficientNetB2 with equalization and homomorphic filtering. *BMC Medical Informatics and Decision Making*, *24*(1), 113. https://doi.org/10.1186/s12911-024-02519-x

PANDIYAN, M., JENISHA, E., MADHURANJANI, G., & BRINDHA DHARSHINI, S. (2024). BRAIN TUMOR DETECTION USING DEEP TRANSFER LEARNING. *International Journal of Scientific Research in Engineering and Management (IJSREM)*, *08*(03). https://doi.org/10.55041/IJSREM29704

Mehmood, Y., & Bajwa, U. I. (2024). Brain tumor grade classification using the ConvNext architecture. *DIGITAL HEALTH*, *10*, 20552076241284920. https://doi.org/10.1177/20552076241284920

Hsu, S., Lin, M.-H., Lin, C.-F., Hsiao, T.-Y., Wang, Y.-M., & Sun, C.-W. (2024). Brain tumor grading diagnosis using transfer learning based on optical coherence tomography. *Biomedical Optics Express*, *15*. https://doi.org/10.1364/BOE.513877

Shchetinin, E. Y. (2024). Brain tumor segmentation by deep learning transfer methods using MRI images. *Computer Optics*, *48*(3), 439–444. https://doi.org/10.18287/2412-6179-CO-1366

Zia-ur-Rehman, Awang, M. K., Rashid, D.-J., Ghulam, A., Hamid, D., Mahmoud, S., Saleh, D., & Ahmad, D. (2024). Classification of Alzheimer disease using DenseNet-201 based on deep transfer learning technique. *PLOS ONE*, *19*. https://doi.org/10.1371/journal.pone.0304995

Sorour, S. E., El-Mageed, A. A. A., Albarrak, K. M., Alnaim, A. K., Wafa, A. A., & El-Shafeiy, E. (2024). Classification of Alzheimer's disease using MRI data based on Deep Learning Techniques. *Journal of King Saud University - Computer and Information Sciences*, *36*(2), 101940. https://doi.org/10.1016/j.jksuci.2024.101940

Raina, D., Dawange, A., Bandha, T., Kaur, A., Wasekar, R., Verma, K., Verma, S., & Dhingra, K. (2024). Convoluted neural network and transfer learning algorithm for improved brain tumor classifications in MRI. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (Online)*, *3*, 200–212. https://doi.org/10.60087/jklst.v3.n4.p200

Rustom, F., Moroze, E., Parva, P., Ogmen, H., & Yazdanbakhsh, A. (2024). Deep learning and transfer learning for brain tumor detection and classification. *Biology Methods and Protocols*, *9*(1), bpae080. https://doi.org/10.1093/biomethods/bpae080

Zhou, J. (2024). Deep learning applications in MRI for brain tumor detection and image segmentation. *Applied and Computational Engineering*, *33*, 42–48. https://doi.org/10.54254/2755-2721/33/20230229

Shedbalkar, J., & Prabhushetty, K. (2024). Deep transfer learning model for brain tumor segmentation and classification using UNet and chopped VGGNet. *Indonesian Journal of Electrical Engineering and Computer Science*, *33*, 1405. https://doi.org/10.11591/ijeecs.v33.i3.pp1405-1415

Bhardwaj, N., Sood, M., & gill, sandeep. (2024). Design of Transfer Learning based Deep CNN Paradigm for Brain Tumor Classification. *WSEAS TRANSACTIONS ON BIOLOGY AND BIOMEDICINE*, *21*, 162–169. https://doi.org/10.37394/23208.2024.21.17

Ravikumar, K., Sahoo, S., Mandhavi, B., Mohan, V., Babu, G., & Panigrahi, B. (2024). Detection of Brain Tumour based on Optimal Convolution Neural Network. *EAI Endorsed Transactions on Pervasive Health and Technology*, *10*. https://doi.org/10.4108/eetpht.10.5464

Murugesan, S., B V, B., D, P., S, A., & Kumar M, S. (2024). Efficient brain tumor grade classification using ensemble deep learning models. *BMC Medical Imaging*, *24*. https://doi.org/10.1186/s12880-024-01476-1

Kumar M, S., Sonaimuthu, S., Murugesan, S., Rajadurai, H., & Shivahare, B. (2024). Employing deep learning and transfer learning for accurate brain tumor detection. *Scientific Reports*, *14*. https://doi.org/10.1038/s41598-024-57970-7

Ali, M., Kim, K., Khalid, M., Farrash, M., Zafar, A., & Lee, S. (2024). Enhancing Alzheimer's disease diagnosis and staging: A multistage CNN framework using MRI. *Frontiers in Psychiatry*, *15*. https://doi.org/10.3389/fpsyt.2024.1395563

Naveen, N., & Nagaraj, G. C. (2024). Enhancing Early Alzheimer's Disease Detection: Leveraging Pre-trained Networks and Transfer Learning. *International Journal of Intelligent Systems and Applications(IJISA)*, *16*(1), 52–69. https://doi.org/10.5815/ijisa.2024.01.05

Shah, Dr. D. (2024). Impact of Dimensionality Reduction Method in Brain Tumor Classification Using Transfer Learning. *Journal of Electrical Systems*, *20*, 1470–1480. https://doi.org/10.52783/jes.5320

Albalawi, E., T R, M., Thakur, A., Kumar, V. V., Gupta, M., Bhatia, S., & Almusharraf, A. (2024). Integrated approach of federated learning with transfer learning for classification and diagnosis of brain tumor. *BMC Medical Imaging*, *24*. https://doi.org/10.1186/s12880-024-01261-0

Khaw, L. W., & Abdullah, S. S. (2024). MRI Brain Image Classification Using Convolutional Neural Networks And Transfer Learning. *Journal of Advanced Research in Computing and Applications*, *31*(1), 20–26. https://doi.org/10.37934/arca.31.1.2026

Rao, B., Aparna, M., Kolisetty, S. S., Janapana, H., & Koteswararao, Y. (2024). Multi-class Classification of Alzheimer's Disease Using Deep Learning and Transfer Learning on 3D MRI Images. *Traitement Du Signal*, *41*, 1397–1404. https://doi.org/10.18280/ts.410328

Kako, N. A., Abdulazeez, A. M., & Abdulqader, D. N. (2024). Multi-label deep learning for comprehensive optic nerve head segmentation through data of fundus images. *Heliyon*, *10*(18), e36996. https://doi.org/10.1016/j.heliyon.2024.e36996

Gottipati, S., & Thumbur, G. (2024). Multi-modal fusion deep transfer learning for accurate brain tumor classification using magnetic resonance imaging images. *Indonesian Journal of Electrical Engineering and Computer Science*, *34*, 825. https://doi.org/10.11591/ijeecs.v34.i2.pp825-834

Alotaibi, S., Rehman, A., Raza, A., Alyami, J., & Saba, T. (2024). CVG-Net: Novel transfer learning based deep features for diagnosis of brain tumors using MRI scans. *PeerJ Computer Science*. https://doi.org/10.7717/peerj-cs.2008

Kilani, S., Aghili, S. N., Fathi, Y., & Sburlea, A. I. (2024). Optimization of transfer learning based on source sample selection in Euclidean space for P300-based brain-computer interfaces. *Frontiers in Neuroscience*, *18*. https://doi.org/10.3389/fnins.2024.1360709

Neamah, K., Mohamed, F., Kurdi, W., Yaseen, A., & Kadhim, K. (2024). Utilizing Deep improved ResNet50 for Brain Tumor Classification Based MRI. *IEEE Open Journal of the Computer Society*, *PP*, 1–12. https://doi.org/10.1109/OJCS.2024.3453924