International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

MobileNet-Based Transfer Learning: A Novel Approach for Improved Alzheimer's Disease Classification from Brain Imaging

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Submitted: 25/01/2024 **Revised**: 03/03/2024 **Accepted**: 11/03/2024

Abstract: Alzheimer's can result from various illnesses or incidents that severely impact normal brain functions. While Alzheimer's Disease (AD) does not have a specific treatment, initial Alzheimer's disease diagnosis requires neuroimaging, which is among the most promising disciplines for this purpose. It is possible to provide patients with the appropriate care if Alzheimer's disease is detected early. In numerous investigations, machine learning and statistical methods are used to diagnose AD. Deep Learning systems have shown effectiveness similar to that of humans in various fields. The research suggests utilizing deep learning methods such as transfer learning and fine-tuning for classifying and predicting AD. The neural networks DenseNet121, MobileNet, InceptionV3, and Xception are trained using the ADNI 5-class dataset. While the previous state-of-the-art technique achieves an overall accuracy of 86.57%, the proposed MobileNet architecture outperforms it with a validation accuracy of 98% with fine-tuning and 94% without fine-tuning. This research advances the classification of AD through utilizing pre-trained convolutional neural network models, promoting the exploration of unconventional indicators like eye-tracking, memory impairment, and concentration difficulty, amongst others.

Keywords: *Early Alzheimer's disease, ADNI 5-class, Transfer Learning, MobileNet, DenseNet121, InceptionV3, Xception Net*

1. Introduction

The human brain is one of the most intricate organs in the body due to its unique anatomical and functional features. To develop successful diagnostic and treatment plans and understand the cause of brain illnesses like AD, it is crucial to have an understanding of the disease's dynamic functional network. [1]. In the previous decade, there have been notable progressions in medical imaging, a substantial increase in the processing capabilities of affordable computing platforms, and enhanced availability of neuroimaging data sets (e.g., those provided by the Alzheimer's Disease Neuroimaging Initiative (ADNI)). These developments have created a more favourable environment for the advancement of machine learning methods that aim to automatically identify, classify, and quantify diseases [2].

Machine learning techniques, particularly deep learning, are increasingly being utilised to analyse Functional Magnetic Resonance Imaging (fMRI) data for disease diagnosis and classification. [3]. This methodology presents the capacity to automate the process of diagnosing neurological disorders, including Alzheimer's disease. Nevertheless, notwithstanding these progresses, difficulties endure in attaining accurate and reliable classification, specifically in the context of extensive and complex datasets like the ADNI 5-class dataset. The principal goal of this study is to assess the applicability of transfer learning and deep learning in the classification of brain MRI images, with a primary focus on AD, using the ADNI 5-class dataset [4]. Brain functional network analysis in recent studies [5] and the application of machine learning in neuroimaging provide valuable insights and motivation.

Pre-trained Convolutional Neural Networks (CNN) models have the benefit of simplifying training and maximising learnt picture characteristics. The study leverages the advantages of pre-trained CNN models to accomplish the following major contribution:

The research compares advanced pre-trained CNN models and proposes methods for fine-tuning them for AD classification using the ADNI 5-class dataset. Leveraging pre-trained CNN models, the approach aims to balance processing efficiency with detailed feature representation. The integration of computational neuroscience principles with Magnetic Resonance Imaging (MRI) data aims to propel advancements in neuroimaging-based Alzheimer's disease classification [6]. The objective is to enhance the comprehension and treatment of neurological disorders within the field through thorough evaluation and experimentation.

The rest of the paper is structured such that: Section 2 covers the works that are thought to be pertinent to this research while section 2.1 mentions the gaps found in the review of

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literature. A thorough description of the methodology can be found in section 3. Section 3.1 gives a brief description about the dataset used while section 3.2 outlines the methodologies employed in the collection of the primary and secondary datasets. In section 4, the models are evaluated for accuracy and other evaluation metrics. Sections 5 and 6 outline the conclusion and prospective future works respectively.

2. Literature Review

Within the medical sector, advancements in deep learning have been instrumental in aiding the diagnosis of Alzheimer's disease, among various conditions. Deep learning, notably, finds significant application in image analysis, particularly in identifying and assessing Alzheimer's disease.

The most difficult aspect of classifying clinical data, like Alzheimer's disease, has always been determining which features are the most discriminative. Saffar et al. [7] perform classification by using LeNet-5, a well-known CNN architecture. Al Saeed et al. [8] suggest using MRI images to automatically extract features for the diagnosis of Alzheimer's disease using a pre-trained CNN deep learning model called ResNet50. These are later applied on algorithms like Support Vector Machine (SVM), Random Forest and traditional Softmax. The main obstacle in multi-class classification is the existence of strongly linked features in the brain anatomy. Nawaz et al. [9] propose an intelligent and precise method based on an imbalanced three-dimensional MRI dataset to diagnose AD using a two-dimensional deep convolutional neural network (2D-DCNN).

Gunawardena et al. [5] delve into the utilization of Convolutional Neural Networks for the preliminary detection of Alzheimer's Disease using structural MRI data. They analyze the efficacy of SVM classifiers alongside CNNs, integrating image segmentation methods. Even with noisy labelling, deep learning models (FCN, SegNet, U-Net) successfully partition tau pathology in Alzheimer's disease [10]. The best performance was attained by SegNet (DICE loss = 0.234). According to Yi et al. [10], these models may be used for whole-slide picture analysis and future research should concentrate on enhancing data quality and model interpretability for clinical usage.

Khagi et al. [11] explore employing either pre-trained AlexNet CNNs or CNNs trained from scratch as generic feature extractors for MRI-derived images, followed by dimensionality reduction using Principal Component Analysis (PCA) and t-distributed Stochastic Neighbour Embedding (tSNE). Classification is then executed using machine learning algorithms like K-Nearest Neighbour (KNN) and Naive Bayes Classifier. While the results are not groundbreaking, the study suggests the potential superiority of using pre-trained CNNs over training from scratch, particularly evident in softmax classification based on probability scores. Alon et al. [12] leverage deep learning models on MRI images and offer potential for early AD identification. Current studies investigate CNNs, transfer learning, and handling of unbalanced data. In contrast to categorization techniques, the study suggests YOLOv3 for object identification, providing a distinctive strategy.

Early Alzheimer's Disease Diagnosis Using Autoencoders (EADDA) [13] utilizes an innovative deep-learning technique to address early AD detection. In contrast to single-model approaches, it combines an autoencoder for feature extraction with a varied ensemble classifier for perhaps increased accuracy and efficiency. Although it shows promise in combining multi-modal data and providing interpretability, more testing on bigger datasets and comparisons with conventional methods are required to assess its actual efficacy and beneficial significance. When analyzing complicated AD data from neuroimaging, deep learning performs better than previous approaches. Research by Jo et al. [3] utilizing both pure and hybrid deep learning techniques demonstrates encouraging outcomes, with classification accuracy for AD above 96%.

Convolutional neural networks, in particular, are used in the work of Helaly et al. [14], to improve medical picture classification in Alzheimer's disease (AD). The authors leverage both simple architectures (93-95% accuracy) and transfer learning (97% accuracy) on ADNI-4 class dataset, utilizing pre-trained models like VGG19, to improve their model's performance. A transfer learning method for Alzheimer's disease prediction was put forth by Sreeja Sasidharan Rajeswari et al. [15]. Alzheimer's disease prediction was improved with the application of transfer learning with models like VGG-16, VGG-19, Xception, and Resnet-50.

Fazal ur Rehman Faisal et al. [16] created an automated method to detect Alzheimer's disease and mild cognitive impairment using whole brain MRI. As recommended by the authors, the complete collection of images ought to be employed as input for the multi-label Alzheimer's disease biomarker detection procedure when a custom-layered deep convolutional neural network architecture is utilised from initiation to completion. Yet, patient history information is not currently incorporated into the proposed CNN for 3D whole-brain image processing. When it comes to identifying healthy and AD/MCI persons for early AD detection, Stacked Denoising Autoencoders SDAEs) perform better than raw gene expression data. Li et al. [2] optimize the architecture of the model to improve efficiency and merge information from many layers resulting in 100% classification accuracy. This work raises the possibility of using deep learning to analyze gene expression data and support the diagnosis of AD in its early stages.

2.1. Research Gap

Most of the previous works utilize the ADNI-4 class dataset with minimum work on the ADNI-5 class dataset on which extensive experimentations have been performed using the methodology proposed in this study. The previous state-of-the-art technique for classification of Alzheimer's Disease achieves an overall accuracy of 86.57% which suggests that there is scope for improvement. With an extra class of medical conditions present in the ADNI-5 class dataset and by using robust and deep CNN architectures, we aim to offer more accurate diagnostic insights, helping patients as well as doctors.

3. Methodology

3.1. Dataset Description

For this proposed research, the Alzheimer's dataset was obtained from Kaggle [4] and collected from the Alzheimer's Disease Neuroimaging Initiative (ADNI) repository [17]. The dataset utilised contains 1296 MRI pictures. The data is further segmented into five groups:

1. Alzheimer's disease (AD),

2. Cognitive Normal (CN),

3. Early Mild Cognitive Impairment (EMCI),

4. Late Mild Cognitive Impairment (LMCI), and

5. Mild Cognitive Impairment (MCI).

EMCI, **LMCI**, and **MCI**: These individuals have observable cognitive deficiencies that interfere with their day-to-day activities even if they are able to perform their regular chores. With a Clinical Dementia Rating [18] of 0.5, these individuals vary in Mini-Mental State Examination (MMSE) [19] score from 24 to 30. MCI that progresses to AD is called pMCI, whereas MCI that stays the same is called sMCI.

AD: Patients with memory, language, judgement, and problem-solving issues find it challenging to remain independent. These individuals have a Clinical Dementia Rating of 0.5 to 1 with an MMSE score ranging from 20 to 26.

CN: Individuals with cognitively normal minds have standard memory, language, and attention skills, among other abilities. Research has been performed to uncover potential risk factors or protective variables to gain a greater knowledge of the underlying causes of cognitive decline. These individuals have a Clinical Dementia Rating of zero, with MMSE scores ranging from 24 to 30. Figure 1 Brain MRI Images of the 5 classes.

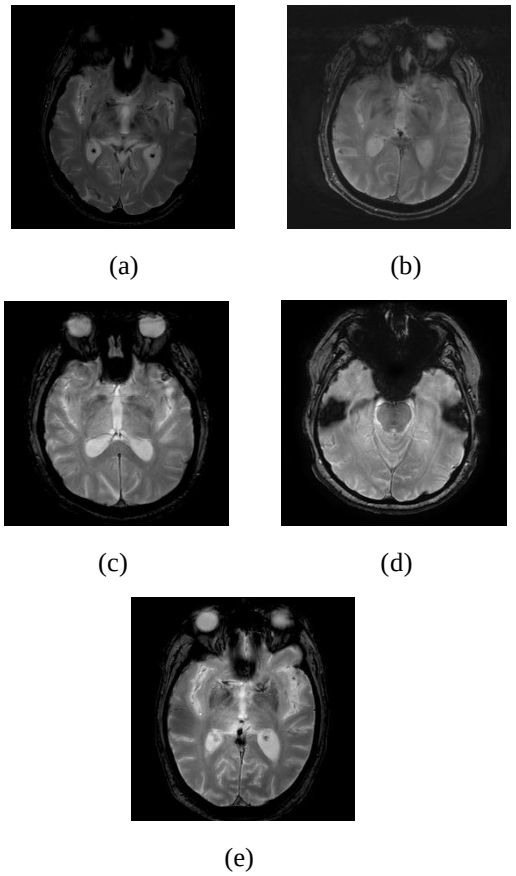

Fig. 1. Brain MRI Images of 5 classes of Alzheimer's Disease

(a) MCI (b) LMCI (c) EMCI (d) CD (e) AD

3.2. Proposed System

This research deals with using deep learning models to classify different forms of AD by analyzing the ADNI 5-Class dataset. The goal is to employ transfer learning to enhance the efficiency and predictive capabilities of four distinct pre-trained models: DenseNet121, InceptionV3 [20], MobileNet [21], and XceptionNet [22].

The process begins with the preprocessing of the ADNI 5-Class dataset, which is already partitioned into train and test sets with five classes. The images are standardized to (224, 224, 3). Data augmentation techniques like as rescaling, shear, zoom, and horizontal flip are only used on the training set to enhance the model's resilience.

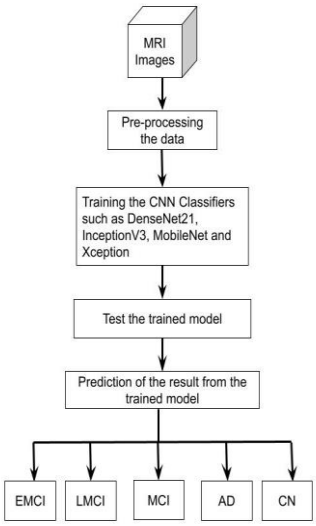

Fig. 2. Proposed workflow of methodology

The core of the approach lies in transfer learning, utilizing the models as feature extractors with prior training on the ImageNet dataset. This expedited training and harnessed the models' ability to discern intricate features in images. Each of the four selected models is individually integrated into the framework. For each model, a dense neural network architecture is constructed by appending global average pooling layers and dense layers. The models serve as the baseline for subsequent experiments. Implementing a fine-tuning phase to improve the models' performance. Supplementary layers such as fully linked, dropout, and dense layers are selectively incorporated. This enhancement improves training accuracy and prediction capabilities without requiring complete retraining.

During the fine-tuning process, various hyperparameters are adjusted to obtain the best possible trade-off between the model's complexity and effectiveness. Following two fully connected layers and three dropout layers come three dense layers. Alzheimer's disease photos are categorised into five unique groups using an output layer that has a softmax classifier. The experiment covers both transfer learning and fine-tuning stages, adjusting the number of epochs based on each model's convergence properties. Accuracy during training, validation, and testing is meticulously documented to understand the learning process and generalization abilities of the models.

Throughout the process of fine-tuning, two entirely connected layers—one comprising 128 units and the other 256 units—are integrated. To prevent overfitting, three dropout layers with dropout rates of 0.5, 0.3, and 0.3 are intelligently positioned. A greater quantity of dense layers augments the capability of the model to discern intricate patterns within the dataset. The methodology involves using four prominent deep learning models along with careful data preprocessing, strategic transfer learning, and fine-tuning procedures. The studies aim to determine the most efficient setups by leveraging the current knowledge stored in the pre-trained weights of the models. This will make substantial contributions to the field of categorizing Alzheimer's disease types. Figure 2 illustrates how to train a CNN classifier for AD stage distinction using MRI images. This involves pre-processing the data, training the model, evaluating its performance, and using it to make predictions on unknown data. Algorithm 1 explains the entire methodology algorithmically.

Algorithm 1:

Input: Training, validation, and testing instance set 'T', an image set, and a label value. – Image Set I(i) = I1 (i), I2 (i),.., In (i) – Label Set L(i) = {Class1, Class2, ------, Class n}
Initialization: Step 1: Define the paths for the dataset, including the training and testing directories. Step 2: Specify the image dimensions and batch size for processing.
Preprocessing Phase: Step 3: Implement data augmentation techniques for the training set to enhance model generalization. Step 4: Prepare the validation set without data augmentation.
Define the model: Step 5: Utilize the MobileNet architecture with fine-tuning and additional layers for feature extraction and classification. Step 6: Freeze the base MobileNet layers to prevent retraining. Step 7: Compile the model with the Adam optimizer and categorical cross-entropy loss function
Training Phase: Step 8: Train the model using the training generator with fine-tuning for a specified number of epochs. Step 9: Save the trained model for future use.
Evaluation Phase: Step 10: Evaluate the model's performance on the test set. Step 11: Calculate and print the test accuracy. Step 12: Generate predictions on the test set and compute classification metrics such as the classification report and confusion matrix.
Visualization Phase: Step 13: Estimate the training and validation accuracy over epochs to assess model performance during fine-tuning. Step 14: Track the training and validation loss over epochs to monitor the training process by estimating error over time.

Validation Step:
Step 15: Review the results to assess the model's effectiveness and potential areas for improvement.
Step 16: Make any necessary adjustments to the model or training process based on the evaluation outcome.

Fig. 3. Fine-tuned MobileNet Architecture with added layers

4. Experimentation and Results

In this work, 20% of the data was used for testing during cross-validation and the remaining 80% for training. Transfer learning was used in the experiment along with fine-tuning. MobileNet model displayed the best results, with the highest training and validation accuracy without and with fine-tuning as shown in Table 1 and Table 2 respectively. From the Figure 6, MobileNet performed with a training accuracy of 96% and a validation accuracy of 94% without fine-tuning and with fine-tuning the accuracies increased to 98% for training and validation.

Figure 5 shows that after fine-tuning, InceptionV3's accuracy increased significantly. Without fine-tuning, the training and validation accuracy was 89% and 83%, respectively; with fine-tuning, these numbers rose to 96% and 94%. XceptionNet followed a similar trend too, with its accuracies increasing with fine-tuning as shown in Table 1 and 2, along with Figure 6. The accuracy improved with DenseNet21 as well, but validation accuracy in particular saw a substantial rise from 85% to 95% before and after fine tuning, respectively shown in Figure 4.

Table 1. Model results before fine-tuning

CNN Architecture	Training Accuracy	Validation Accuracy
DenseNet121	93%	85%
InceptionV3	89%	83%
MobileNet	**96%**	**94%**
XceptionNet	91%	90%

Table 2. Model results after fine-tuning

CNN Architecture	Training Accuracy	Validation Accuracy
DenseNet121 with Fine-tuning	95%	95%
InceptionV3 with Fine-tuning	96%	94%
MobileNet with Fine-tuning	**98%**	**98%**
XceptionNet with Fine-tuning	96%	95%

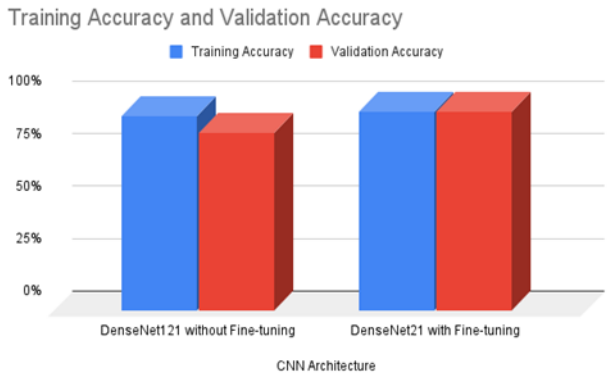

Fig. 4. Performance of DenseNet121

The graphs from Figure 4 depicts a stark improvement of accuracy with fine-tuning for DenseNet21. The training accuracy as well as the validation accuracy are the same after fine-tuning.

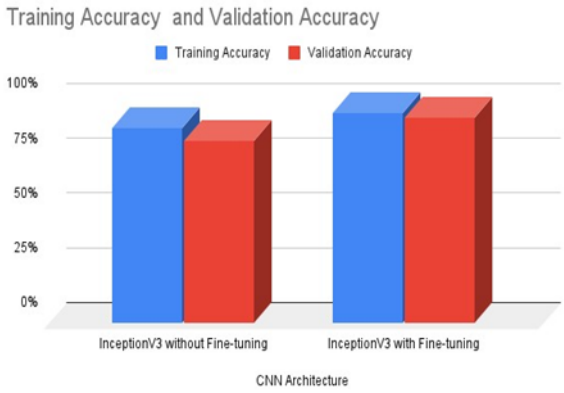

Fig. 5. Performance of InceptionNetV3

InceptionNetV3 witnessed the most drastic increase in accuracies for both training and validation accuracy, 7% and 11% respectively. This increment is visualised in Figure 5.

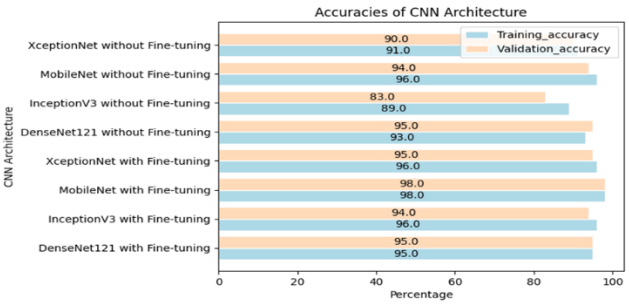

Fig 8. Performance comparison of various CNN architectures

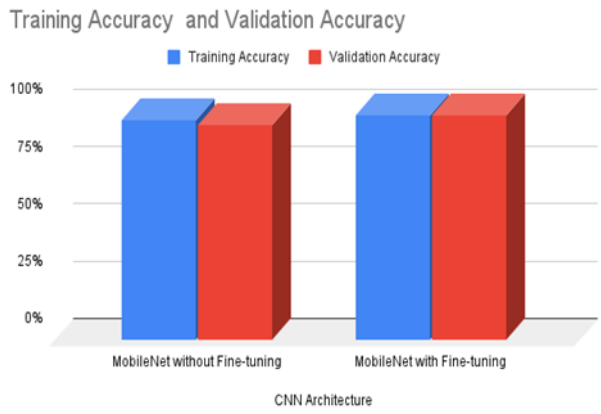

Fig. 6. Performance of MobileNet

MobileNet results were relatively better without fine-tuning too, achieving an accuracy of 96%, in comparison to other models utilized in the research. Fine-tuning makes it achieve the highest accuracies for training and validation with 98%, as analyzed from Figure 6. MobileNet outperformed other models, possibly due to its architecture, which has been optimised for mobile and embedded vision applications.

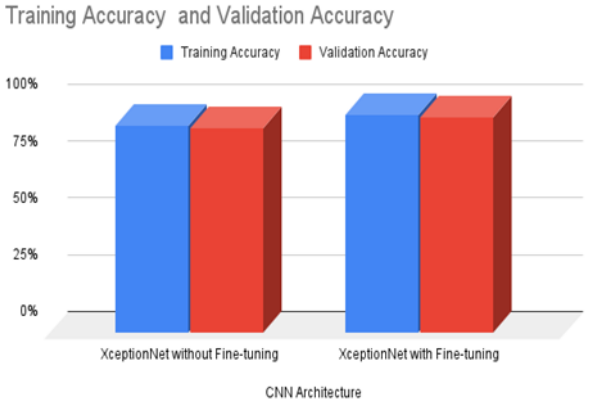

Fig. 7. Performance of XceptionNet

MobileNet uses depth wise separable convolutions, which substantially decrease the number of parameters while maintaining performance.

XceptionNet underwent the same improvement for training and validation accuracy after fine-tuning. Both training and validation accuracy rose by 5% and hence the difference between them remained the same as seen in Figure 7.

Figure 8 is a comparative overview of all the models used, specifying their training and validation accuracies.

5. Conclusion

The study used the ADNI 5-class dataset and employs deep learning techniques to categorize Alzheimer's disease. The methodology utilized advantageous components from current deep learning models to extract and classify information. The study showed that using pre-trained CNN models like DenseNet121, MobileNet, InceptionV3, and Xception on the ADNI 5 class dataset led to significant performance enhancements after fine-tuning. The models initially showed inferior accuracy because of limitations like insufficient domain knowledge, possible overfitting to pre-training data, and untapped learning capacity tailored to the individual job.

Yet, by refining, these obstacles were successfully resolved. Refining pre-existing characteristics, transferring general knowledge, reducing overfitting, and enhancing model efficiency. Success in fine-tuning depended on aspects such as task similarity, data quality for fine-tuning, and careful layer selection. MobileNet achieved a training accuracy of 96% and a validation accuracy of 94% prior to fine-tuning on the ADNI 5 class dataset. After refinement, the accuracies improved to 98%, demonstrating the efficacy of this strategy in enhancing model performance. Although not certain, fine-tuning is a powerful method for improving precision and effectiveness, especially in situations with little data and intricate jobs. The results emphasize the importance of optimizing pre-trained Convolutional Neural Networks to fully utilize the capabilities of deep learning models in analyzing biomedical images.

6. Future Work

This study establishes the groundwork for concrete advancements in the classification of Alzheimer's Disease through the utilization of pre-trained CNN models and subsequent fine-tuning. When incorporating multimodal data, it is crucial to expand beyond conventional sources and incorporate atypical indicators like speech patterns and eye-tracking data in order to improve the model's understanding of Alzheimer's disease symptoms. Further research should prioritize longitudinal analysis in order to identify biomarkers of disease progression that are temporally dependent, taking into account subtle nuances in illness progression.

References

[1] E. Pellegrini et al., “Machine learning of neuroimaging for assisted diagnosis of cognitive impairment and dementia: A systematic review,” Alzheimers Dement. Diagn. Assess. Dis. Monit., vol. 10, pp. 519–535, Jan. 2018, doi: 10.1016/j.dadm.2018.07.004.

[2] T. Zheng-Lin, W. Hai-Xing, Y. Shao-Xun, S. Xiao, and X. Jian-Ming, “Classification of Alzheimer’s Disease Based on Stacked Denoising Autoencoder,” in 2018 4th Annual International Conference on Network and Information Systems for Computers (ICNISC), Wuhan, China: IEEE, Apr. 2018, pp. 248–253. doi: 10.1109/ICNISC.2018.00056.

[3] T. Jo, K. Nho, and A. J. Saykin, “Deep Learning in Alzheimer’s Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data,”

Front. Aging Neurosci., vol. 11, p. 220, Aug. 2019, doi: 10.3389/fnagi.2019.00220.

[4] M. Charan, “Alzheimer's-disease-5-Class-Dataset-ADNI,” Kaggle, https://www.kaggle.com/datasets/madhucharan/alzheimersdisease5classdatasetadni (accessed Feb. 22, 2024).

[5] K. A. N. N. P. Gunawardena, R. N. Rajapakse, and N. D. Kodikara, “Applying convolutional neural networks for pre-detection of alzheimer’s disease from structural MRI data,” in 2017 24th International Conference on Mechatronics and Machine Vision in Practice (M2VIP), Auckland: IEEE, Nov. 2017, pp. 1–7. doi: 10.1109/M2VIP.2017.8211486.

[6] D. Chaihtra and S. Vijaya Shetty, “Alzheimer’s Disease Detection from Brain MRI Data using Deep Learning Techniques,” in 2021 2nd Global Conference for Advancement in Technology (GCAT), Bangalore, India: IEEE, Oct. 2021, pp. 1–5. doi: 10.1109/GCAT52182.2021.9587756.

[7] Sarraf, Saman, and Ghassem Tofighi. "Classification of alzheimer's disease using fmri data and deep learning convolutional neural networks." arXiv preprint arXiv:1603.08631 (2016).

[8] AlSaeed, D.; Omar, S.F. Brain MRI Analysis for Alzheimer’s Disease Diagnosis Using CNN-Based Feature Extraction and Machine Learning. Sensors 2022, 22, 2911. https://doi.org/10.3390/s22082911.

[9] A. Nawaz, S. M. Anwar, R. Liaqat, J. Iqbal, U. Bagci and M. Majid, "Deep Convolutional Neural Network based Classification of Alzheimer's Disease using MRI Data," 2020 IEEE 23rd International Multitopic Conference (INMIC), Bahawalpur, Pakistan, 2020, pp. 1-6, doi: 10.1109/INMIC50486.2020.9318172.

[10] A. Wurts, D. H. Oakley, B. T. Hyman, and S. Samsi, “Segmentation of tau stained alzheimer's brain tissue using convolutional neural networks,” 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Jul. 2020. doi:10.1109/embc44109.2020.9175832.

[11] B. Khagi, C. G. Lee and G. -R. Kwon, "Alzheimer’s disease Classification from Brain MRI based on transfer learning from CNN," 2018 11th Biomedical Engineering International Conference (BMEiCON), Chiang Mai, Thailand, 2018, pp. 1-4, doi: 10.1109/BMEiCON.2018.8609974.

[12] H. D. Alon, M. A. D. Ligayo, M. A. Misola, A. A. Sandoval and M. V. Fontanilla, "Eye-Zheimer: A Deep Transfer Learning Approach of Dementia Detection and Classification from NeuroImaging," 2020 IEEE 7th International Conference on Engineering Technologies and Applied Sciences (ICETAS), Kuala Lumpur, Malaysia, 2020, pp. 1-4, doi: 10.1109/ICETAS51660.2020.9484315.

[13] M. R. Syed, N. Kothari, Y. Joshi, and D. A. Gawade, “EADDA: Towards Novel and Explainable Deep Learning for Early Alzheimer’s Disease Diagnosis Using Autoencoders,” Int. J. Intell. Syst. Appl. Eng.

[14] H. A. Helaly, M. Badawy, and A. Y. Haikal, “Deep Learning Approach for early detection of alzheimer’s disease,” Cognitive Computation, vol. 14, no. 5, pp. 1711–1727, Nov. 2021. doi:10.1007/s12559-021-09946-2S.

[15] S. S. Rajeswari and M. Nair, “A Transfer Learning Approach for Predicting Alzheimer’s Disease,” in 2021 International Conference on Nascent Technologies in Engineering, ICNET 2021 - Proceedings, 2021. doi: 10.1109/ICNTE51185.2021.9487746.

[16] F. U. R. Faisal and G. R. Kwon, “Automated Detection of Alzheimer-s Disease and Mild Cognitive Impairment Using Whole Brain MRI,” IEEE Access, vol. 10, 2022, doi: 10.1109/ACCESS.2022.3180073.

[17] “Alzheimer’s disease neuroimaging initiative,” ADNI, https://adni.loni.usc.edu/ (accessed Feb. 22, 2024).

[18] J. C. Morris, "The clinical dementia rating (cdr): Current version and scoring rules," Neurology, vol. 43, no. 11, 1993, doi: 10.1212/wnl.43.11.2412-a.

[19] M. F. Folstein, S. E. Folstein, and P. R. McHugh, "Mini-mental state'. A practical method for grading the cognitive state of patients for the clinician," J Psychiatr Res, vol. 12, no. 3, 1975, doi: 10.1016/0022-3956(75)90026-6.

[20] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected Convolutional Networks,” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jul. 2017. doi:10.1109/cvpr.2017.243.

[21] A. G. Howard et al., “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications.” arXiv, Apr. 16, 2017. Accessed: Feb. 23, 2024. [Online]. Available: http://arxiv.org/abs/1704.04861.

[22] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jul. 2017. doi:10.1109/cvpr.2017.195

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