

Deep Learning and MRI Methods for Alzheimer's Disease Detection

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CHAPTER -2

LITERATURE REVIEW

A couple pre-training techniques for [Alzheimer's disease identification using brain MRI](#) were tested by Dhinagar et al. in 2022. The techniques used T1-weighted brain MRI scans from the ADNI and OASIS3 cohort with several architectures to diagnose AD comprising supervised within-MRI domain, supervised out-of-domain, self-supervised learning, as well as contrastive learning. Although deep neural networks exhibit significant potential for detecting brain illnesses, strong predicting accuracy frequently necessitates large, labelled training datasets. For downstream problems, like the categorization of Alzheimer's disease, where there is a shortage of substantial training data, transfer learning and pre-training techniques can be employed to produce meaningful representations. Transfer learning provided a 7.7% performance gain. Once the model that had been trained was employed for AD classification, there was a noticeable improvement in the clustering of diagnostic groups for test individuals. Saliency maps display the additional brain regions that were activated during the brain scans and added towards the final prediction value. It is doubtful that an MRI-based model will be utilised alone, without the use of additional data sources like amyloid- or tau-sensitive PET, FDG-PET, or clinical information like the MMSE, etc.

A novel approach for the categorization of AD through magnetic resonance imaging (MRI) information is proposed by (Ramya et al. in 2022). 2D Adaptive Bilateral Filter (2D-ABF) is used to filter the image at first. The denoised image is improved using Enhanced Histogram Equalisation (ECLAHE). Through the use of Enhanced Expectation, the area of interest is segmented. Clustering and thresholding strategies use adaptive histograms and maximisation, respectively. MATLAB software was used to simulate the suggested system. The ROI is used to build the Grey Level Co-Occurrence Matrix features. The frequency of pairs in a picture is calculated using a feature called GLCM. PCA is used to minimise these features' dimensionality. The features acquired are categorised. In this study, categorization is carried out using logistic regression. The standard machine learning methods k-NN, Naive Bayes, random forest, and SVM were compared to the Logistic Regression algorithm for classification in terms of all performance evaluation parameters. The confusion matrix correctly detected Alzheimer's disease with a 96.92% accuracy rate. The confusion matrix led to performance evaluation metrics for the framework, such as accuracy, sensitivity, F-score, precision, and specificity. Additionally, it achieved 98.49%, 96.95%, 95.63%, and 96.21% with respect to of specificity,

accuracy, recall, and F-score, respectively, in the assessment of performance metrics.

Balasundaram et. al., 2023 consider a novel approach by utilizing a reduced version of one of the datasets used to achieve a considerably accurate prediction while also enabling quicker training. Image segmentation is used to compare models learned on the segments to models trained on full images. In this study, two Kaggle image classes, a well-known OASIS 2 MRI dataset, and a demographic dataset were employed. In order to perform severity classification on the Kaggle dataset and train supervised and ensemble learning algorithms to identify Alzheimer's disease using MRI images of the hippocampus, deep learning models including the CNN model, multilayer model, Resnet50, and others were also used. We employed discrete wavelet transforms as a pre-processing method. The precision of classification is a statistic used to evaluate the performance of models. The suggested method has been shown successful in the early detection of Alzheimer's disease. Half the amount of the dataset allowed for accuracy of 94%, demonstrating how training time may be reduced without significantly reducing accuracy. The XGBoost method has been used to the smaller dataset after segmenting it to concentrate on the hippocampal region, which produced the best accuracy.

Farina et. al., 2023 examine whether the addition of MRI and CSF biomarkers improved cognitive status classification based on cognitive status questionnaires (MMSE). Although MRI and CSF biomarkers could provide better categorization, it is mostly uncertain how classification might be improved in population-based investigations. This analysis made use of the ADNI dataset. With multiple combinations of MMSE and CSF/MRI biomarkers, the author estimated a number of multinomial logistic regression models. When comparing variance explained (pseudo-R²) between the MMSE only model and the model with MMSE and CSF/MRI biomarkers, a slight improvement was found. Additionally, when comparing predicted prevalence for each cognitive status, a slight improvement was found between the MMSE only model and the model with MMSE and CSF/MRI biomarkers. Additionally, the author observed no enhancement in the accuracy of dementia prevalence prediction.

Salehi et. al., 2023 use LSTM (Long-Short-Term-Memory) networks to evaluate time-series Magnetic Resonance Imaging (MRI) data analysis to overcome the shortcomings of conventional Alzheimer's disease (AD) detection techniques. The Kaggle dataset was used for training our LSTM network for this study. The network was developed to effectively record and assess the sequential patterns present in MRI scans using the temporal memory properties of LSTMs. This model has a 98.62% accuracy rate, and the graded Shuffle-Split Cross Validation technique was used to assess the model's effectiveness. This methodology enhances the precision and effectiveness of disease diagnosis overall.

Pruthviraja et. al., 2023 study detection of alzheimer's disease based on cloud-based deep learning paradigm. For identifying medical images, researchers employed deep learning convolutional neural network (CNN) architectures, particularly the transfer learning principle. The GoogLeNet model has been enhanced to take advantage of image classification task capabilities. Transfer learning aids in reducing generalisation process errors. Alzheimer's disease-related datasets are gathered from ADNI

and used as data for training for Google Neural Network. For the purpose of classifying the AD variety to four phases with an accuracy of 98%, a local cloud-based solution has been built. Doctors can use this tool to remotely check if a patient has AD.

Morsy et. al., 2023 in this study proposed Gaussian descriptors-based features are the efficient new biomarkers using Magnetic Resonance Imaging (MRI) T-weighted images to differentiate between Alzheimer's disease (AD), Mild Cognitive Impairment (MCI), and Normal controls (NC). The Gaussian Map characteristics of the Hippocampus and Amygdala were retrieved once each. Examine the shape's overall changes once more upon mixing both of the regions. Among the Gaussian map-based attributes that are returned are the Gaussian shape operator, Gaussian curvature, and mean curvature. Two fusion levels, such as the Feature-fusion level and the ROI-fusion level, were applied for a more precise evaluation. The data is classed using hierarchical criteria, with NC being distinguished from aberrant cases first before AD and MCI. The aforementioned features are subsequently provided to the Support Vector Machine (SVM) classifier. The effectiveness of the indicated extracted characteristics will then be evaluated using ROC Analysis and estimates for sensitivity, specificity, and accuracy. Using region fusion Gaussian shape operators, the suggested model exhibits 98% accuracy.

Chen 2022, uses brain MRI data to classify various stages of dementia using a cascaded model framework that combines a Convolutional Neural Network (CNN) and a Random Forest (RF) model. The Kaggle Alzheimer's Dataset is used in this study. The CNN+RF model, which was trained using the supplemented dataset, outperformed the other two models using the same data, with a value of 93.07%, however the differences between them are not significant. In terms of weighted recall, weighted precision, and weighted f-1 score, it likewise did well. This work has some flaws, including high memory requirements for the GPU and expensive computation. The model outperformed competing models and obtained high f-1 score, accuracy, precision, and recall.

Sinhaa et. al., 2021 explores the use of brain imaging techniques to detect Alzheimer's disease (AD) before memory loss occurs. They used a Convolutional Neural Network (CNN) model and an Attention-Guided Generative Adversarial Network (GAN) to harmonize brain images from different datasets, and to improve the accuracy of AD classification. The researcher examined adversarial domain adaptation can boost the performance of a Convolutional Neural Network (CNN) model in the classification of AD. ADNI, AIBL and OASIS are the three datasets employed here. GAN is used to harmonize images also proposed AG-GAN for translated MRI images and compared the performance of two sets of data. The popular 2D AlexNet CNN is used in AD classification of 2D images. So this work shows, by harmonizing MRI scans from different sources to a uniform format significantly improves the classification performance as compared to the original, heterogeneous MRI formats.

Turkan et.al., 2021 discusses the use of deep learning techniques to classify Alzheimer's disease using 3D MRI brain scans. 3D VGG model is improved by increasing the filters in the 3D convolutional layers and then added an attention mechanism for better classification. The performance of the proposed approaches for the classification of Alzheimer's disease versus mild cognitive impairments

and normal cohorts on the ADNI dataset. It is found that, by increasing the number of filters the accuracy of the network can be improved. Moreover, our addition of an attention layer to the VoxCNN16 model yielded better AUC and accuracy in AD vs. NC and AD vs. EMCI classification. The researchers improved an existing model and found that it performed better in accurately classifying the disease. However, they also noted that deep neural networks can be difficult to interpret, so they compared different methods to explain the model's predictions.

Hsu et. al., 2022 hypothesize that glymphatic activity mediates the deposition of amyloid and tau proteins and thus affects cognitive dysfunction in patients with AD. This research combines amyloid and tau position emission tomography (PET) and MRI DTI-ALPS to explore associations between glymphatic activity and amyloid and tau deposition and cognitive dysfunction in patients with AD. The regional SUVRs of F-AV-45 PET images and F-APN1607 PET images were used to represent the burden of amyloid and tau deposition in patients with AD. In contrast the ALPS-indexes were used to surrogate anatomical marker of glymphatic system activity. Mediation analysis showed that ALPS-index acted as a significant mediator between regional standardized uptake value ratios (SUVRs) of amyloid and tau images and cognitive dysfunction even after correcting for multiple covariates in AD-related brain regions. Few limitations of this study shows that as the relationship between the ALPS-index and glymphatic clearance has not yet been validated, so a cautious interpretation is required for the analysis. Also, only a few direct comparisons of glymphatic activity measurements between different imaging modalities and diffusion MRI methods are found yet, and the associations between glymphatic activity and AD biomarkers have not been well studied in humans.

Sharma et. al., 2022 propose a novel wavelet packet transform-based structural and metabolic image fusion approach using MRI and PET scans. Neuroimaging techniques like magnetic resonance imaging (MRI) and positron emission tomography (PET) are practical research approaches that provide structural atrophies and metabolic variations. metabolic and structural changes in AD patients can be visible even ten years before the disease's onset. MRI and PET scans taken from the ADNI dataset for classification of CN, AD and MCI are fused using a wavelet packet-based approach. An eight-layer trained CNN is used to extract features from multiple layers and then feed in to the non-iterative RVFL network with the s-membership fuzzy activation function is used to overcome deviation. The results are averaged and fed to the RVFL classifier for the classification of AD. Maximum classification accuracy of 97.33% is achieved in this ensemble model. Two modalities are considered for this research is considered as a limitation for this work.

Kwak et. al., 2023 propose a deep learning-based framework that employs Mutual Knowledge Distillation (MKD) to jointly model different sub-cohorts of patients based on their respective available image modalities. This MKD framework includes three key components, initially the model with more modalities like MRI and PET are considered as a teacher model which is student oriented called it as Student-oriented Multi-modal Teacher (SMT), through multi-modal information disentanglement. Then the model with fewer modalities preferably MRI alone is considered as a student model is trained using SMT teacher also with minimized its classification errors. Then through transfer learning the teacher model is updated with feature extractor of student's model. ADNI dataset is used in AI for

addressing the challenges of incomplete multimodal neuroimage datasets for early AD detection and treatment strategies

Hu et. al., 2022 aim to further evaluate the diagnostic performance of ML to distinguish patients with probable Alzheimer's disease (AD) from normal older adults based on structural magnetic resonance imaging (MRI). The Quality Assessment of Diagnostic Accuracy Studies-2 (QUADAS-2) tool and Checklist for Artificial Intelligence in Medical Imaging (CLAIM) were used to evaluate all potential bias. 24 models based on different brain features extracted by ML algorithms were used in this study. The pooled sensitivity, specificity, positive likelihood ratio, negative likelihood ratio, diagnostic odds ratio, and area under the summary receiver operating characteristic curve for ML in detecting AD were calculated for all the models considered. This research work concluded that ML using structural MRI data performed well in diagnosing AD.

Illakiya et. al., 2023 attempt to analyze different deep learning methods like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transfer Learning (TL) applied for AD detection using neuroimaging modalities like Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), etc.

Liang et. al., 2023 introduce Masked Modality Cycles with Conditional Diffusion (MMCCD), a method that enables segmentation of anomalies across diverse patterns in multimodal MRI. Based on cyclic modality translation as a mechanism for enabling abnormality detection and Image-translation models for modality mappings, proposed this model for effective segmentation of MRI. Then combined the image translation with a masked conditional diffusion model, which attempts to 'imagine' what tissue exists under a masked area, further exposing unknown patterns as the generative model fails to recreate them. Proposed model is evaluated on a proxy task by training on healthy-looking slices of BraTS2021 multi-modality MRIs and testing on slices with tumours. The resulting MMCCD model outperforms all compared approaches for unsupervised segmentation of tumours based on image reconstruction and denoising with autoencoders and diffusion models.

Russo et. al., 2022 proposed a technique to assess if metrics obtained from a DL model, which are intended to explain its intricate internal reasoning, may be used to get more knowledge about the neurological processes behind language comprehension in humans. It is demonstrated that the Generative Pre-trained Transformer version 2 (GPT-2) DL tool for natural language processing produces significant brain encodings in functional MRI during narrative listening. The analyses showed that the GPT-2 seems to be able to explain the neural signals, as measured with functional MRI (fMRI), in the brains of human listeners, brain activations associated with context-related word prediction, highlighting a mechanism that is probably essential to language comprehension in humans.

Bagley et. al., 2023 For MRI deartifacting, he suggests Generative Editing through Convolutional Obscuring (GECO), a Generative Adversarial Network. The genuine traits that researchers are trying to identify can frequently be skipped over by machine learning systems, which then use separate bogus connections to generate predictions. This research focuses on developing a method for removing

these spurious correlations in an unsupervised manner, leveraging generative techniques to produce images that maintain image quality while learning how to remove technical artefacts. GAN, which exhibits impressive efficacy in image generation and editing tasks, is used in this research. GECO, which changes the input into a new picture with some desirable qualities, is used for image-to-image translation. CycleGAN is designed to maintain the quality of the original image. Furthermore, the research demonstrates a 98% structural similarity between the original and deartifacted images, possibly eradicating many other forms of unwarranted associations from medical images.

Chandrasekaran et. al., 2023 uses MRI and 3D brain images to diagnose the cancer using machine learning models, and there are many factors to consider before making a diagnosis. Researchers are seeking to use quantum intelligence in their effort to analyse data related to Parkinson's disease. In addition to 3D brain pictures from OASIS, a generalised, specialised neuroimaging dataset of MRI patients, decision trees and random forest techniques from machine learning are used, as well as neural networks and RNNs from deep learning models.

Dhinagar et. al., 2023 T1-weighted MRI images and data from the benchmark Alzheimer's disease datasets ADNI and OASIS3 were used to assess the vision transformer class of architectures for the detection of the disease. The primary contribution of this research is the creation of trained and evaluated models typical of the Vision Transformers (ViT) class of architectures for tasks varied in sex and AD categorization datasets using constrained neuroimaging data settings. One may create an almost infinite, diversified set of synthetic training data conditioned on clinical characteristics and gain better performance via pretraining of huge vision models by pretraining deep learning methods on synthetic data from a generative model. On 100,000 simulated 3D brain MRI scans produced by a recently suggested latent diffusion model, this model is tested using pre-training ViTs. The impact of advanced training approaches such learning rate warm-ups after annealing, run-time augmentation, pretraining, and other training tactics are presented and subsequently tested. The accuracy, precision, F1-score, sensitivity, and specificity of the models were assessed using the receiver-operator characteristic curve-area under the curve (ROC-AUC) and a threshold derived from Youden's Index. To imitate quick training with little data, models are typically trained for up to 25 epochs. They discovered that training for extended periods of time (up to 50 epochs) enhanced performance.

Badža et. al., 2020 introduce a new CNN architecture for the categorization of three different tumour kinds in brain tumours. The created network was evaluated on T1-weighted contrast-enhanced magnetic resonance imaging and is less complex than pre-existing, pre-trained networks. Four different approaches—combinations of two 10-fold cross-validation techniques and two databases—were used to assess the network's performance. Subject-wise cross-validation, one of the 10-fold approaches, was used to assess the network's generalisation capacity, and an enhanced picture database was used to test for improvement. The proposed model, which had a 96.56% accuracy rate, strong generalizability, and execution speed, made it a useful decision-support tool for radiologists in the field of medical diagnosis.

Iglesias, 2023 We introduce EasyReg, a learning-based registration tool that is open-source and

simple to use from the command line without the need for specialised hardware or deep learning knowledge. Volumetric registration of brain MRI has been successfully accomplished using traditional registration approaches based on numerical optimisation, which are implemented in popular software suites like ANTs, Elastix, NiftyReg, or DARTEL. Adoption of these modules is difficult due to their lack of robustness to dynamic MRI modality and affine registration modules, lack of symmetry, and need for deep learning competence. A learning-based registration programme that is open-source and combines traditional registration techniques with deep learning capabilities as well as MRI modality and resolution robustness was thus presented by the author. The suggested model can adapt to significant changes in scan orientation, resolution, and pulse order. When robustness or minimising directional bias are priorities, even though it exhibits a minor loss of accuracy at label borders, it is a superior option.

Bi et. al., 2023 introduce the multimodal vision transformer (MultiViT), a novel deep learning-based model created with the express purpose of improving the accuracy of classifying schizophrenia through structural MRI (sMRI) and functional MRI (fMRI) data both separately and concurrently while leveraging all of the data from both modalities. The mutual information among each of the modalities is retained by using cross attention approaches to achieve this. Segmented grey matter volume (GMV) is used as the sMRI feature, while functional network connectivity data from a completely automated independent component analysis approach is used as the fMRI feature. By using saliency mapping to neuroimaging data, the suggested model produced an AUC of 0.833, which is much higher than the average 0.766 AUC from control participants and patients with schizophrenia. This model underwent rigorous validation against unimodal and multimodal baselines.

Şentürk et. al., 2022, provides a cervical cancer early detection approach based on transfer learning. Prior to train the deep learning model, noise from the Pap smear pictures was removed using a median filter to improve categorization. Pre-trained networks can tell out cancerous from non-cancerous cervical cells. The benefits of transfer learning were taken advantage of, and several pre-trained networks were contrasted. SqueezeNet, VGG-19, AlexNet, ResNet-50, and InceptionV3 are five well-known pre-trained networks that have been used and compared for the task. The SqueezeNet outperformed other neural architectures in terms of validation accuracy (96.90%) and has been presented as a lightweight decision support system. This research focuses on median filter-based preprocessing, which is a useful step for the deep learning model's performance-improving agent. The outcomes show that the suggested strategy can offer a private, affordable, and quick decision support system for cervical cancer diagnosis.

Leo et. al., 2023, examined the effect of the preprocessing method on categorization accuracy. This study examines the effects of selective median filtering on a dental caries system of classification using deep learning models, despite the fact that the goal of the research is to improve the accuracy and reliability of dental caries diagnosis by lowering noise, eliminating artefacts, and preserving crucial details in dental radiographs. compares trained photos with raw images that have not undergone any preprocessing using deep learning models. Selective median filtering has the ability to enhance the calibre of dental radiographs and maximise the efficiency of caries classification

algorithms by lowering noise, eliminating artefacts, and conserving crucial features. Experimental findings show that the deep learning model performs much better when selective median filtering is used. With selective median filtering, the outcome demonstrates that our hybrid neural network (HNN) classifier achieves an accuracy of 96.15%. This therefore makes it possible for more precise and trustworthy identification, which improves treatment planning, prompts intervention, and improves patient outcomes.

Telrandhe et. al., 2023, proposed K-Means segmentation with picture preprocessing for adaptive brain tumour identification. Segmented images are preprocessed using a median filter, which also performs skull masking on images with diagonal and antidiagonal masks. After that, the image was segmented using K-Mean segmentation and labelled with HOG objects. Labelling of objects to provide more precise information about the tumour region. The brain structure is represented by major feature points based on statistical data. SVM is utilised for pattern mapping in an unsupervised manner. Here, preprocessing with a median filter will enhance the image quality for increased certainty and simplicity in identifying the tumour.

Mahmoud et. al., 2023, suggest a battery-powered hardware application for a low-energy median filter. To improve the outcomes of subsequent analysis and processing, noise removal is frequently a normal pre-processing step. The median filter serves as a typical nonlinear filter that is often used in digital image processing to remove impulse noise. The speed and power of this technology are optimised via parallelism and pipelines. The versions are non-pipelined, two distinct pipelined structures, and two parallel architectures. For a fair comparison with the traditional median filtering methods, the selection and even-odd sorting-based median filters are also used. The throughput is improved 35% more by the suggested non-pipelined median filter design than by the alternatives.

Panachakel Telrandhe et. al., 2017, suggests a CAD (Computer Aided Diagnosis) tool that uses Non-negative Matrix Factorisation (NMF), Haralick features, and SVM (Support Vector Machine) to distinguish between neural lesions caused by CVA (Cerebrovascular Accident) and lesions caused by other neural disorders. Over 86% of classifications made by the were accurate.

Brynnolfsson et. al., 2017, in this study aims to evaluate the sensitivity of the apparent diffusion coefficient (ADC) MR images' Haralick texture features to variations in five parameters related to image acquisition and pre-processing: noise, resolution, the method used to build the ADC map, the quantization method, and the number of grey levels in the quantized image. Haralick texture features, which are easy to implement and produce a set of comprehensible texture descriptors, are frequently used to represent image texture. They are calculated from a grey level co-occurrence matrix (GLCM). They came to the conclusion that the majority of texture features were significantly influenced by noise, resolution, the chosen quantization method, and the number of grey levels in the quantized images, with the size of the effect varying between different features.

Losquadro et. al., 2020 examines how to distinguish between benign and malignant salivary gland tumours using Haralick's characteristics computed from MR T2-weighted data. Medical image textural

patterns are frequently captured using Haralick's features based on GLCM. According to the study, these textural characteristics can be used to distinguish between different types of tumours. Haralick's textural features, which involve six affected patients, are calculated using four different spatial relationships and a normalised grey level co-occurrence matrix (GLCM). The findings of this study showed that the 14 extracted features reveal distinct values depending on whether a tumour is benign or malignant, and that Haralick's features may be helpful in identifying salivary gland tumours. Utilising 3D patient examinations, another objective is to study the Haralick's features approach to volumetric data. Textural features estimated from volumetric data may have greater discriminative power than 2D data.

Iqbal et. al.,2022 the analysis of mitotic nuclei in breast histopathology pictures using a new heteromorphic Deep Convolutional Neural Network (CNN) with feature grafting technique. The number of mitotic nuclei in breast cancer samples can be used to gauge the tumor's aggressivity and assign it a grade. This method's initial step is to identify potentially mitotic patches in areas of histopathological imaging, and it then divides those patches into mitotic and non-mitotic nuclei. The Local Binary Pattern (LBP) method, which uses statistical level and local structure and requires less computations and is simpler to implement, is used for texture extraction and texture differentiation. The several variations that have been suggested to get around the LBP algorithm's drawbacks include Completed Robust Local Binary Pattern (CRLBP), Dominant Local Binary Pattern (DLBP), Gabor based LBP (GLBP), Local Ternary Patterns (LTP), and more. The pretrained CNN outperforms state-of-the-art CNNs with a 7-9% boost in performance.

Mubarak et. al.,2022 employed seven automatic deep learning models and a manually created local binary pattern (LBP). To enhance the performance of the classifier, extracted features were used to train support vector machines (SVM) and K-nearest neighbour (KNN) classifiers. The non-parametric LBP operator is effective for describing local picture attributes. To train the KNN and SVM, a concatenated LBP and deep learning feature was suggested. The most accurate model, VGG-19 + LBP, was proposed and attained 99.4% accuracy.

Sharma et al.'s article from the year 2022 examines the value of early skin cancer detection and suggests a novel model that blends ConvNet, a deep learning technique, with manually created features based multi-layer perceptrons to increase efficiency and accuracy. In order to show higher precision for dermatologist-level diagnosis of skin cancer in comparison to the standalone ConvNet model, hybrid handcrafted features consisting of texture features and colour moments are proposed. These features integrate the advantages of feature extraction methods and deep learning models. The proposed model's accuracy is 98.3%, which is higher than the prior model's accuracy of 85.3%.

In order to distinguish between stable MCI and progressing MCI, Majlan et al.,2022, suggested a multi-stream deep convolutional neural network fed with patch-based imaging data. In order to classify MRI images, it is first necessary to compare MRI scans of Alzheimer's disease with those of cognitively normal subjects to identify distinct anatomical landmarks using a multivariate statistical test. These landmarks are then used to extract patches from the MRI scans that are then fed into the proposed

multi-stream convolutional neural network. Using the multivariate T2 Hotelling statistical test technique, a brain-shaped p-value map is produced from MRI images and is matched with a 3D coordinate. We propose a multi-stream deep convolutional neural network with these patches as input. Using the ADNI-1 dataset, this multi-stream CNN technique for transfer learning is utilised to categorise patients with pMCI and sMCI.

Sharma et al.'s proposal from 2023 calls for the use of all available picture markers in a "multibranch" convolutional neural network architecture to improve classification performance between AD and normal-controls (NC) images. Brain PET imaging techniques provide in-vivo information on the two characteristics of Alzheimer's disease (AD), which are the brain metabolism and the density/distribution of amyloid and tau proteins. In this investigation, the ADNI dataset is employed, and three training "branches" were created using CNN. 1832 scans in total were used as training data. In order to manage missing data, a multibranch-CNN is created using a multimodal classification CNN. When compared to the independently trained multi-modal CNN, the multi-input branch had a higher classification accuracy. For identifying sMCI and pMCI, a multi-stream convolutional neural network (CNN) is utilised, and it is fed patch-based imaging data extracted using a novel data-driven method.

Angkoso et. al., 2022, proposes that, Three two-dimensional (2D) CNNs are used in a multiplane technique to gather discriminative information on all accessible planes. This technique is a fresh fusion approach to address the drawbacks of shape-based multi-view methods. They proposed the Multiplane Convolutional Neural Network (Mp-CNN), a brand-new technique for recognising 3D objects. The three largest 3-planes are chosen as the framework's three slices in order to represent whole 3D-MRI objects as multi-2DCNN inputs. The analysis of the suggested method makes use of structural MRI data that is T1-weighted and includes 500 participants with AD, 500 subjects with mild cognitive impairment (MCI), and 500 subjects with normal cognition (NC). The proposed method can perform better than the 2DCNN method, which only employs one plane, with an accuracy of 93%, according to extensive trials.

Ajagbe et.al., 2021 This study's objective is to divide AD images into four categories that are well-known to neurologists. The research's findings are then subjected to a range of evaluation standards. DCNN and transfer learning are employed to categorise AD. The classification of AD using magnetic resonance imaging (MRI) has advanced thanks to the use of deep convolutional neural networks (DCNN), which integrate convolutional neural networks (CNN) and transfer learning (Visual Geometry Group (VGG)16 and VGG19). CNN has been acknowledged for its substantial contributions to a number of developments, including computer vision research on object identification and recognition as well as picture segmentation and classification. The analysis showed that VGG-19 performed better than CNN in two categories and VGG-16 in three. Numerous factors are used in the study, which includes accuracy, area under the curve (AUC), F1-score, precision, recall, and computation time. According to the study's findings, there are numerous approaches to categorise medical photos using deep convolutional neural network techniques.

Using an artificial neural network (ANN) as a deep learning model that classifies and forecasts a patient's health or infection state, Swaraj et al., 2021, construct a quick response system that unquestionably identifies the disease through a quicker validation process. The ANN forecasts and classifies patient infection. To prepare the picture datasets for classification, it employs a feature extraction model based on entropy-weighted approaches and a preprocessing model based on the Symmetric Minority Over Sampling Technique (SMOTE). The simulation, which is being used to validate, shows that patients may be classified more rapidly and effectively than with existing deep learning models.

The contact-free, non-ionized, and non-invasive thermal imaging approach for the neonate was developed by Savasci et al. in 2019. 19 healthy neonates and 19 sick neonates' 190 photographs were used in this study. The three key phases of this work are segmentation based on the temperature map of the images, feature extraction using a variety of multi-resolution techniques like Discrete Wavelet Transform (DWT), Curvelet Transform (CuT), and Contourlet Transform (CoT), and efficient classification using an artificial neural network. The classification's outcome demonstrates the possibility of making a significant medical advancement.

In this study, Hemanth et al. (2017) developed a modified ANN that combines BPN (Back Propagation Neural) and HNN (Hopfield Neural Network) to address the shortcomings of conventional ANN, such as accuracy limitations, slow convergence times, and computational complexity. They are blended in the proposed back propagation Hopfield network's (BPHN) training method. This model is examined using experiments for the classification of magnetic resonance brain images. Thus, for brain image analysis, a hybrid technique is used. The suggested method's effectiveness is assessed using accuracy metrics, generalisation potential, computational complexity, convergence speed, and stability. The proposed approach has also proven to be significantly more effective than many of the standard neural networks, according to a comparison with conventional networks. The experimental findings point to an improvement in the proposed BPHN's learning procedure.

In this study by Rajakumari et al. (2020), an automated approach is suggested for employing artificial neural networks to categorise breast tissues as normal, benign, or cancerous. The image is normalised using the Gaussian Mixture Model, and CLAHE equalisation is applied to enhance the image's appearance. The region of the mammography is utilised to extract features such contrast, correlation, energy, homogeneity, global mean, uniformity, entropy, and skewness. These features are extracted using the Grey Level Co-occurrence Matrix (GLCM), texture, and gradient-based hybrid feature extraction. This increases classification accuracy with fewer feature dimensions. To find the anomaly, segmentation using K-Means clustering is used. The examination takes into account the MIAS database images. Additionally, the feed forward neural network classifier is employed for classification. The confusion matrix and ROC curve give an overview of a classifier's performance. According to the findings, the proposed breast cancer identification approach is less difficult than all other methods now in use and gives a classification accuracy of up to 96%.

A deep convolutional neural network-based (DCNN) on Visual Geometry Group (VGG-19) architecture

is suggested by Saranya et al.,2022, via their research, to identify the cancerous section of the brain region from the brain magnetic resonance imaging (MRI) dataset. Our experimental work makes use of the BraTS dataset, which is openly accessible. The brain tumour component of the MRI image dataset is detected using the DCNN approach in this study model, and the VGG-19 architecture is used to train the deep neural network model. Preprocessing, segmentation, feature extraction, and classification are carried out in the hierarchy of the proposed DCNN using a layer-based automatic segmentation and classification technique. To effectively classify the brain MR images, a softmax classifier is employed in conjunction with the classification procedure. This system outperforms other methods like support vector machines, random forests, and convolutional neural networks in terms of better detection accuracy results. The training and testing accuracy of the suggested DCNN-based VGG-19 framework was roughly 99.2%, while the training and testing loss results were 0.158 and 0.138, respectively.

Hiremath et al.'s investigation and comparison of various deep learning-enhanced CT scan image processing methods in 2022. Here, two Covid19 Image classification models are created using images from a lung CT scan. To categorise and diagnose the disease, the first classification model was created using the VGG16 Transfer Learning framework, and the second model was created using the Deep Learning Technique Convolutional Neural Network CNN. The most distinctive feature of VGG16 is that it prioritised having convolution layers of a 3×3 filter with a stride 1 and always used the same padding and maxpool layer of a 2×2 filter with a stride 2. The investigation reveals that both models have the highest levels of accuracy.

Wen et al. (2018) suggested a VGG-19 DNN-based DR model for diabetic patients' fundus image classification. In this proposed technique, 35,126 photos from the standard KAGGLE dataset are employed. Prior to applying vessel segmentation based on GMM, the grayscale conversion and shade correction techniques are performed in the preprocessing stage. To extract the important information from the fundus photos, VGG-19 was used. As 3×3 convolutional layers are mounted on top of VGG-19 to boost its depth level, it is chosen for its simplicity. Utilising the pooling layer a handler in VGG-19, volume size can be decreased. The large-scale retinal fundus pictures underwent faster data reduction using PCA and SVDGMM with adaptive learning based on vessel segmentation was employed for ROI detection. By combining a Gaussian mixture model (GMM), visual geometry group network (VGGNet), singular value decomposition (SVD), Principle Component Analysis (PCA), and softmax, for region segmentation, high dimensional feature extraction, feature selection, and fundus image classification, respectively, the DR classification system in this study achieves a symmetrically optimised solution. In terms of classification accuracy, the proposed VGGNet DNN based DR model outperforms AlexNet and the spatial invariant feature transform (SIFT) by 92.21% and 98.34%, respectively, as well as in terms of computing time.

A classification technique for Alzheimer's disease using MRI scans and the pre-trained deep convolution neural network model VGG-19 with transfer learning was proposed by Manimurugan 2020. The three main procedures carried out in this study are feature extraction, preprocessing, and classification from the OASIS database dataset. Data preprocessing is the first stage of the suggested

model's execution, which was divided into four steps. Extraction of the image's features follows preprocessing, and the retrieved features are then fed into the classifier for training. 373 samples of MRI images are used to test the model after training. Accuracy, recall, precision, specificity, and f-measure are performance indicators that are assessed in order to improve validation results. The model performed 1.9% to 5.3% better than the AlexNet and GoogLeNet models, achieving 96.04% training accuracy and 95.82% testing accuracy. The use of a new deep transfer learning model with improved classification performance, according to the author, can boost this performance even further.

To improve their diagnostic effectiveness and accuracy for the classification of two frequently diagnosed neurodegenerative disorders like Alzheimer's and Parkinson's, Bhatele et al., 2020, introduce an automated system. The Alzheimer and Parkinson disease (ADPP) dataset from ADNI and PPMI is used to implement, hypertune, and train the proposed model's VGG19 deep transfer learning model. Modifying the deep transfer learning VGG-19 model for improved classification accuracy after manually selecting meaningful MRI scans and customising and training the model with the aid of the ADPP dataset. ResNet 50, Inception Net, and VGG 16 are some other well-known deep transfer learning models that are deployed over the same ADPP dataset and their performance is compared with the proposed system based on VGG19 architecture. With an average accuracy of 90% for the multiclass categorization of Alzheimer disease, Healthy Control ADNI, Healthy Control PPMI, and Parkinson illness, the suggested system based on VGG 19 beats the other three well-known deep transfer learning models.

Inspired by the original VGG-19, Maji et al., 2022 proposed a novel DNN-based model for separating AD and MCI patients from Cognitively Normal (CN) people. They used VGG-19 as a reference model when they created the network's 19 deep levels. The vanishing gradient and information loss issues are resolved using the Dense-Block idea from the original DenseNet architecture. Apart from the other two flaws, the VGG-19 deeper models also have a significant processing time latency. Therefore, depth-wise convolutional processes are constructed by swapping out all convolutional operations for depth-wise convolutional operations in order to increase computing efficiency. The suggested model outperformed some well-known DNN models with an average performance rate of 95.39%, including LeNet, AlexNet, VGG-16 & 19, Inception-V3, ResNet152-V2, InceptionResNet, MobileNet-V2, EfficientNet-B7, Xception, NasNet-C, and DenseNet-121. The main limitations of this work are thought to be the large number of features as a result of too many bridge connections and the absence of GradCam display.

A technique to categorise the severity of AD was developed by Hadiyoso et al. in 2012 utilising the Convolutional Neural Network (CNN) method and VGG-16 and VGG-19 modelling based on MRI brain scans. Three categories make up the AD classification: no dementia, mild dementia, and moderate dementia. The Kaggle-4 dataset of MRI images with Alzheimer's disease dementia phases such as no dementia, mild dementia, and moderate dementia is used in this work. For image processing, CNN is employed, and for classification, VGG-16 and VGG-19 architectures are used. To find the best weights for minimising errors and maximising accuracy, Adam Optimizer is employed. The scenario 4 results

utilising epoch 15 and batch size 80 yield the highest accuracy results in the VGG-16 architecture, with an accuracy value of 97.33%. In terms of the VGG-19 architecture, scenario 2 with epoch 15 and batch size 80 yields the best accuracy results, with a value of 98.28%. Due to the differences in the two architectures' processes, the VGG-19 architecture is superior to the VGG-16 architecture. and came to the conclusion that the more layers (19 levels), the higher the classification's accuracy level.

In order to expand the number of annotated samples, Shi et al., 2020, introduced a novel three-channel picture creation technique (virtual RGB image), in which trained networks on real-world images are used to extract spatial information. To get over the input restriction of FCN models, a new three-channel picture is built. The RGB wavelength-corresponding hyperspectral bands are excluded. The method of using Gaussian weights to combine the respective bands is introduced by replicating the Gaussian effect of photographic sensing on the RGB band. In order to create three-channel images, depth model feature extraction and the hyperspectral processing technique are both used. A multi-layer feature fusion approach based on fully convolutional networks is suggested. The feature is more expressive thanks to the cross-layer jointing's ability to preserve both semantic and detail information. A new set of features is used to account for the peculiarities of distinct layers, dimensions, and semantic scales. The feature change based on principle component analysis (PCA) can keep as much data as possible. The characteristics are then normalised and inserted one layer at a time. Directly combining their matching layers can avoid the disadvantages of the feature dimension rising caused by doing so, making the process more efficient and helpful for accurate and quick classification. The hyperspectral data are discarded as a whole by the trained network. They suggest a multiscale feature fusion approach in this work to incorporate both the detailed and semantic properties, improving classification accuracy. The proposed method can produce optimal results more effectively than state-of-the-art methods, according to experiments. The virtual RGB image can also be applied to further hyperspectral processing techniques that demand three-channel images. The suggested method can better adapt to the properties of the deep learning networks on natural images by avoiding PCA's simple and crude reduction of data through the synthesis of three-channel images.

A unique RGB-D salient object recognition approach using cross-modal joint feature extraction and low-bound fusion loss was proposed by Fub et al. in 2021. The depth map and RGB picture saliency maps are created using a two-stream framework. A cross-modal joint feature extraction module (CFM) is suggested to extract useful joint features from the two streams throughout the feature extraction process. The CFM investigates supplementary data from the feature extraction and feeds the combined features to the network's aggregation step. The multi-scale features of each stream and the joint features are then combined to create the updated features using the fusion block (FB). Additionally, a low-bound fusion loss is intended to increase the lower bound of saliency values, confine the predictions of the two streams, and provide a unique saliency map. Five datasets used in the experiments show that the suggested strategy performs better.

Using facial landmarks to identify and cut 12 blocks, Horng et al. suggested a unique approach for extracting facial thermal imaging features in 2020. The method creates a new feature matrix based

on colour mean values and standard deviation values. On facial thermal pictures, it may clearly define features. The core component of the suggested healthcare system is the application of a deep learning framework built on the Caffe platform and running on the DIGITS platform. GoogleNet, a predecessor of CNN, is run by the Caffe. Four models were trained and employed for the raw RGB picture, raw thermal image, RGB feature image, and thermal feature image based on the acquired images and new feature types. In the experiment, 200 photos were used for testing, while 800 images were used for training and validation. For random testing, an additional 40 photos were employed. The results of the experiment demonstrate that while thermal images can accurately identify a person's health status, RGB images cannot, and thermal feature photos have the highest prediction accuracy.

With the use of a single stream network created by Zhang et al. in 2020, early and middle fusion between RGB and depth are guided directly by the depth map, saving the feature encoder of the depth stream and resulting in a light-weight and real-time model. The depth information is used in two ways, including, We built a single stream encoder to achieve early fusion, taking full advantage of ImageNet's pre-trained backbone model to extract rich and discriminative features – as initial process. We then designed a novel depth-enhanced dual attention module (DEDA) to efficiently provide the fore-/background branches with the spatially filtered features, allowing the decoder to effectively decode the image. Another method for precisely localising objects of various scales is the pyramidally attended feature extraction module (PAFE). Numerous tests show that the suggested model outperforms the majority of cutting-edge techniques using various assessment metrics. Additionally, this model processes a 384 384 image at a real-time speed of 32 FPS and is 55.5% lighter than the currently lightest model.

Salvatore et al., 2020 evaluated the potential of ensemble transfer-learning techniques for the early diagnosis and prognosis of AD in comparison to a fusion of conventional-ML approaches based on Support Vector Machine directly applied to structural brain MRI. The ensemble transfer-learning techniques were pretrained on generic images and then transferred to structural brain MRI. The ADNI repository is used, which contains people with AD, mild cognitive impairments (MCIc) that are converting to AD, mild cognitive impairments (MCInc) that are not converting to AD, and cognitively-normal (CN) subjects. On the basis of T1-weighted brain MRI data, training is provided. a 3D Convolutional Neural Network (CNN) trained from scratch on MRI volumes; an ensemble of five transfer-learning architectures pretrained on generic images; and a combination of two traditional ML classifiers derived from various feature extraction/selection techniques coupled with SVM. Comparisons between AD and CN, MCIc and CN, and MCIc and MCInc were looked into. The results, even when trained on generic images beforehand, offer fresh perspectives on the application of transfer learning in conjunction with neuroimages for the automatic early identification and prognosis of AD.

Allada et.al, 2023, proposed an efficient model termed competitive swarm multi-verse optimizer + deep neuro-fuzzy network (CSMVO + DNFN) is designed to accurately classify stages of AD. The hybrid optimisation approach is used to classify AD using a deep neuro-fuzzy network (DNFN)

model. After being pre-processed with a median filter, the resulting picture is segmented using the channel-wise feature pyramid network module (CFPNet-M) to identify the regions that are of interest. The main features extracted from the segmented image include texture features, Haralick, and convolutional neural network features. The energy, contrast, correlation, angular second moment (ASM), homogeneity, and dissimilarity of haralick characteristics are obtained using the grey level co-occurrence matrix (GLCM). To extract textural features, holoentropy-based local binary patterns (HELBP) are utilised. All of this data are processed using DNFN for several phases such as LMCI, MCI, EMCI, AD, and CN in order to categorise the image. The competitive multi-verse optimizer (CMVO) and competitive swarm optimizer (CSO) are combined to create the hybrid algorithm, which performs better according to metrics like accuracy (0.899), sensitivity (0.896), and specificity (0.870) based on the k-value.

Abualigah 2020, presents a comprehensive and full review of the so-called optimization algorithm, multi-verse optimizer algorithm (MOA), and reviews its main characteristics and procedures. This optimizer is a recent powerful meta-heuristic algorithm that draws inspiration from nature, and it has been successfully applied to a number of optimisation issues in a number of different sectors. This paper covers the theoretical properties of the multi-verse optimizer method, including the binary, modified, hybrid, chaotic, and multi-objective versions. Benchmark test functions, machine learning applications, engineering applications, network applications, parameter control, and other uses of the multiverse optimizer method are also included in the list of applications. According to the study's findings, the multiverse optimizer algorithm helps to enhance the capability of the original multiverse optimizer algorithm to handle a variety of optimisation problems, including binary, hybrid, chaotic, multi-objective, and parameterless problems. Additionally, it was discovered that its field of applications covers a wide range of industries, including engineering (such as scheduling, control of power systems, and renewable energy systems), image processing, and machine learning (such as feature selection and training neural networks).

Kuran et.al., 2022, presented a study for the improvement of the enhancement of medical images, a method combining the coot optimisation algorithm (COA) with Mean and variance based sub-image histogram equalisation (MVSHE). The fitness of the coot swarm population is assessed using the blind/referenceless image spatial quality evaluator (BRISQUE) and natural image quality evaluator (NIQE) measures. The experimental results demonstrate that our strategy outperforms the majority of current state-of-the-art methods, or at the very least, performs competitively. Visual results further show that for the majority of the photos in the dataset used, our technique offers a balanced augmentation.

Pashaei et.al, 2023 proposed the binary COOT (BCOOT) optimisation method, whose capacity to resolve gene selection issues was investigated, was offered as a novel gene selection strategy. To find the targeting genes to categorise cancer and disorders, three binary COOT algorithm versions are proposed. BCOOT, BCOOT-C, and BCOOT-CSA are the three suggested algorithms. Ten well-known microarray datasets are used to evaluate the suggested algorithms, which are then contrasted with other potent optimisation algorithms and contemporary cutting-edge gene selection methods. The

experimental findings show that, in most circumstances, the BCOOT-CSA strategy beats other methods in terms of prediction accuracy and the number of selected genes, and it is superior to BCOOT and BCOOT-C.

Pashaei 2023, The most informative features are chosen using a new version of Binary Sand Cat Swarm Optimisation (referred to as PILC-BSCSO), which incorporates a crossover operator and pinhole-imaging-based learning technique. The crossover operator is employed in the beginning to improve BSCSO's search capabilities. In order to successfully boost exploratory capacity while preventing premature convergence, the pinhole-imaging learning approach is used. The classification accuracy is evaluated using a Support Vector Machine (SVM) classifier with a linear kernel. When compared to the 11 most recent state-of-the-art approaches, experimental results on three benchmark datasets show that the recommended PILC-BSCSO-SVM method can achieve a greater classification accuracy with a lesser number of features simultaneously. While the PILC-BSCSO technique appears to have promise, it is vital to be aware of any potential drawbacks. One such constraint is the need for additional validation in larger and more varied datasets, including single-cell data, to make sure the algorithm is generalizable.

CNN is extensively recognized for its capability to execute highly accurate [medical image classification](#) in deep learning. The median filter is a commonly used pre-processing technique in image processing. It shows a prominent role in the image pre-processing step which help in precise segmentation of medical images by reducing the impact of noise, particularly salt-and-pepper noise and more. Optimizing medical images offers several advantages that contribute to enhanced diagnostic accuracy, improved treatment planning, and more efficient healthcare practices. Competitive swarm multi-verse optimizer, Competitive Swarm Coot Optimization, Fractional CSCOOT optimization are various available optimization which we involved in this research work for better result.

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