Dementia Identification using a Class of CNN based Methods and Transfer Learning

LIZA MEDHI, BEAUTI PRIYA CHOUDHURY, SURAJIT DEKA, KANDARPA KUMAR SARMA
Department of Electronics and Communication Engineering,
Gauhati University,
Guwahati-781014, Assam,
INDIA

Abstract: - Through the use of transfer learning techniques and multiple Convolutional Neural Networks (CNNs), our study offers a novel method for the early identification of dementia. Through data augmentation, we ensure robustness and enhance the model's ability to extract complex patterns from MRI data by utilizing pre-trained models such as VGG19, ResNet50, and Inception V3. We improve the identification of dementia-related patterns by utilizing well-established models, presenting promising advances in our field. In addition, our study explores the theoretical underpinnings of using MRI imaging to differentiate between different phases of dementia, offering important new perspectives on the course of the disease. We initialized the models with weights of pre-trained image net equivalents and perform dataset pre-processing, segmentation. Our results well exceeds with VGG19 topping with 91.5% accuracy followed by Inception V3 as 87.19%. ResNet50 also got an impressive score of 74.76%. The future work shows the potential to identify clearer differences to be used as early diagnostic aid for Dementia in patients who don’t have neurological symptoms with mere CNNs using transfer learning.

Key-Words: - Cognitively Normal (CN), Convolutional Neural Network (CNN), Deep Neural Network (DNN), Mild Cognitive Impairment (MCI), Residual Neural Network (ResNet), Visual Geometry Group (VGG).

Received: March 14, 2024. Revised: October 15, 2024. Accepted: November 13, 2024. Published: December 31, 2024.

1 Introduction

Dementia, is a disease of brain which is irreversible. It affects one’s memory, thinking capability and many other. It is a long-term neurodegenerative disease and is related to one person’s loss of memory which affects the decision-making skill of the person and also can obstruct social activity, [1]. Therefore, early detection of the disease is very important for the patient’s health.

In the United States, it is one of the most important cause for death having 3.6% of all casualties in the 2014 death statistics, [2]. Artificial intelligence (AI) based tools are preferred to provide preliminary diagnostic support in case of many disease. Likewise, AI tools have also been used for the early detection of the condition of a patient suffering from dementia. Many AI tools can be effectively design and configured to provide initial support to the patients and the healthcare community to formulate treatment for people suffering from this disorder. Through this research we aim to use CNN and Transfer learning by combining deep learning techniques with the existing knowledge to thoroughly study the MRI scans. Using well-known pre-trained models like VGG-19, Inception V3 and ResNet-50 will help us to make some progress in this field, [3]. These models act like tools that identify important patterns from the MRI scans, which are useful for detecting dementia. This helps the system to learn faster and accurately detect the disease.

Transfer learning makes the task of applying sophisticated models to brain scans easier by customizing pre-existing neural networks to address the unique difficulties associated with dementia detection, [4].

1.1 Motivation

Detection of dementia beforehand is an important element in the process of taking corrective steps to arrest the onset of the serious stages of the disease. If the early symptoms of the disease are detected early, treatment can be initiated to arrest the degradation of the condition of the patient. Once dementia sets in, a person’s ability to carry out day to day functioning is seriously affected, [1]. Several serious difficulties like inability to concentrate, errors in judgment, forgetting, repeating tasks, or saying the same sentences etc. are observed. At times, these might prove to be life-threatening for the patient. Each year the world-wide death rates due to dementia are rising. Many deaths due to dementia remain unreported, [5]. The seriousness of the situation and the requirement to provide respite to patients suffering from such disorders have become a necessity. One of the key attributes in this regard is to formulate technology supported solutions. Such support through which early detection of onset of dementia is possible become critical to help a section of the society which are likely to be affected by this disease, [6]. If such solutions provide early detection, personalized care can be initiated. While the onset of such a disease is ascertained by the use of magnetic resonance imaging (MRI), trained healthcare professionals give the decision regarding the stages of the disorder. Lately, it has been observed that several AI based approaches have been adopted for detection of the onset of dementia and its stages from MRI samples. MRI samples applied to train CNN are found to be effective for such a purpose. In this work we highlight the application of a set of CNN based methods for detection of dementia.

1.2 Contribution

The key contributions of our works can be summarized as below:

- Firstly, a hybrid method formed using transfer learning and the CNN is designed, configured and trained for detecting dementia using MRI samples. After extensive training and testing we find that the combination is robust and reliable while providing reliable decision regarding the occurrence of dementia.
- Next, we apply certain data augmentation methods to increase the number of training samples and to nullify the ill-effects of having insufficient MRI samples. As a result, the training becomes robust and the method turns out to be reliable,
- Finally, several pre-trained models like Inception V3, ResNet50, and VGG-19 are employed for the purpose to ascertain the effectiveness of these AI tools.

2 Background Study

AI-based tests showcased the ability to improve the detection of dementia process, according to past research. These tests give physicians more precise and reliable findings than older methods, and they provide a direct, unbiased sign of dementia in its early stages, [7]. Robust CNN models have shown great diagnostic accuracy in dementia diagnosis after being trained and evaluated on multiple independent groups, [8]. Relevance maps, which correlate hippocampal relevance scores with volume - a significant MRI marker for Alzheimer's disease - were used to assess these models, [8]. Bayesian networks for Alzheimer's disease detection have been developed, tested, and examined with machine learning techniques, [9]. These networks derive interpretation and meaning from complex data using probability models. These become more reliable with each training cycle. This is true with early detection of dementia as well, [9]. The work [10] reported the application of a set of techniques to distinguish between various groups of speakers categorized as healthy, with mild cognitive impairments (MCI), and mild Alzheimer’s disease. Moreover, the work [3] reported the formulation of techniques that distinguishes signs and symptoms of MCI and Alzheimer’s disease applying distinct patterns and markers which are linked with the disorder. This has enhanced the accuracy of the clinical analysis.

3 Proposed Approach

In this work, we adopted and trained three popular CNN models namely VGG19, ResNet50, and Inception V3 for identification of dementia using MRI samples. The VGG19 is efficient in feature learning and image identification tasks due to unique 19 layers constituted by 3x3 convolutional filters, [11]. Additionally, the VGG19 is an excellent candidate for applying transfer learning in specialized neuroimaging requirements for deriving critical decisions about dementia onset using MRI samples. VGG19 is known to be efficient in recognizing complex patterns and structure engrossed in MRI images, [12].

Residual Network has 50 layers hence called ResNet50, is configured using a distinctive architecture where there are residual blocks that are trained to handle the issue of vanishing gradients, [3]. The network is known for its efficiency and has been found to be excellent for image classification.

ResNet50's residual connections contribute towards its neuroimaging efficiency by strengthening its ability to capture subtle variations in MRI scans. It improves the accuracy of the dementia detection, [3].

The Inception V3 is constituted by the use of mixed convolutional filters in one layer and processing in the subsequent layers through simultaneous flow of the input streams. Also, the computation efficiency of the Inception V3 is renowned [3] which makes it a reliable candidate for analysing MRI data and recognizing early signs of dementia.

While the residual blocks in ResNet50 helps in preventing the occurrence of the vanishing gradient problem, the Inception V3 provides computational efficiency and the VGG19 demonstrates its excellence in capturing minute variations in the MRI data, these networks form a reliable platform for efficient discrimination of MRI samples for reliable detection of onset of dementia, [12]. A wide variety of features can be gathered with great accuracy using Inception V3's mixed filter system. These models together will allow us to further enhance dementia detection accuracy and progress neuroimaging methods.

4 Proposed Method

4.1 Configuring and Training the CNN for the Proposed Approach

We used three well-known architectures—VGG19, Inception V3, and ResNet50—for CNN models to detect dementia. For better performance, transfer learning was applied to initialize these models with weights that had already been learned on the ImageNet dataset, [12]. In order to improve model interoperability, the MRI images were adjusted to match the input dimensions used during ImageNet training. The deep design and 3x3 filters of VGG19 allowed it to pick up intricate elements in the structure of the brain, [12]. Global average pooling eliminated overfitting while facilitating effective feature extraction via Inception V3's novel convolutional connections, [12]. Training efficiency was boosted by ResNet50's application of remnant connections, paving the way for easier convergence. We improved the pre-trained models capacity to identify dementia stages by fine-tuning them employing labeled MRI data, making them useful tools for identifying the minute abnormalities in the brain.

4.2 Block Diagram

The process logic of the proposed work is summarized using Figure 1.

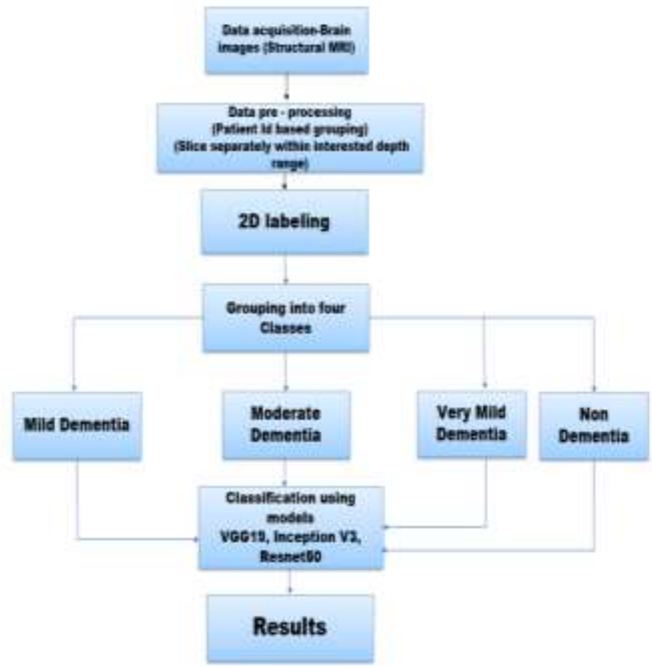

Fig. 1: Block diagram

In this research, we used three CNN models- VGG19, Inception V3, and ResNet50, to use transfer learning to the identification of different stages of dementia based on neuroimaging data. We were able to improve model performance and accelerate convergence for the dementia detection challenge by using pre-trained ImageNet weights. The models were able to effectively record crucial brain properties including structural shifts and changes in volume, which are important signs of dementia, because the MRI images had been pre-processed and shrunk to meet the necessary input dimensions.

After feature extraction, a dropout was applied to the data before it was sent through fully connected layers to prevent overfitting, [12]. A softmax layer was used for the final classification, giving each dementia form its probability. utilizing an accurate categorization approach, the dataset was split into four categories: non-dementia, mild dementia, moderate dementia, and very mild dementia. With the help of each model's unique strengths, pattern recognition in Inception V3, deeper learning in ResNet50, and broad feature selection in VGG19 the phases of dementia could be successfully classified, (Figure 2).

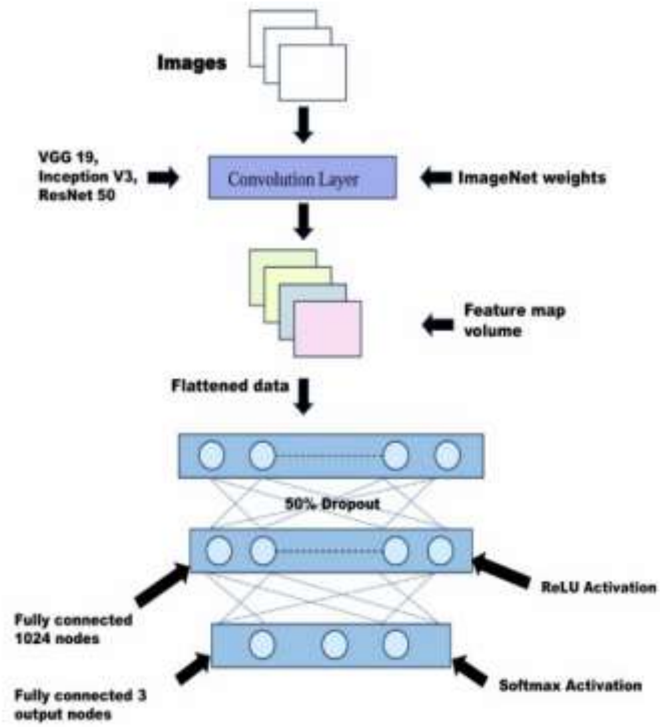

Fig. 2: Classification using CNN models

5 Results and Analysis

In this section we discuss the results and also include certain discussion. The results are in terms of the performance obtained from three different networks. Learning curves obtained during training and validation checks are shown. Further, confusion matrix is used to depict the cases of different stages of dementia.

5.1 VGG 19 Model

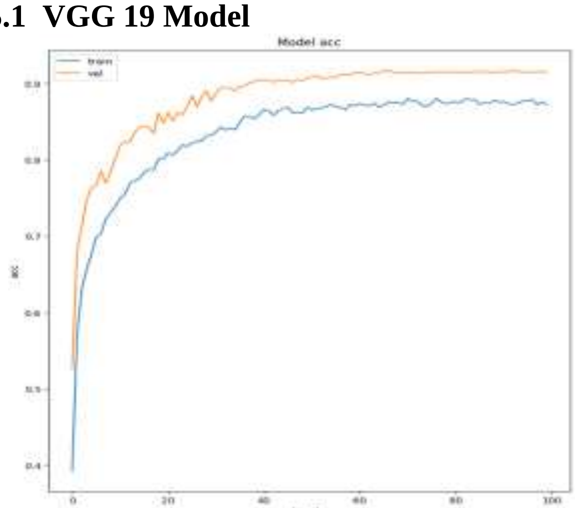

Fig. 3: VGG 19 Model accuracy

Figure 3 shows that the model achieved a validation accuracy of 91.50%.

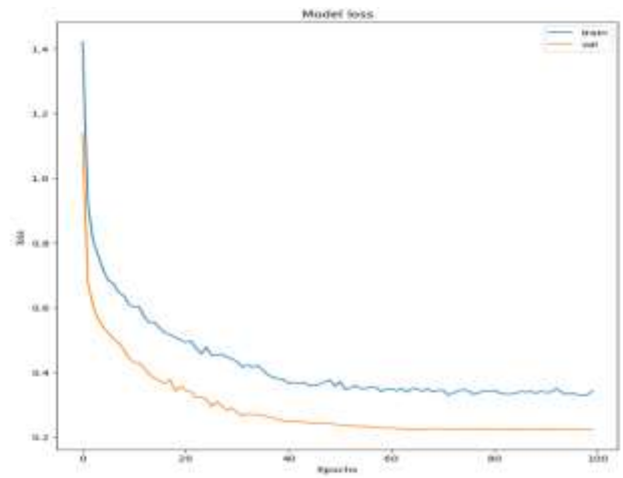

Fig. 4: VGG 19 MODEL LOSS

Figure 4 shows that the model achieved a validation loss of 21.99%.

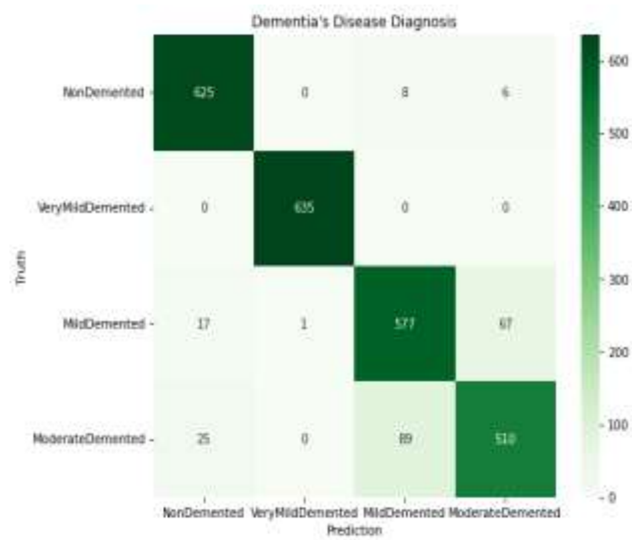

Fig. 5: VGG 19 Model confusion matrix

In Figure 5, the confusion matrix shows the true positive counts for dementia diagnosis across different stages: 625 for Non-Demented, 635 for Very Mild Demented, 577 for Mild Demented, and 510 for Moderate Demented.

5.2 ResNet-50 Model

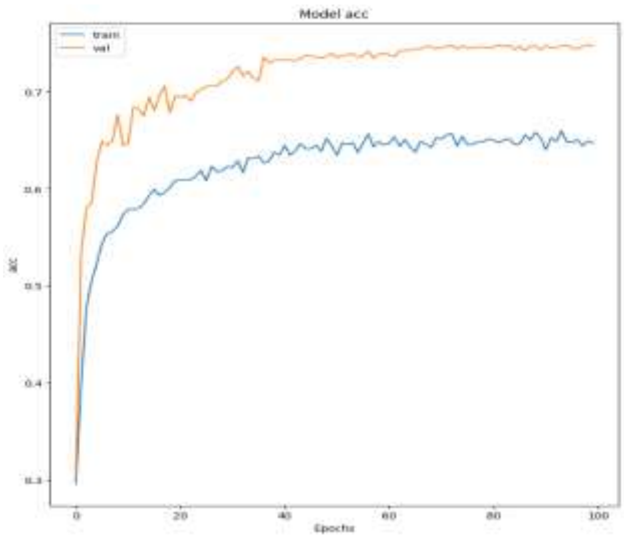

Fig. 6: ResNet-50 Model accuracy

Figure 6 shows that the model achieved a validation accuracy of 74.76%.

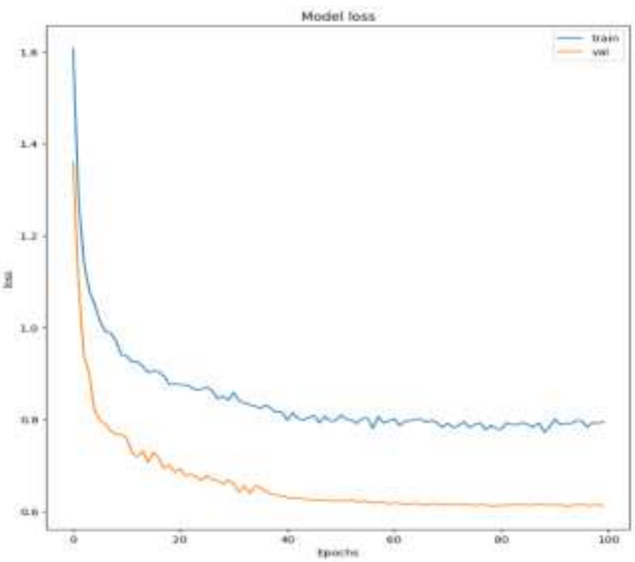

Fig. 7: ResNet-50 Model loss

Figure 7 shows that the model achieved a validation loss of 60%.

5.3 Inception V3 Model

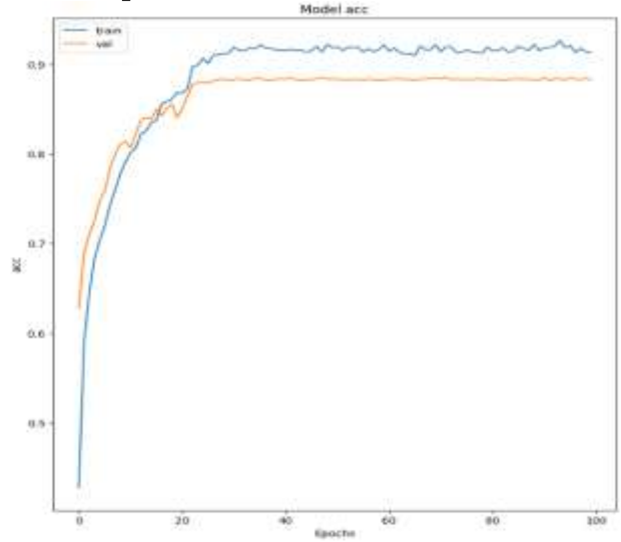

Fig. 8: Inception V3 Model accuracy

Figure 8 shows that the model achieved a validation accuracy of 88.18%.

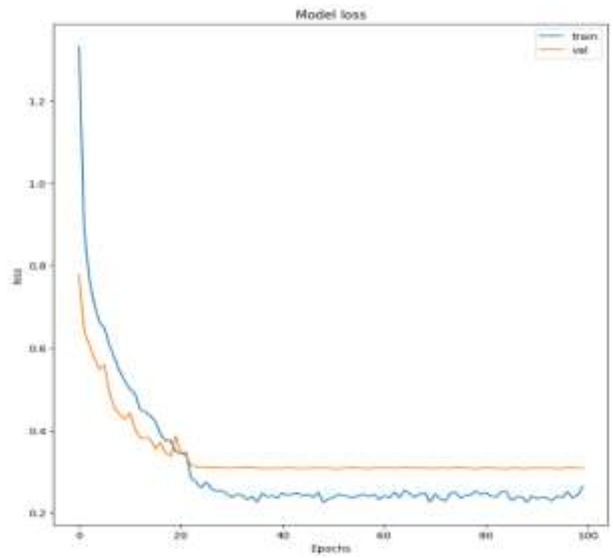

Fig. 9: Inception V3 Model loss

Figure 9 shows that the model achieved a validation loss of 32.70%.

Therefore, the highest accuracy, at 91.50%, was achieved with VGG19, underscoring its effectiveness in dementia detection.

5.4 Prediction of MRI Images

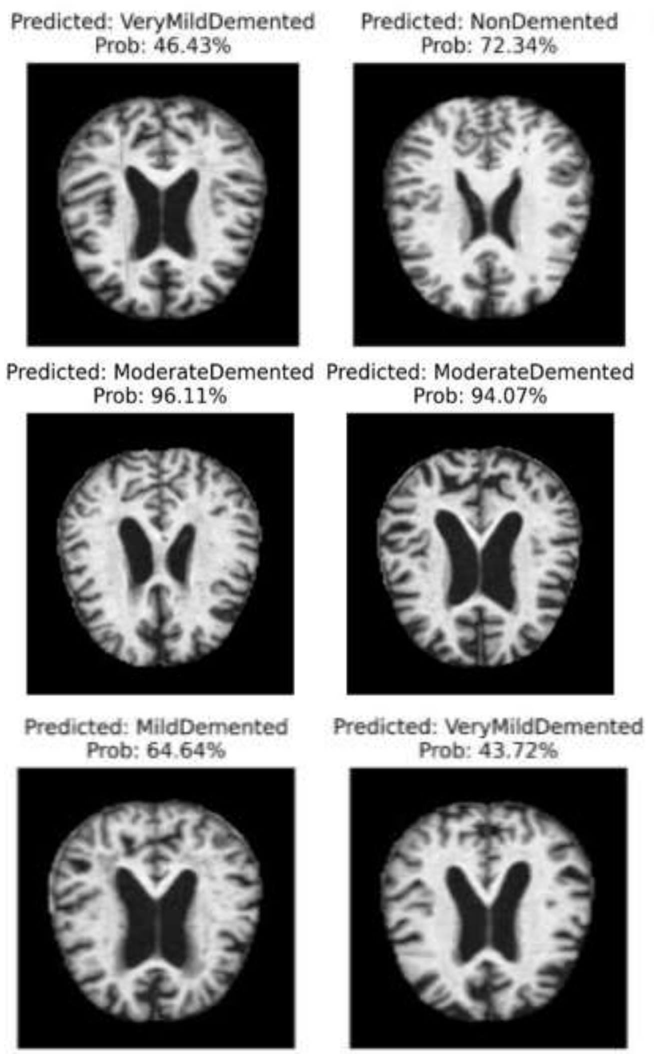

Fig. 10: Prediction of MRI images

Fig. 10 shows predicted images of different stages of dementia obtained from trained VGG19. There are cases of very mild dementia, mild dementia, moderate dementia and non-dementia cases. The MRI images collected from public database and labelled using expert knowledge are used to train the deep networks and obtain the predicted state of the dementia.

6 Conclusion

In conclusion, our study focused on the importance of identifying brain biomarkers from MRI scans in order to recognize early warning signs of dementia. We used three alternative models of deep neural networks, each with unique architectural strengths: VGG19, Inception V3, and ResNet50. After extensive pre-processing, we used transfer learning to separate the dataset into training, testing, and validation sets. We then initialized our models using ImageNet's pre-trained weights. With VGG19 scoring approximately 91.5% accuracy, Inception V3 scoring 87.19%, and ResNet50 scoring 74.76%, our results indicated good performance. These results highlight the benefit of pre-trained models in the classification of dementia and the future potential of neural networks for more precise and timely diagnosis. Our results support greater efforts to improve neurological illness diagnosis, especially as dementia advances through the use of neuroimaging datasets.

Although we classified genetic markers related to dementia based on our analysis of MRI visuals, future research will need access to OCT images of Dementia patients, which are not yet available.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the authors used Grammarly for language editing. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References:

[1] P. Saltz, S. Y. Lin, S. C. Cheng and D. Si, "Dementia Detection using Transformer-Based Deep Learning and Natural Language Processing Models," *2021 IEEE 9th International Conference on Healthcare Informatics (ICHI)*, Victoria, BC, Canada, 2021, pp. 509-510, doi: 10.1109/ICHI52183.2021.00094.

[2] Jiaquan Xu, Kenneth D Kochanek, Sherry L Murphy, and Betzaida Tejada-Vera. Deaths: final data for 2014. 2016.

[3] M. T. Abed, U. Fatema, S. A. Nabil, M. A. Alam and M. T. Reza, "Alzheimer's Disease Prediction Using Convolutional Neural Network Models Leveraging Pre-existing Architecture and Transfer Learning," *2020 Joint 9th International Conference on Informatics, Electronics & Vision (ICIEV) and 2020 4th International Conference on Imaging, Vision & Pattern Recognition (icIVPR)*, Kitakyushu,

Japan, 2020, pp. 1-6, doi: 10.1109/ICIEVicIVPR48672.2020.9306649

[4] R. Ribani and M. Marengoni, "A Survey of Transfer Learning for Convolutional Neural Networks," *2019 32nd SIBGRAPI Conference on Graphics, Patterns and Images Tutorials (SIBGRAPI-T)*, Rio de Janeiro, Brazil, 2019, pp. 47-57, doi: 10.1109/SIBGRAPI-T.2019.00010.

[5] Association Alzheimer's. 2015 alzheimer's disease facts and figures. Alzheimer's & dementia: the journal of the Alzheimer's Association, 11(3):332, 2015, [Online]. https://www.alz.org/media/documents/2015factsandfigures.pdf (Accessed Date: October 4, 2024).

[6] T. Subetha, R. Khilar and S. K. Sahoo, "An Early Prediction and Detection of Alzheimer's Disease: A Comparative Analysis on Various Assistive Technologies," *2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE)*, Keonjhar, India, 2020, pp. 1-5, doi: 10.1109/CISPSSE49931.2020.9212240

[7] R. Li, X. Wang, K. Lawler, S. Garg, Q. Bai, and J. Alty, "Applications of artificial intelligence to aid early detection of dementia: A scoping review on current capabilities and future directions," *Journal of Biomedical Informatics*, vol. 127, p. 104030, Mar. 2022, doi: 10.1016/j.jbi.2022.104030.

[8] M. Dyrba et al., "Improving 3D convolutional neural network comprehensibility via interactive visualization of relevance maps: evaluation in Alzheimer's disease," *Alzheimer's Research & Therapy*, vol. 13, no. 1, Nov. 2021, doi: 10.1186/s13195-021-00924-2.

[9] W. H. Land and J. D. Schaffer, "A Machine Intelligence Designed Bayesian Network Applied to Alzheimer's Detection Using Demographics and Speech Data," *Procedia Computer Science*, vol. 95, pp. 168–174, 2016, doi: https://doi.org/10.1016/j.procs.2016.09.308.

[10] G. Gosztolya, V. Vincze, L. Toth, M. Pakaski, J. Kalman, and I. Hoffman, "Identifying Mild Cognitive Impairment and mild Alzheimer's disease based on spontaneous speech using ASR and linguistic features," *Computer Speech & Language*, vol. 52, pp. 37-55, Aug. 2018, doi: 10.1016/j.csl.2018.07.007.

[11] A. Fathima, F. Taranum, M. Hijab, S. M. A. Hashmi, S. S. Ahmad and G. Gupta, "Classifying Alzheimer Disease using VGG19," *2024 11th International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 2024, pp. 1749-1753, doi: 10.23919/INDIACom61295.2024.10498804.

[12] Ian Goodfellow and Yoshua Bengio and Aaron Courville, "Deep Learning" [Online] https://www.deeplearningbook.org/ (Accessed Date: October 4, 2024).

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare.