Deep Learning-based Transfer Learning Model in Diagnosis of Diseases with Brain Magnetic Resonance Imaging

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Abstract: Computer-aided diagnosis (CAD) is an effective resource for diagnosing brain disorders rapidly and is also used for reducing human diagnostic errors to enhance and extend the quality of patient life. The deep learning model can self learn and generalize over a huge volume of data, it has recently gained a lot of interest over the research community in classifying medical images. But deep learning model created from the scratch takes more training time as well as a huge amount of data. Using pre-trained networks for a new, similar problem is the fundamental idea of transfer learning. In this work, the survey on disease diagnosis using deep learning-based transfer learning with Brain MRI images alone is carried out over the last 5 years. The inference drawn from this work is that a hybrid architecture based on transfer learning produced more than 90% accuracy in most of the cases with minimal training time. In hybrid architecture, more than one pre-trained models are integrated to extract high-level features. Pre-trained models are good at recognising high-level features like edges, patterns, and so on. The model designed with pre-trained model starts with learned weights rather than assigning a random value. This promotes faster convergence and, as a result, reduces the amount of time required to train the model.

Keywords: Deep learning; Brain MRI; Convolution Neural Network; Deep neural network; Transfer Learning

1 Introduction

One of the imaging methods most frequently used in the diagnosis of brain-related disorders is brain MRI images. Nowadays, in the health care field, deep learning techniques produce promising results involving enormous amounts of data. This paper provides a brief overview of the application of transfer learning in the diagnosis of brain-related problems using a brain MRI dataset with pre-trained deep learning models. Deep learning has remained the most powerful and extensively used machine learning method for detecting and predicting various diseases over the last five years. As Deep learning can learn from the huge volume of raw data [1] without preprocessing, it is preferred over traditional machine learning. Whereas, machine learning algorithms are preferred mainly for a small volume of data and take less time for training the model. Further, unlike deep learning, these algorithms do not require high-end processors such as GPUs for training. The success of deep learning is its capability of automatically extracting the features from input images [2].

In medical diagnosis with different medical imaging such as MRI, CT scans, WSI, and PET images, a lot of work based on deep learning-based transfer learning was done as it has become a very popular and increasingly growing field [3]. Instead of going to survey the entire application environment, this work concentrated specifically on diagnosing diseases using brain MRI images. Keywords such as Deep Learning, Brain MRI images, Classification, Diagnosis, Transfer Learning, Alzheimer's, Brain Tumor, Parkinson's, Haemorrhage, and Stroke are searched in standard databases such as Scopus, IEEE, PubMed, and ScienceDirect to accomplish this review.

This survey limits the papers published from 2016 to 2020 and comprises only the papers for diagnosis of diseases from Brain MRI images using Transfer Learning on Deep learning. The remainder of this article includes the introduction to transfer learning in Section 2, Magnetic Resonance Imaging used for the diagnosis of brain-related diseases is described in Section 3, Section 4 explains the types of diseases diagnosed with brain MRI images, Section 5 defines various datasets for brain MRI images, Section 6 presents different transfer learning models developed for the diagnosis of Brain MRI diseases, Section 7 explains the work carried out using transfer learning with brain MRI images and last Section describes conclusions and various challenges involved in the Transfer Learning Models.

2 Introduction to Transfer Learning

2.1 Deep Learning vs Transfer Learning

Models for deep neural networks are highly resource-intensive. It is made up of tens of millions of weights connecting the neurons in various layers together. These weights are adjusted in each layer during the training process and applied to inputs as well as to feed-forward for the classification of output. The model created from the scratch takes more training time as well as needs a huge amount of data (Fig. 1). Using pre-trained networks for a new, similar problem is the fundamental idea of transfer learning. Training for the new problem can be started with pre-initialized weights estimated during previous training.

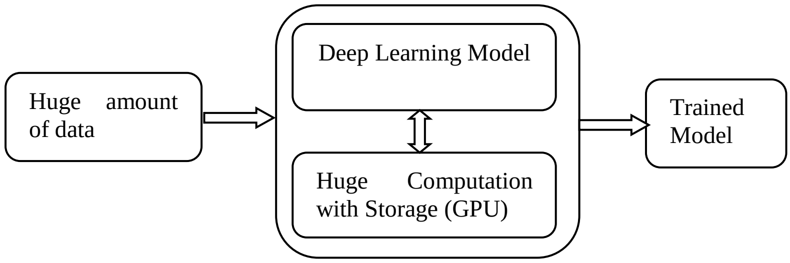

Figure 1
Deep Learning Model developed from scratch

Fig. 2 illustrates that transfer learning requires less amount of data for training. In Transfer learning, a model built for one domain is reused for another domain as the baseline instead of designing a model from the scratch. Saving training time, significant performance improvements, and not needing a lot of data are the benefits of this type of methodology. The pre-trained model is the one created to solve a particular problem by someone else. Instead of designing a model from scratch, this model could be used as a starting point to solve a similar problem. It is then fine-tuned to obtain the exact solution using the given application domain [4].

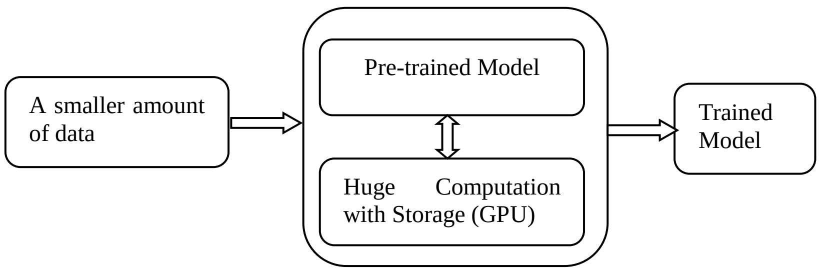

Figure 2
Transfer Learning Model

Reducing training time, improving neural network performance, and not demanding a large amount of data are the key strengths of Transfer Learning Models. Training a model from the ground up usually involves a huge volume of data, but the availability of a huge volume of data is not always possible. This is the reason for transfer learning comes into the picture. Since the model has already been trained, transfer learning requires a relatively small amount of training data [5, 6]. Besides, time for training a complex model using transfer learning is reduced since it is already trained in a similar domain. But for developing the same model, training from scratch often takes more days or sometimes takes weeks.

2.2 Different Approaches to Fine Tune the Model

Based on the dataset available in the target domain and the dataset used to train the pre-trained model, the model can be fine-tuned to the target dataset using any of the following approaches:

- Classifier: Pre-trained model is used directly for classifying new images.
- Feature extraction: Pre-trained model can be used for extracting the features by dropping the output layer and using the entire network as a feature extractor for the new data set.
- Pre-trained model Architecture: In this approach, only the model architecture can be used without applying assigned weights, instead the weights are randomly initialized and again train the model with a new target dataset.
- Freeze layers: Some layers are frozen in this technique and other layers are trained with a target dataset. Frozen layer weights are kept set with trained weights, while only the higher layers are retrained.

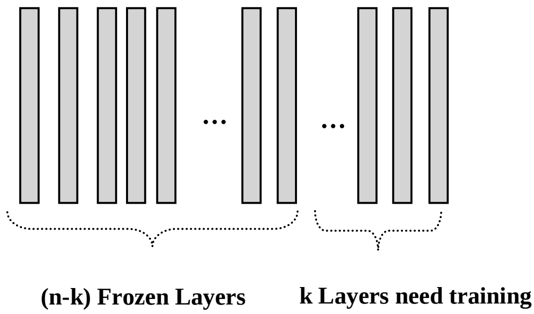

Figure 3
Training with an n-layer pre-trained model

Fig. 3 shows n layer model with (n-k) frozen layers that keeps its trained weights and k-layers to be trained within the target domain. Figure 4 will help in deciding a methodology for designing a model for the new target dataset.

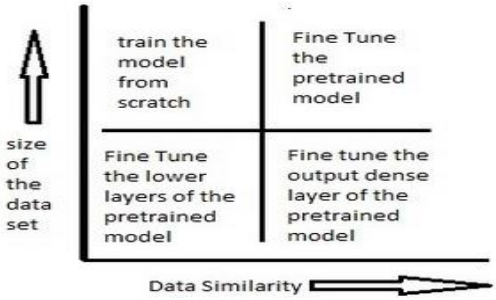

Figure 4
Training level of the pre-trained model
(Source: https://datascience.stackexchange.com/questions/52294/selection-of-base-model-for-transfer-learning)

2.3 Pre-trained Models used in Transfer Learning for Brain Disease Diagnosis

For image processing, many pre-trained models are available such as AlexNet, VGG, GoogleNet, Inception, ResNet, LeNet, etc. Some of the pre-trained models that have been used to classify brain MRI images to diagnose different diseases over the past 5 years are listed in Table 1. This section aims to provide a summary of the deep learning-based pre-trained models used for disease diagnosis. Even though different pre-trained models exist for diagnosing different diseases, out of the 53 models most of the models were developed using AlexNet (13 models), Google Net (7 models), VGG16/VGG19 (9 models), and ResNet (10 models). Among these four algorithms, AlexNet has gained more attention towards providing a solution to disease diagnosis.

Table 1
Summary of Pretrained models used in Transfer Learning for disease diagnosis

S. No.	Pre-trained model	Deep Learning technique	Details of Pre-trained model	Link for accessing Pre-trained model source code	Reference
1.	Alex Net	CNN	It is a multiclass classification model consists that of up to 8 layers and is used to classify the input into one of the 1000 objects.	https://github.com/onnx/models/tree/master/vision/classification/alexnet	4,10,21,22,32,34,38, 40-42, 46,50,51
2.	Google Net	CNN	It consists of up to 22 layers. It is more efficient than VGG and AlexNet. Size of this model is lesser than VGG.	https://github.com/onnx/models/tree/master/vision/classification/inception_and_googlenet/googlenet	10,19,25,38,46,54,56
3.	VGG16/ VGG19	CNN	It consists of up to 19 layers and similar to AlexNet. This model provides high accuracy since it is developed with smaller kernel-sized filters.	https://github.com/onnx/models/tree/master/vision/classification/vgg	11,17,28, 38,39,43, 44,46,53

4.	ResNet	CNN	It is a model of CNN which consists of up to 152 layers. When classifying images it uses shortcut links to achieve higher precision.	https://github.com/onnx/models/tree/master/vision/classification/resnet	9,15-17, 24,30,35, 39,49,52
5.	Inception V3	CNN	This image classification model used batch normalization as an adaptation. This model takes less computation costs and increases the image quality compared to Inception v1.	https://github.com/keras-team/keras-applications/blob/master/keras_applications/inception_v3.py	18,39
6.	Unet	CNN	This model was constructed to deal with semantic segmentation on biomedical images. Only Convolutional layers were used to create this model. Since it lacks a Dense layer, it can accommodate any image size.	https://github.com/yihui-he/u-net	14,23,29, 31,55
7.	Dense Net	Neural Network	Each and every layer of this model are linked with every other layer. Features from each layer is passed to other layers to extract the most suitable feature. It is designed for visual object recognition.	https://github.com/onnx/models/tree/master/vision/classification/densenet-121	26,48
8.	WGAN	Unsupervised Neural Network	It is an unsupervised learning task in which learns the pattern and features from the input and applies the learned model to output a new result which is modeled based on the input weights.	https://github.com/ChengBinJin/WGAN-TensorFlow	27
9.	DBN	Supervised Neural Network model	It's a deep learning network made up of many RBMs stacked on top of each other. Each RBM module is trained one at a time in an unsupervised manner. Finally, to improve classification performance, the whole network is fined tuned with supervised learning.	https://github.com/albertbup/deep-belief-network	7,36
10.	LeNet	CNN	It is a CNN designed for handwritten and printed character recognition.	https://github.com/topics/lenet-5	32,47
11.	Caffe Net	CNN	It is a Deep CNN variation of AlexNet. It is designed for the classification of images. In this model, max-pooling precedes the local response normalization to reduce computational and memory requirements.	https://github.com/onnx/models/tree/master/vision/classification/caffenet	12,13

3 Magnetic Resonance Imaging used for Diagnosing Brain-related Diseases

Magnetic resonance imaging (MRI) of the brain is a common diagnostic technique that offers accurate images of the soft tissues of the body [7]. Brain MRI is used to diagnose many brain conditions such as Alzheimer's disease, Parkinson's disease, brain tumor, Hemorrhage, stroke, cysts, aneurysm, swelling, infections, blood vessel problems, etc. Several MRI techniques have been suggested in the medical domain. Any of the following approaches is selected based on the alleged disorder:

(1) Structural MRI (sMRI) – used to test the brain structure and diagnosis of intracranial disease and injury.

(2) Functional MRI (fMRI)-The structure and functional activity of the brain are tested. It is used for the diagnosis of Alzheimer's disease, Parkinson's disease, brain injury, and brain cancer.

(3) Diffusion-weighted imaging (DWI) is used for the early diagnosis of ischemic stroke and helps separate a tumor from a cerebral abscess. Perfusion-weighted imaging (PWI) can detect areas of hypo-perfusion in early ischemic stroke.

(4) Diffusion tensor imaging (DTI) is a DWI extension that can display 3-dimensional tracts of white matter and can be used to monitor the integrity of CNS tracts affected by aging and disease.

Other sophisticated diagnostic imaging methods are also used for disease diagnosis nowadays, such as T1 weighted, T2 weighted, NMS, FLAIR, MTI, etc.

4 Diseases Diagnosed with Brain MRI Images using Deep Learning Models

Several types of research have been done using deep learning approaches with brain MRI images to identify brain disorder-based diseases. Table 2 summarizes the work carried out on various disease diagnoses using the Brain MRI dataset during the last 5 years. The researchers mostly used T1-weighted and T2-weighted sMRI images for diagnosing Alzheimer’s, Brain Tumor, and Hemorrhage diseases and, used functional MRI images [8, 9] for Brain activity related diseases such as Parkinson disease.

Table 2

Works carried out on different disease diagnosis using brain MRI datasets

S.No.	Disease	Dataset	Modality	References
1	Alzheimer’s	ADNI	sMRI	4,10-16
			fMRI	17,18
			T1 w MRI	19-22
		AIBL	T1 w MRI	21
		HMS	T1 w MRI	40
		MIRIAD	T1 w MRI	22
		OASIS	T1 w MRI	21,32

2	Brain Tumor	BRATS, ISLES	DWI,FLAIR,T1,T2,T1C, FLAIR sMRI,T1-GadoMR,CBV, CBF	7
		Figshare	T1-CE MRI,T1 w MRI	35,36,45
		HUP, BWH	FLAIR, T2, T1	24
		Radiopaedia	T1 w MRI	42
		REMBRANDT	T1 w MRI	25
		TCIA	T1 w MRI	24-26
		Own		38
3	Hemorrhage	Own	MRI, SWI-CMB, SWI, T1 w MRI	41,49
4	Parkinson	ADHD-200	sMRI, fMRI	9
		CMU2008	fMRI	8
		HCP	fMRI	9
		PPMI	3T T1-MRI	27-31
		UPDRS-III	T2 w MRI	54
		Own	3T T1 w MRI	50
5	Stroke	ISLES 2017	DWI, FLAIR	23
		Own	DWI, DWI-T2, T2 MRI, T1 w MRI	2,43,47

5 Datasets for Brain MRI Images

This section aims to provide a description of various datasets used with Brain MRI images to diagnose different diseases. Table 3 summarizes the different Brain MRI datasets available, the number of articles that use such datasets, the description of the dataset, along with its repository URL. The above table also shows that the ADNI dataset [4,10-22] is used by a greater number of articles for diagnosing Alzheimer's disease, BRATS [7, 23] & TCIA [24-26] datasets for diagnosing brain tumors, PPMI data set [27-31] for diagnosing Parkinson's disease, OASIS [21, 32] for diagnosing Alzheimer's disease, etc. ABIDE [33] dataset is used for Autism Brain Imaging disorder, Figshare dataset [35, 36, 45] is for Brain tumors.

Table 3
Summary of MRI Datasets used in medical diagnosis with Transfer Learning

S. No.	DATASET	No. of Papers	Disease detected	Repository URL	Reference
1.	ADNI	14	Alzheimer's disease	http://adni.loni.usc.edu/data-samples/access-data/	4,10-22
2.	BRATS	2	HG glioma and LG glioma	http://www.med.upenn.edu/sbia/brats2018.html	7,23
3.	PPMI	5	Parkinson's Disease.	https://www.ppmi-info.org/access-data-specimens /download-data/	27-31
4.	Figshare	3	Brain tumors	https://figshare.com/articles/brain_tumor_dataset/1512427	35,36, 45

5.	OASIS	2	Alzheimer's disease	http://www.oasis-brains.org/	21,32
6.	TCIA	3	brain tumor	http://www.cancerimagingarchive.net	24-26
7.	ISLES	2	stroke.	http://www.isles-challenge.org/	7,23
8.	ABIDE	1	Autism Brain Imaging disorder	http://fcon 1000.projects.nitrc.org/indi/abide	33
9.	ADHD-200	1	Parkinson's disease.	http://fcon_1000.projects.nitrc.org/indi/adhd200/	9
10.	AIBL	1	Alzheimer's disease.	http://adni.loni.usc.edu/category/aibl-study-data/	21
11.	MIRIAD	1	Alzheimer's disease	https://www.nitrc.org/projects/miriad/	22
12.	RADIOPAEDIA	1	brain tumor	https://radiopaedia.org/articles/imaging-data-sets-artificial-intelligence	42
13.	REMBRANDT	1	grades of glioma.	https://wiki.cancerimagingarchive.net/display/Public/REMBRANDT	25

6 Transfer Learning Models Developed for Diagnosing Diseases with Brain MRI Images

This section aims to outline the work carried out for the classification of different diseases using Transfer learning models with brain MRI images. We have categorized the work carried out on classification into Transfer learning with Pre-trained Deep learning model and Hybrid Deep learning Pre-trained models.

6.1 Deep Learning-based Transfer Learning Models for Brain MRI Processing

The method of transfer-learning plays an important role in trying to find a solution to classification problems. The small number of labeled data is one of the key issues in medical data analysis with deep learning. The process of labeling the data by medical experts is expensive and time-consuming. Hence, we can use pre-trained models designed for similar, but different problems instead of training the deep learning model from scratch [37]. Table 4 summarizes several works carried out over the past five years for diagnosing diseases with brain MRI images using transfer learning from already trained models such as Alexnet, GoogleNet, VGG, Inception, ResNet, CaffeNet, etc.

Table 4
Application of Transfer Learning in disease diagnosis using Brain MRI images

Reference	Proposed Model Name	Medical Domain	Dataset	Modality	Deep learning model	No. of subjects/ Samples	Performance(%)
4	Fine-tuned CNN	Alzheimer	OASIS	MRI	AlexNet	382	ACC:93, SE:92.8,SP:74.27
11	CNN –MGTSC	Brain Tumor	Radiopaedia	T1 w MRI	CNN-VGG19	121	ACC:94.58, SE:88.41, SP:96.12
38	Deep CNN	Brain Tumor	Figshare	T1-CE MR	GoogLeNet	233/ 3064	ACC:TL:92.3,CNN+SVM:97.8 ,CNN+KNN:98, SP:98.97,RE: 7.6,PR:97.3,F1:97,AUC:99.7
17	2D CNN	Parkinson, Alzheimer	PPMI: PD,OASIS: AD	T2 w MRI	VGG16, ResNet	PPMI: 08/6030, OASIS: 200/ 6400	ACC: PD: VGG16 :82, Resnet50:82 AD :VGG16:64.3, Resnet50:67.1
39	DCNN	Haemorrhage	Own	MRI	Inception-ResNet-v2	1300	ACC:90,SE:90, AUC:96
12	CNN-DTI MD -sMRI	Alzheimer	ADNI	sMRI, DTI	CaffeNet	1029	ACC:AD+NC:92.5, AD+MCI:85, MCI+NC:80, SE:AD+NC:94.7, AD+MCI:93.7, MCI+NC:92.8 SP:AD+NC:90.4, AD+MCI:79.1, MCI+NC:73
21	AlexNet model for fMRI	Alzheimer	ADNI	rs-fMRI	Alexnet	197/ 1322085	ACC:AD: 94.97, EMCI:95.64, LMCI:95.89, NC:98.34, SMC:94.55
34	CNN based Model with SVM, KNN	Alzheimer	OASIS	MRI-CDR	Alexnet	50/ 5220	ACC: SVM:99.75, KNN:99.84 SE: SVM:99.48, KNN:99.74 SP: SVM:99.95, KNN:99.97
24	RDCNN	Brain Tumor	Own	T2 w MRI, T1 w MRI	ResNet18, 34,50	155	ACC:ResNet18:76.75, ResNet34:80.72, ResNet50:94.90 RE:ResNet18:78, ResNet34:91, ResNet50:97 PR:ResNet18:80, ResNet34:80, ResNet50:97 F1:ResNet18:75, ResNet34:82, ResNet50:97
13	CNN+FreeSurfer	Alzheimer	ADNI	MRI	Caffe	818	ACC:79.50, SE:86.1, SP:68.8, AUC:86.1
43	VGG-ELM-GBA	Haemorrhage	ILSVRC	MRI	VGG16	13031	ACC:90.50, SE:93.08, SP:87.12
40	ALEXNET3D	Parkinson	PPMI	PET-FDG, FP-CIT SPECT	AlexNet	642	ACC:94.10, SE:96.7, SP:96.9, F1:94.5
22	Deep CNN	Alzheimer	OASIS	T1 w MRI	AlexNet	382	ACC:99.21
56	ICAE-TL, CAE-TL	Alzheimer	ADNI	MRI	GoogLeNet	694	ACC:CAE-TL:73.23, ICAE-TL:73.95 ,CAE-TL:74.96, ICAE-TL:77.46

							SP:CAE-TL:71.53, ICAE-TL:70.71
15	SISR-MFES-CNN With SVM	Brain Tumor	TCIA	T1-Gdsequence MRI	ResNet	200	ACC:95,AUC:94
18	CNN+ SbDL	Brain Tumor	BRATS	FLAIR MRI	Inception V3	1222	ACC:98.3,97.8,96.9,92.5 for BRATS2013,2015,2017,2018 respectively.
35	CNN-DL(PD-APS)	Parkinson	NIMHANS	NMS-MRI, FLAIR	ResNet50	100	ACC:85.70,SE:100,SP:50
41	Deep CNN	Parkinson	PPMI	T2 w MRI	AlexNet	182/ 7646	ACC:88.90,SE:89.3 SP:88.4
42	AlexNet-TL	Alzheimer	HMS	MRI(T1 weighted)	AlexNet	215	ACC:100,SE:100,SP:100
44	Deep CNN-CFML	Brain Tumor	Figshare	CE MRI	VGG19	233/ 3064	ACC: 96.13
28	TL+Fine tuned CNN	Brain Tumor	Own	T1 w CE MRI	VGG19	233/ 3064	ACC:94.82,SE:94.25, SP:94.69, PR:89.52,F1:91.73
25	Deep CNN-SVM	Brain Tumor	Figshare	MRI (T1-CE MRI)	GoogleNet	233/ 3064	ACC:98,SP:98.97,RE:97.6,PR: 97.3,F1:97
16	DenseNet201+TL	Haemorrhage	Own	MRI	ResNet	20/56651383	ACC:97.71,SE:97.78, SP:97.64
8	TNN	Parkinson	CMU 2008	fMRI	TensorNet	/2880	ACC:2 class task:85

The binary and multi-class classification scheme proposed in [4] to classify the images using transfer learning with AlexNet. The multi-class classification model achieved an overall precision of 92.85%. The input given for this model is not segmented images.

The author in [11] proposed a novel CNN for classifying different grades of brain tumors. MR images are segmented to get Tumor regions with InputCascadeCNN architecture and, feature extraction and classifications are performed with a fine-tuned VGG19 model. In [38], the authors proposed a new classification model BrainMRNet based on a CNN and achieved 96.05% accuracy. This model uses some layers of CNN architecture, a dense layer, and the Softmax layer as the last layer. To perform a classification task, the author in [27] proposed a new model called Deep neural networks with Broad Views (DBV). It is built with Wasserstein Generative Adversarial Networks (WGAN) and ResNeXt.

The author in [17] employed two famous architectures VGG16 and Resnet to classify Parkinson’s disease and Alzheimer's disease from Healthy Control. The classification system in [39] is the Deep Convolutional Neural Networks which uses four pre-trained models VGG16, ResNet-50, Inception-v3, and Inception-ResNet-v2. The proposed system generates predictions, attention maps, and a prediction basis for acute intracranial hemorrhage as the output.

The framework proposed in [20] consists of two CNN models: EDD Net and MUSCLE Net, which aim to remove false positives. The proposed algorithm in [34] elaborates an efficient method that used AlexNet for extraction of features and Support Vector Machine (SVM) or K Nearest Neighbor (KNN) to obtain an optimal number of features. This model proves worthy in the context of 99.75 percent classification accuracy, time-efficient, and hardware optimization. Table 4 shows that most of the transfer learning model is developed using AlexNet [4, 21, 22, 34, 40-42], VGG19 [11, 17, 28, 39, 43, 44], and ResNet [15-17, 24, 35, 39] pre-trained models for diagnosis of diseases with brain MRI images.

6.2 Hybrid Deep Learning Pre-trained Models

In recent times more than one pre-trained model or pre-trained model with a deep learning algorithm can be combined to create hybrid models to achieve significant accuracy. Generally, CNN or CNN-based pre-trained model is used for extracting higher-level features from the sample images. These models are cascaded with each other to get higher classification accuracy. Table 5 summarizes several works carried out over the past five years for diagnosing diseases with brain MRI images by combining different pre-trained models.

Table 5

Application of Hybrid models in disease diagnosis using Brain MRI images

Reference	Proposed Model Name	Medical Domain	Dataset	Modality	Deep learning model	Classifier	No. of subjects/ Samples	Performance (%)
10	AlexNet-GoogleNet Fusion	Brain Tumor	BRATS, ISLES	MRI,DWI, CBV,CBF	AlexNet+ GoogleNet	softmax	BRATS:285, ISLES: 103	ACC: BRATS:99.39, ISLES: 75.68 SE: BRATS:100, ISLES: 80.01 SP:BRATS:98.92, ISLES:63.80
30	2D CNN-ResNet18-TL	Alzheimer	ADNI	rs-fMRI	2D CNN, ResNet-18	Softmax	138/ 850080	ACC:97.88, RE:97.89, PR:98.1, F1:97.93, AUC:99.97
45	ISR-MFES-CNN	Brain Tumor	TCIA	T1 w MRI	SISR+MFES+ ResNet	SVM	200	ACC:95
46	FT AlexNet, FTGoogLe Net, FT-VGG16, Freeze Alex Net-Conv5, FreezeGoogLe Net-inception-4e, Freeze-VGG16-Conv5-1	Brain Tumor	Figshare	MRI	AlexNet, GoogLeNet, VGGNet		233/ 3064	ACC: FTAlexNet:97.39, FTGoogLeNet:98.04, FT-VGG16:98.69, Freeze AlexNet-Conv5:95.77, Freeze GoogLeNet-inception-4e: 95.44, Freeze-VGG16-Conv5-1:89.79

27	DBV	Parkinson	PPMI	MRI	WGAN, ResNeXt	CNN	578/ 3347	ACC: 76.46
32	LeNet based, AlexNet Based	Parkinson	PPMI	MRI	LeNet, AlexNet	LD	269	ACC: LeNet :95.1, AlexNet:95.1 SE:LeNet :94, AlexNet :95 SP:LeNet :9, AlexNet:95 AUC: LeNet :97, AlexNet :97
47	Adopted LeNet	Alzheimer	ADNI	fMRI	LeNet, CNN	SVM	43	ACC:96.85

The approach is presented in an article [10] is used to classify the MR images for diagnosing brain tumors. In this article, feature learning is performed through two pre-trained models AlexNet and GoogleNet. Two vectors obtained from each training model is glued and it is supplied to multiple classifiers to improve classification accuracy. Deep residual neural networks combined with a transfer learning approach were used in the study suggested in [30] to perform 6 different stages of AD classification using functional MRI data. This proposed system produced the accuracy 100%, 96.85%, 97.38%, 97.43%, 97.40%, and 98.01% for CN, SMC, EMCI, LMCI, MCI, and AD respectively. The hybrid model discussed in the paper [45] is composed of segmentation and classification techniques. They used a single image super-resolution (SISR) and maximum fuzzy entropy segmentation (MFES) for brain tumor segmentation on an MRI image, and used pre-trained ResNet architecture for feature extraction, and Support vector machine (SVM) for classification. In the framework proposed in [46], the authors presented three transfer learning models using three pre-trained architectures AlexNet, GoogLeNet, and VGGNet to classify different grades of brain tumors.

The work implemented in [32], uses two well-known CNN architectures, Lent and AlexNet to classify DaTScan images with an average accuracy of 95.1% and AUC = 97%. The system proposed in [47] uses a Convolutional Neural Network (CNN) and LeNet-5 to classify functional MRI data for diagnosing Alzheimer's disease with an accuracy of 96.85%. Apart from these works, the model for Alzheimer’s disease classification is carried out in [26, 37, 48, 49], Brain tumor classification is done in [51-54], and Stroke classification is done in [55].

Table 6

Number of Papers published for disease diagnosis with Transfer learning using Brain MRI images

Year of Publication	**Reference of Published Papers**	**No. of Papers Published**
2016	7,47,51	3
2017	20,24	2
2018	2,8,9,12,14,33,40,50	8
2019	4,10,11,15-19,25-28,30,32,34-37,39,42,44, 45,48,54,56	25
2020	2,13,22,23,29,31,38,41,43,46,49,52,53,55	14

7 Discussion

In transfer learning, the model is designed with a pre-trained model which is initialized with learned weights rather than assigning a random value. This leads to faster convergence and hence reduces the learning time. Transfer learning is a distinctive and effective approach for building a deep learning model and helping to address several issues with existing models. Most of the transfer learning models use CNN-based pre-trained models as the basis for diagnosing diseases. Some of the proposed hybrid models use CNN based model for feature extraction.

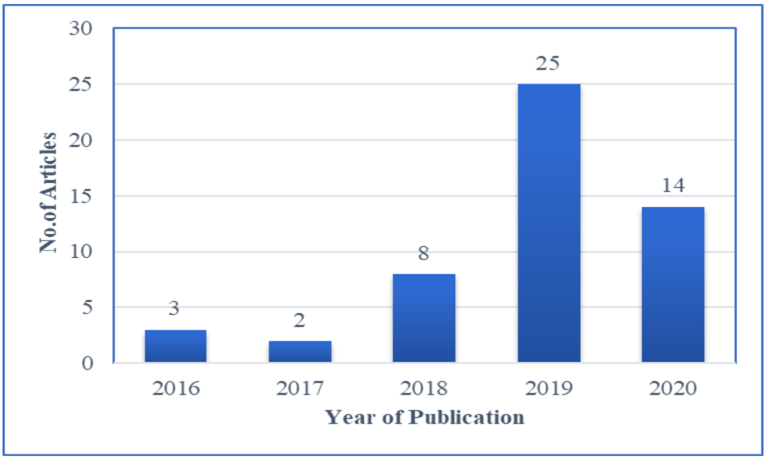

Figure 5
No. of Papers published on Deep learning-based Transfer Learning applied for disease diagnosis with Brain MRI images

The transfer learning model and hybrid models produce higher classification accuracy with lesser learning time than the models developed from scratch. Fig. 5 shows that number of works had been done with deep learning-based transfer learning for diagnosing brain-related diseases with MRI images. Table 6 gives references of papers published for disease diagnosis with Transfer learning using Brain MRI images.

Fine-tuned CNN model [4] that uses AlexNet developed for diagnosing Alzheimer disease with OASIS dataset produced 93% of accuracy, 92.8% of Sensitivity, and 74.27% of Specificity. The AlexNet based model [34] that uses the same OASIS dataset produced 99.75% accuracy while using SVM as a classifier and 99.84% accuracy while using KNN classifier. The model with SVM and KNN classifier produced a sensitivity of 99.48% and 99.74%, and specificity of 99.95% and 99.97% respectively. The Deep CNN model in [22] that uses AlexNet and OASIS dataset produced 99.21% accuracy.

Deep CNN [38] and Deep CNN with SVM classifier [25] developed for diagnosing BrainTumor with GoogleNet pre-trained model trained on Figshare dataset (3064 images) produced the accuracy of 92.3% and 98% respectively. GoogleNet with SVM classifier produced more accuracy than the model with GoogleNet alone. The Deep CNN-CFML [28] uses the VGG16 model trained on the same dataset produced.

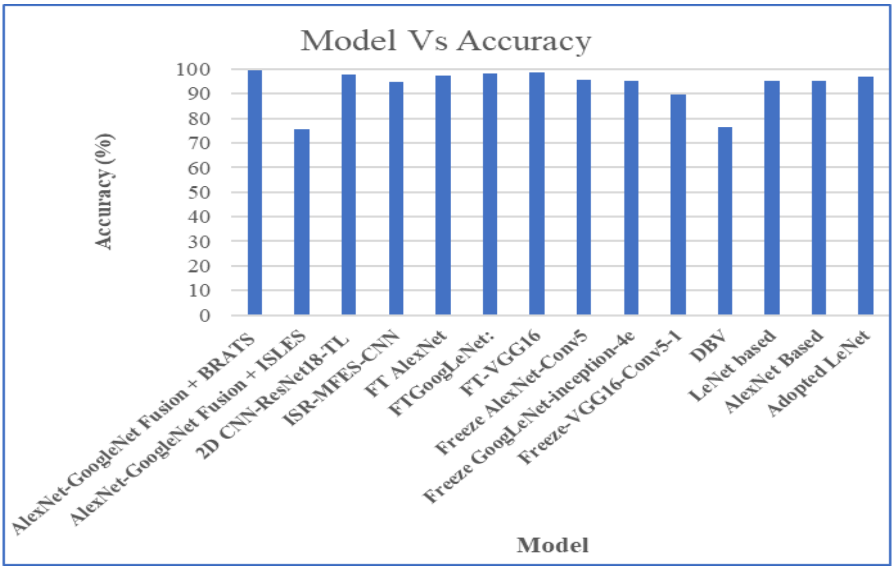

Figure 6
Accuracy of various model considered

The binary class classification model CNN-DTI MD [12] that uses CaffeNet for diagnosing Alzheimer's disease trained on ADNI dataset produced an accuracy of 92.5% for AD vs NC, 85% for AD vs MCI, 80% for MCI vs NC. The multiclass classification model CNN+FreeSurfer [13] designed with the same pre-trained model produced an accuracy of 79%. The multiclass classification model with AlexNet [21] trained on fMRI images from the ADNI dataset produced the accuracy 94.97%,95.64%, 95.89%,98.34% and 94.55% for classifying AD, EMCI, LMCI, NC and SMC respectively. The models that use GoogleNet [56] ICAE-TL and CAE-TL based on gives the accuracy of 73.23% and 77.46% respectivly. In Figure 6, the accuracy of various models considered in this work is presented.

Conclusion

Transfer learning has great potential for current learning algorithms and is a widely needed enhancement. Additionally, there are some important issues related to transfer learning that involves further study and investigation. There are significant barriers to negative transfer and transfer boundaries. There are some scenarios when transfer learning can lead to a decrease in performance.

When applying the transfer of knowledge from the source domain to the target domain with transfer learning, there is no improvement in performance instead there is a drop in the overall performance of the target. This is called Negative transfer learning. There are different reasons for negative transfer, such as instances where the source task is not adequately connected to the target task or where the transfer approach is unable to achieve a high level of correlation between the source and target tasks. It is very important to avoid negative transfers and needs careful investigation. It is also very important to measure the transfer through transfer learning, which affects the efficiency of the transfer and its viability.

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