International Journal of Biotech Trends and Technology
ISSN: 2249–0183 / https://doi.org/10.14445/22490183/IJBTT-V13I3P601

Volume 13 Issue 3, 1-6, Sep-Dec 2023

Original Article

Deep Learning Based Convolutional Geometric Group Network for Alzheimer Disease Prediction

Shiva Kumar Sriramulugari[1], Venkata Ashok K Gorantla[2]

Solution Architect, Texas, USA.

[1]Corresponding Author : shivakumar.sriramulugari@gmail.com

Received: 15 October 2023 Revised: 28 November 2023 Accepted: 14 December 2023 Published: 30 December 2023

Abstract *- Alzheimer's Disease (AD) is the most prevalent form of dementia among the elderly. A rising interest in applying machine learning to discover the origins of prevalent metabolic illnesses like Alzheimer's and Diabetes has emerged. The alarming annual rise in their frequency is really worrying. In Alzheimer's disease, brain cells deteriorate, leading to the illness's hallmark symptoms. As the global population ages, so too will the incidence of diseases that cause cognitive and physical decline. This will have far-reaching monetary, social, and economic consequences. Diagnosing Alzheimer's disease in its early stages is challenging. Treatments for Alzheimer's disease have a higher success rate and fewer side effects if given early on. As a result, in this study, an original Adam-optimized Convolutional geometric group network was built to detect dementia in its earliest stages. Accuracy is used to evaluate the success of Open Access Kaggle data used to make Alzheimer's disease predictions. Clinicians will be able to utilize the suggested categorization approach to identify these conditions in their patients correctly. The proposed approach has the potential to significantly improve yearly death rates associated with Alzheimer's disease by facilitating earlier detection. The suggested study improves upon prior efforts, as shown by a 95.7% average accuracy in validating AD test data. The test's accuracy is far greater than that of previous efforts.*

Keywords **-** *Alzheimer's Disease, prediction, Adam optimization, Convolutional geometric group network.*

1. Introduction

In 2020, the number of individuals affected by Alzheimer's disease was over 55 million, and it was projected to surpass 152 million by 2050 (Report, 2018). Alzheimer's disease is a prevalent neurodegenerative condition that results in cognitive dysfunction. This impairment may have an impact not just on the individuals affected but also on their loved ones and the broader community. Pathological alterations in the brain of individuals with Alzheimer's disease, such as aberrant cellular demise or synaptic impairment, start to manifest at least two decades prior to the manifestation of observable symptoms. While there is now no remedy for AD, it is nonetheless essential to have a precise AD diagnosis in order to guide treatment choices. Precise diagnosis of Alzheimer's disease is also crucial for the development of AD medications since the condition of the participants has to be assessed before, throughout, and after the conclusion of clinical trials to track the success of the therapy.

In recent times, due to the progress in deep learning algorithms and the rise of deep learning, several studies have been conducted to develop a prognostic instrument that uses neuroimaging to aid doctors in diagnosing AD. They may be used for visual or non-visual data. Although deep learning algorithms have been successful, they need the training of several parameters, which sometimes leads to overfitting and necessitates huge training datasets. In order to address the issue of overfitting, this research provides a methodology in this research that integrates deep learning with optimisation. Therefore, the primary contribution of this study is the development of a unique and efficient deep learning model, namely a Convolutional Geometric Group Network classifier, using the Kaggle dataset.

The rest of this manuscript is organized as follows: Section 2 presents the literature survey, and Section 3 presents the proposed methods and evaluation criteria. Results, including classification performance, will be reported in Section 4. Finally, 5 Conclusions and the future are discussed.

2. Related Work

Using the longitudinal dataset and a feature selection and extraction method, ML algorithms can reliably foretell the development of Alzheimer's disease. A brief summary of the various methods [1],[2] for assessing brain images with the aim of diagnosing brain diseases. This work responds to certain urgent concerns about using machine learning and deep learning to detect brain illnesses based on results from the examined literature. Findings from this study may be utilised to create improved diagnostic tools for various brain disorders. The goal of this effort is to incorporate recent discoveries on neurological disorders, including Alzheimer's, brain tumours, epilepsy, and Parkinson's, into existing machine learning and deep learning frameworks. The authors employ 22 brain disease databases that were used extensively throughout the assessments to develop the optimal diagnosis strategy.

To probe AD data analysis, [3] uses deep convolutional autoencoders. Cognitive symptoms and the underlying neurodegenerative process in a certain patient may be identified by data-driven deconstruction of MRI images. Next, need to calculate the effect of each coordinate of the autoencoder manifold on the brain and utilise regression and classification analysis to examine the distribution of the recovered features across a wide variety of configurations. The diagnostic accuracy of employing MMSE or ADAS11 scores in conjunction with imaging-derived markers for AD may exceed 80%.

Binary categorization is achieved by using a deep neural network with connected layers [4], [5]. Several activation procedures are utilized to unveil the various layers. The best-performing model is chosen once k-fold validation has been performed. The Lancet Commission found that 35% of Alzheimer's risk factors are under the control of individuals. Lack of formal education, impaired hearing, obesity, depression, diabetes, insufficient exercise, smoking, and social isolation all contribute to an increased risk. No matter where you are in life, it's advisable to get rid of these items. Studies [6] have shown that early intervention and treatment of modifiable risk factors may prevent or postpone the onset of Alzheimer's disease in 30% of cases [7]. To calculate one's risk of acquiring Alzheimer's disease based on known risk factors, the Lifestyle for Brain Health (LIBRA) index [8],[9],[10],[11] is recommended by the Innovative Midlife Intervention for Alzheimer's Deterrence (In-MINDD) research [12],[13]. Dementia interventions fall into one of three broad categories outlined by the National Academy of Medicine: cognitive training, hypertension therapy, and increased physical activity [13], [14]. Most cases of dementia are due to Alzheimer's disease (AD). VaD is the second most common form of Alzheimer's disease after Alzheimer's with Lewy bodies. Causes of Alzheimer's disease might include head injuries, infections, and excessive alcohol consumption. Alzheimer's disease and vascular dementia often co-exist in the brain and share some modifiable risk factors; therefore, it may be possible to prevent Alzheimer's disease by addressing modifiable vascular risk factors. [15] Predicted cognitive performance from neuropsychological and demographic data using four different models (support vector machine, decision tree, neural network, and naive-Bayes). When missing values were averaged in place, Naive Bayes did very well. The ADNI trial data is used using ten-fold cross-validation to show the high correlation between genetic, imaging, biomarker, and neuropsychological outcomes. Magnetic resonance imaging scans from the OASIS dataset [16], [17] are evaluated on a voxel-by-voxel basis.

3. Proposed Methodology

In this section, the author will examine the practical use of the proposed methodology. The findings of this study indicate the potential for an alternative methodology in the prediction of dementia. For a schematic illustration of the recommended setup, see Figure 1.

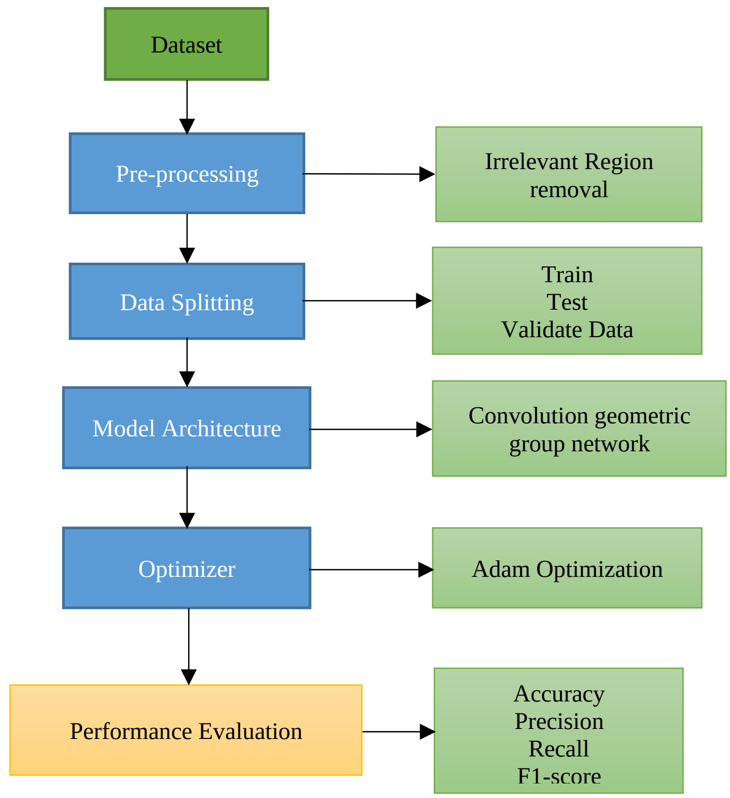

Fig. 1 Schematic representation of the suggested methodology

3.1. Data Source

The dataset was obtained from https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images

"Number of images in train folder:
Class MildDemented: 717 images
Class ModerateDemented: 52 images
Class NonDemented: 2560 images
Class VeryMildDemented: 1792 images

Number of images in the test folder:
Class MildDemented: 179 images
Class ModerateDemented: 12 images
Class NonDemented: 640 images
Class VeryMildDemented: 448 images"

3.2 Data Processing

Noise reduction, background and work area reduction, labeling, resampling, altering contrast, artifact removal, filtering, and manual correction are all commonplace in the preprocessing phase. Alzheimer's brain pictures contain a lot of information, and the size was also high, which will increase the working time and hinder the performance of the suggested algorithms. To get around these constraints, preprocessing has become an important stage. Reducing background is a useful technique for finding dementia. Hence, unwanted areas are eliminated before categorization can proceed normally.

The pixel value of the input pixels in the surrounding bins was pointed. A linear combination may be represented by the equation:

$$I(bg+ci) = bI(g) + cI(i) \tag{1}$$

In this case, use the cropping method is used to determine the unwanted area, which is a quantization measure.

$$DII = \frac{Q_{\text{Processed}}}{Q_{\text{Original}}} \tag{2}$$

$P_{\text{processes}}$ and P_{original} are the cropped image ratio between the treated and unaltered pictures. The unwanted area of an image area is determined by the equation:

$$d = \frac{i-c}{i+c} \tag{3}$$

Foreground and background cropped levels are often represented by "h" and "c," respectively.

3.3. Disease Prediction

The Convolutional Geometric Group Network is formed by the interconnection of many dense blocks. The term "dense block" denotes a grouping of layers that exhibit interconnections with each previous level within the structure. Each thick block is composed of four distinct layers. Batch normalization is a widely used method in the field of deep learning that serves to normalize the activations of a neural network by the manipulation and scale of the inputs to each layer. The purpose of this strategy is to mitigate the issue of internal covariate shift, which refers to the change in distribution inside a model during training. The Rectified Linear Unit (ReLU) activation function is a frequently used non-linear activation function for deep learning models. The term is described as the greater value between zero and the given input. The topic of discussion pertains to the functioning of a 3x3 convolution. Additionally, there was a dropout layer included. The transition layer, which is positioned between two densely linked blocks, is responsible for executing the down-sampling process. Batch normalization is a fundamental component that is included in the architectural framework.
An Adam-optimized convolutional geometric network model is employed for the goal of illness diagnosis and classification.

1. Initialize pixel points
2. Set up iteration
3. Utilize the present mini-batch for computation purposes $\mathrm{d^w}, \mathrm{d^b}$
4. $\mathrm{t} = \mathrm{t} + 1$
5. $Vd^w = \beta 1 V^w + (1-\beta 1)d^w, Vd^b = \beta 1 V^b + (1-\beta 1)d^b$
6. $Sd^w = \beta 2 Sd^w + (1-\beta 2)d^{w2}, Sd^b = \beta 2 Sd^b + (1-\beta 2)d^b$
7. Implementation of the bias correction strategy
8. $\mathrm{Vd^w}_{\text{corrected}} = \mathrm{Vd^w}/(1-\beta 1^{\mathrm{t}}), \mathrm{Vd^b_{corrected}} = \mathrm{Vd^b}/(1-\beta 1^{\mathrm{t}})$
9. $\mathrm{Sd^w}_{\text{corrected}} = \mathrm{Sd^w}/(1-\beta 2^{\mathrm{t}}), \mathrm{Sd^b}_{\text{corrected}} = \mathrm{Sd^b}/(1-\beta 2^{\mathrm{t}})$
10. Update parameters
11. $\mathrm{w_t} = \mathrm{w_{t-1}} - \alpha\left(\mathrm{Vd^w}_{\text{corrected}} / \sqrt{c}\mathrm{Sd^w}_{\text{corrected}} + \varepsilon\right)$
12. $\mathrm{b_t} = \mathrm{b_{t-1}} - \alpha\left(\mathrm{Vd^b}_{\text{corrected}} / \sqrt{c}\mathrm{Sd^b_{corrected}} + \varepsilon\right)$
13. Data Return $\mathrm{w_t}, \mathrm{b_t}$

The Adam optimizer requires the inclusion of certain parameters.

- α : Step size of (0.0001)"

The classifier was trained once the parameters were set and input was provided. Next, the input is sent to the first convolution layer, Conv2D, which generates a feature map by extracting useful features from the input. The first dense block, comprising five convolution layers, receives this feature map and processes it further. Each dense block's convolutional layers include a dropout layer, a 3x3 Conv2D layer, a batch normalization layer, and a ReLU activation layer. Four separate feature maps are generated by the first convolutional layer inside the dense block and combined with the input. The second convolutional layer is then included to produce four more feature maps that are connected to the first feature maps in various ways. All of the compact building blocks use concatenation. It is not possible to concatenate feature maps of different sizes. Hence, it is necessary for the convolution layers inside a dense block to generate feature maps with the same dimensions.

The output of five convolutional layers is concatenated to produce the output of a single dense block. As a result, each dense block has twenty feature maps, five of which were generated by the convolutional layers. Situated between two neighbouring dense blocks, the transition layer uses convolution and average pooling to adjust the feature map's size. A 1x1 convolution is utilised in the transition layer, followed by an average pooling operation on a 2x2 matrix. The under-consideration architectural layout has a total of five dense blocks connected by four transition levels. Each dense block, save the final one, is followed by a transition layer. After the final dense layer, a global average pooling layer and a softmax classifier are used. Alzheimer's illness may now be properly categorized.

4. Results and Discussion

This study analysed the Kaggle dataset of annotated brain images (Figure 2). Classes of Alzheimer's disease were evaluated using testing sets often used to evaluate performance in a Python setting.

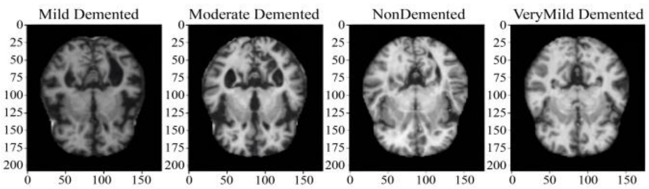

Fig. 2 Sample images from the dataset

The sample input from the dataset is illustrated in Figure 2

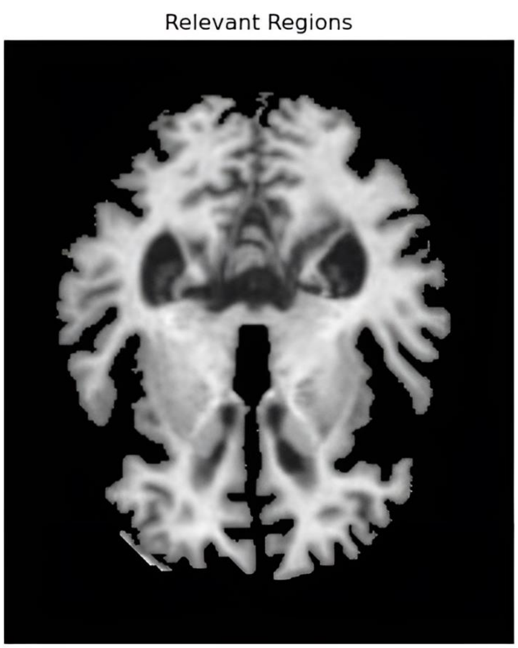

Fig. 3 Extraction of relevant regions

The relevant regions are extracted (see Figure 3) using the preprocessing strategy.

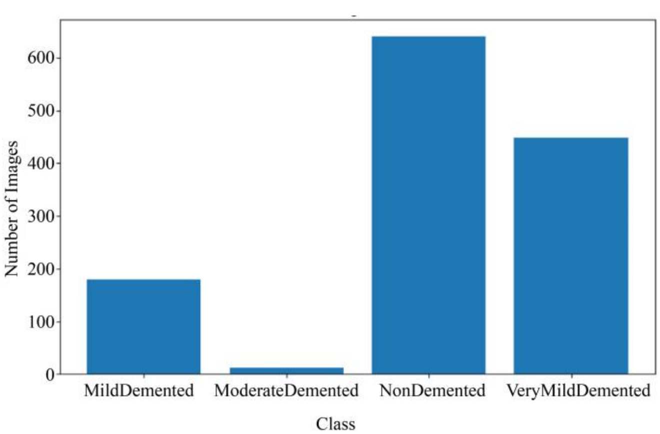

Fig. 4 Simulated output

Figure 4 shows the total output after classification. Figure 4 clearly shows the many types of dementia.

Table 1. Performance metrics for evaluation

"Metrics"	"Description"	"Formula"
"Accuracy"	"The percentage of samples with accurate forecasts."	"Accuracy = $\frac{TP+TN}{TP+FP+TN+FN}$"

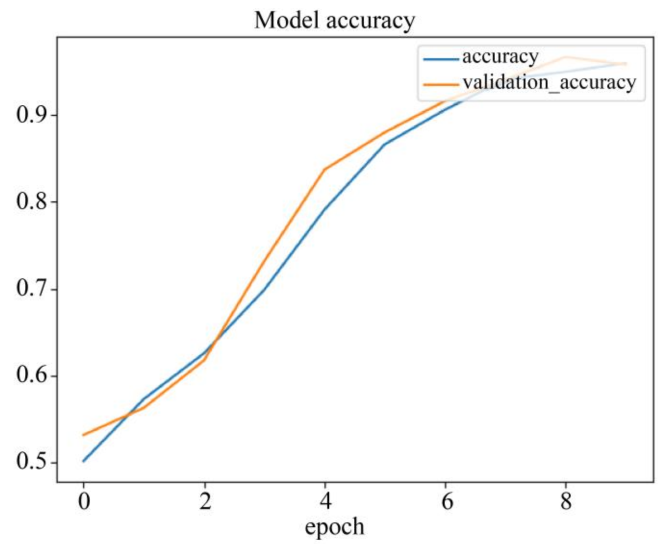

Fig. 5 Evaluation of the validation accuracy

According to the data shown in Figure 5, The validation accuracy is often higher than the training accuracy due to the disparity between the familiarity of the model with the training data and its exposure to the validation data, which consists of novel data points showing the efficiency of the suggested model.

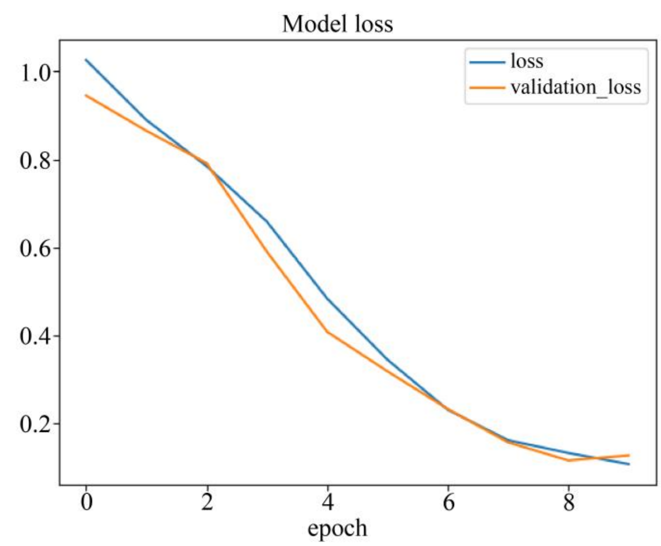

Fig. 6 Evaluation of the validation loss

The quantification of data loss inside an epoch may be determined by a quantitative evaluation of the loss function, calculated for every individual data item included within the epoch. An iterative curve is generated, whereby a small portion of the dataset is discarded at each iteration. Based on the created curve, the training and testing losses of the proposed classifier were seen to be situated towards the lower end of the spectrum.

A comparison was made with existing classification methods [18], focusing on performance criteria for classification to empirically assess the effectiveness of the proposed classification approach.

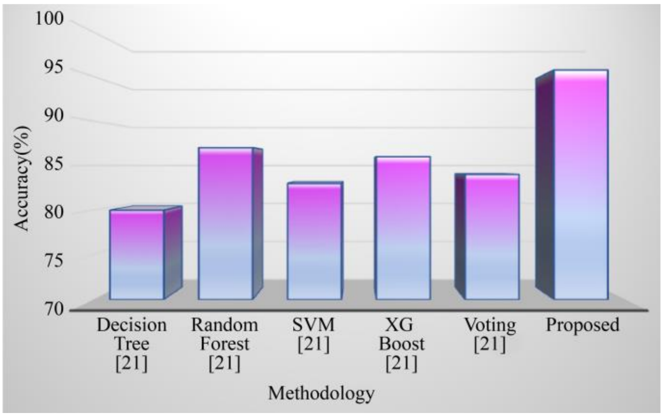

Fig. 7 Comparative performance analysis

In Figure 7, a visual representation of the diagnostic potential of the proposed system is seen. The suggested mechanism's range has extremely good accuracy (95.7%), especially when compared to other current methods. The suggested classification approach achieved better results on a widely used benchmark dataset than the state-of-the-art method. The results appear to indicate that the proposed strategy outperforms the existing mechanisms.

5. Conclusion

Alzheimer's disease is a serious health problem, and preventing it, treating it early, and diagnosing it correctly are all more important than merely trying to discover a cure. According to the review of prior work, various attempts have been made to use deep learning algorithms for Alzheimer's disease diagnosis. Nonetheless, a major obstacle remains the discovery of relevant traits that may successfully identify Alzheimer's at an early stage. This research presents a novel and improved convolutional geometric group network model for image classification of Alzheimer's disease in the brain. The proposed model had behaviour similar to a traditional neural network in the dense layer, leading to an impressively high accuracy score of 95.7% when classifying illnesses. Upcoming studies will concentrate on extracting and analysing fresh traits that are more likely to aid in diagnosing Alzheimer's disease. Efforts will also be made to remove superfluous features from existing feature sets in an attempt to improve the accuracy of detection strategies. Our model may become more accurate at distinguishing between those with Alzheimer's disease and those without the illness if the author includes factors like the Mini-Mental State Examination (MMSE) and degree of education.

References

[1] R. Sivakani, and Gufran Ahmad Ansari, “Machine Learning Framework for Implementing Alzheimer’s Disease,” *2020 International Conference on Communication and Signal Processing (ICCSP)*, Chennai, India, pp. 588-592, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Protima Khan et al., “Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances,” *IEEE Access*, vol. 9, pp. 37622-37655, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Francisco J. Martinez-Murcia et al., “Studying the Manifold Structure of Alzheimer's Disease: A Deep Learning Approach Using Convolutional Autoencoders,” *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 1, pp. 17-26, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[4] Rukesh Prajapati, Uttam Khatri, and Goo Rak Kwon, “An Efficient Deep Neural Network Binary Classifier for Alzheimer’s Disease Classification,” *2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, Jeju Island, Korea (South), pp. 231-234, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[5] Hadeer A. Helaly, Mahmoud Badawy, and Amira Y. Haikal, “Deep Learning Approach for Early Detection of Alzheimer’s Disease,” *Cognitive Computation*, vol. 14, pp. 1711-1727, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] MD Kristine Yaffe, “Modifiable Risk Factors and Prevention of Dementia: What is the Latest Evidence?,” *JAMA Internal Medicine*, vol. 178, no. 2, pp. 281-282, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[7] Gill Livingston et al., “Dementia Prevention, Intervention, and Care,” *The Lancet*, vol. 390, no. 10113, pp. 2673-2734, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[8] David W. Coon, and Abigail Gómez-Morales, “Modifiable Risk Factors for Brain Health and Dementia and Opportunities for Intervention: A Brief Review,” *Clinical Gerontologist*, vol. 46, pp. 143-154, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Kay Deckers et al., “Target Risk Factors for Dementia Prevention: A Systematic Review and Delphi Consensus Study on the Evidence from Observational Studies,” *International Journal of Geriatric Psychiatry*, vol. 30, no. 3, pp. 234-246, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[10] Olga J.G. Schiepers et al., "Lifestyle for Brain Health (LIBRA): A New Model for Dementia Prevention," *International Journal of Geriatric Psychiatry*, vol. 33, no. 1, pp. 167-175, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[11] J.B. Vos Stephanie et al., "Modifiable Risk Factors for Prevention of Dementia in Midlife, Late Life and the Oldest-Old: Validation of the LIBRA Index," *Journal of Alzheimer's Disease*, vol. 58, no. 2, pp. 537-547, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[12] Catherine A O'Donnell et al., "Promoting Modifiable Risk Factors for Dementia: Is there a Role for General Practice?," *British Journal of General Practice*, vol. 65, no. 640, pp. 567-568, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[13] Alan I. Leshner et al., *Preventing Cognitive Decline and Dementia: A Way Forward*, National Academies Press, pp. 1-161, 2017. [Google Scholar] [Publisher Link]

[14] Sana Tariq, and Philip A. Barber, "Dementia Risk and Prevention by Targeting Modifiable Vascular Risk Factors," *Journal of Neurochemistry*, vol. 144, no. 5, pp. 565-581, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[15] Jennifer A. Williams et al., "Machine Learning Techniques for Diagnostic Differentiation of Mild Cognitive Impairment and Dementia," *Workshops at the Twenty-Seventh AAAI Conference on Artificial Intelligence*, pp. 71-76, 2013. [Google Scholar] [Publisher Link]

[16] Chih-Lin Chi, Wonsuk Oh, and Soo Borson, "Feasibility Study of a Machine Learning Approach to Predict Dementia Progression," *2015 International Conference on Healthcare Informatics*, Dallas, TX, USA, pp. 450-550, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[17] Darya Chyzhyk, and Alexandre Savio, "Feature Extraction from Structural MRI Images Based on VBM: Data from OASIS Database," *University of the Basque Country, Internal Research Publication: Basque*, Spain, 2010. [Google Scholar] [Publisher Link]

[18] C. Kavitha et al., "Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models," *Frontiers in Public Health*, vol. 10, pp. 1-13, 2022. [CrossRef] [Google Scholar] [Publisher Link]