Detection of Stage of Alzheimer's Disease Using MRI

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***Abstract*— The use of magnetic resonance imaging (MRI) scans for the identification and categorization of Alzheimer's disease stages is thoroughly examined in this study. Effective intervention and therapy depend on a prompt and correct diagnosis. This study uses modern image analysis techniques to extract significant characteristics from MRI scans and various image filters to segment the image better, concentrating on structural and functional anomalies linked with Alzheimer's progression.**

The dataset consists of MRI scans from people with Alzheimer's disease at different stages, which have been classified according to clinical evaluations. Deep neural networks and other machine learning algorithms are used in the research to identify minute patterns that point to the advancement of the disease. Our accuracy has increased thanks to the HeimerNet CNN architecture that we have adopted. Techniques for feature selection are used to lower dimensionality and improve interpretability of the model. The suggested method seeks to both categorize the phases of Alzheimer's disease and further knowledge of the underlying neuroanatomical alterations connected to each stage.

To evaluate the created model's generalization abilities, it is validated on a separate dataset. The model's effectiveness in correctly identifying the phases of Alzheimer's disease is demonstrated by the results, which also highlight the model's potential as a useful tool for physicians in early diagnosis and individualized treatment planning. The study also explores how interpretable the model's predictions are, providing insight into the particular imaging biomarkers that are involved in the categorization.

The results of this study shed light on the combination of sophisticated image analysis and machine learning methods for MRI scan-based Alzheimer's disease staging and diagnosis. The suggested approach has the potential to improve clinical decision-making and support further attempts to create efficient therapies for Alzheimer's patients.

***Keywords*— HimerNet, Machine Learning, Deep Learning, MRI, Alzhemeir's disease, Image analysis, Feature selection Biomarkers,Neuroanatomical changes**

I. Introduction

This paper explores the early-stage detection of Alzheimer's disease, which uses Machine Learning algorithms and we have improvised on a new CNN model HeimerNet for tackling the issue. Alzheimer's disease, characterized by its progressive neurodegenerative nature, presents a substantial public health challenge, making timely intervention necessary for improved patient outcomes. Recognizing the significance of early detection, machine learning, with its adeptness in deciphering intricate patterns within medical imaging data, emerges as a promising tool for enhancing diagnostic precision.

The introduction lays a solid foundation for our investigation by delineating the scope, objectives, and significance of our research. Providing a succinct overview of Alzheimer's disease, we underscore the critical importance of early detection in the context of this debilitating condition. Furthermore, we highlight the limitations inherent in traditional diagnostic approaches and introduce the transformative potential of machine learning models in reshaping the diagnostic landscape. The introduction serves as a precursor to a detailed discussion, delving into recent studies, methodologies, and advancements in the field.

As we navigate through the subsequent sections, our aim is to unravel the potential of machine learning in the early detection of Alzheimer's disease. By examining recent studies, exploring methodologies, and assessing advancements in neuroimaging and machine learning, we endeavor to contribute valuable insights to the evolving discourse on the role of machine literacy in addressing the challenges posed by Alzheimer's disease. This paper, therefore, stands as a critical exploration into the integration of advanced technologies for early diagnosis, offering a glimpse into the transformative possibilities that machine learning models bring to the forefront of Alzheimer's research and clinical practice.

II. Literature survey

Improved Alzheimer's Disease Detection by MRI Using Multimodal Machine Learning Algorithms

The paper discusses an enhanced approach for Alzheimer's disease detection using multimodal machine learning applied to MRI data. This method combines information from different MRI modalities, utilizing machine learning algorithms for feature extraction and subsequent classification of patients into Alzheimer's and non-Alzheimer's groups. Multimodal machine learning is highlighted for its potential to improve diagnostic accuracy compared to single-modal approaches, facilitating early detection and timely intervention. The non-invasive nature of MRI contributes to patient safety and comfort, providing quantitative data for precise analysis. However, the paper acknowledges that the performance of machine learning models depends on the quality and quantity of available MRI data, with limited data potentially impacting model robustness. Challenges include the computational intensity of machine learning algorithms, the interpretability issues associated with their "black-box" nature, and the necessity for further clinical validation to ensure real-world effectiveness and generalizability.

Brain Imaging in the study of Alzheimer's disease

The paper discusses various brain imaging techniques employed in Alzheimer's Disease (AD) research, encompassing structural methods like MRI for visualizing brain structure and atrophy, and functional techniques such as PET and SPECT for assessing brain function and detecting abnormal protein deposits. It emphasizes MRI's potential as a preferred neuroimaging tool for AD due to its precise measurement capabilities. Brain imaging enables early detection of AD-related changes, facilitating diagnosis at the disease's onset. Moreover, these techniques aid in monitoring disease progression, identifying biomarkers like amyloid plaques and tau protein tangles crucial for diagnosis and research, and providing valuable insights into AD pathophysiology for potential treatment development. However, limitations include the technique's limited diagnostic precision, expense and accessibility issues for advanced methods like PET scans, radiation exposure risks, the complexity of result interpretation requiring expertise, and the inability to directly inform disease-modifying treatments.

Early Detection of Alzheimer’s Disease Using MRI: A Novel Approach Combining Convolutional Neural Networks and Ensemble Learning

The paper proposes an innovative method for the early detection of Alzheimer's disease using MRI, combining Convolutional Neural Networks (CNNs) with ensemble learning. This approach utilizes multi-modal MRI data, including DTI or fMRI data, to enhance Alzheimer's disease detection. Ensemble learning integrates multiple MRI slices or CNNs, improving classification accuracy and stability. Early detection is emphasized as crucial for effective management, and the deep learning approach enhances the capability to identify Alzheimer's disease in its early stages. The use of multi-modal MRI data and deep learning techniques allows for more comprehensive insights into the disease, contributing to improved classification accuracy. However, challenges include the dependence on large and diverse datasets for the success of deep learning models, the computational complexity and resource requirements of models like CNNs, the interpretability issues associated with the "black-box" nature of deep learning models, and the need for further clinical validation to confirm real-world utility and accuracy.

Multimodal deep learning models for early detection of Alzheimer’s disease stage

The paper explores the application of multimodal deep learning models for the early detection of Alzheimer's disease stages by combining data from diverse sources, such as MRI scans, cognitive assessments, and genetic data. Researchers employ feature fusion techniques to enhance prediction accuracy and leverage large datasets for model training. The use of multiple modalities aims to provide a holistic understanding of disease progression, facilitating improved accuracy and timely interventions. However, challenges include integrating data from varied sources due to differences in formats, quality, and availability. Interpretability issues may arise with some multimodal models, hindering the understanding of prediction factors. Ethical concerns surrounding patient privacy and the handling of sensitive medical data also need to be addressed. Additionally, the generalizability of models to different patient populations or datasets is acknowledged as a potential limitation. Despite these challenges, the focus on early detection and a comprehensive approach makes multimodal deep learning promising for advancing Alzheimer's disease research.

Mutliresolutional ensemble PartialNet for Alzheimer detection using magnetic resonance imaging data.

The paper introduces an ensemble deep learning framework, termed Multi-Resolutional Ensemble PartialNet, for Alzheimer's disease (AD) detection using magnetic resonance imaging (MRI) data. Unlike traditional methods, this approach claims to offer improved predictive performance for AD diagnosis. By integrating MRI data, the method enables non-invasive and precise detection of structural and functional brain tissue abnormalities. The ensemble learning technique combines multiple models, potentially reducing overfitting and enhancing accuracy. Deep learning is utilized to automatically learn complex patterns from MRI data, a crucial aspect for effective AD detection. However, challenges include potential limitations in the method's effectiveness due to the availability and quality of MRI datasets. The substantial computational resources required by deep learning methods may also constrain their applicability in resource-constrained settings. Additionally, interpretability issues associated with deep learning models and potential challenges in generalizing the model to diverse populations or datasets are acknowledged but not explicitly addressed in the paper.

Volumetric Convolutional Neural Network for Alzheimer Detection

The paper introduces a volumetric Convolutional Neural Network (CNN) approach for Alzheimer's disease (AD) detection, specifically focusing on classifying AD patients from non-AD individuals using three-dimensional brain image data, such as MRI scans. The volumetric CNN is highlighted for its potential to achieve highly accurate AD classification by learning complex features from neuroimaging data. The automated diagnosis capability of deep learning models is emphasized, facilitating early intervention and treatment planning. Spatial visualization techniques in some CNN-based approaches aid in understanding the brain regions contributing to AD classification. However, challenges include the model's reliance on the availability of high-quality neuroimaging datasets, potential computational intensity requiring substantial resources, interpretability issues associated with deep learning models, and the need to assess the model's generalization to diverse populations and datasets for broader applicability.

A multi-modal, multi-atlas-based approach for Alzheimer detection via machine learning

The paper employs a multi-modal, multi-atlas-based approach for Alzheimer's detection, integrating data from different sources such as structural MRI and neuroanatomical measures. Using multiple atlases for spatial alignment, the method applies machine learning techniques, like Random Forest classifiers, to analyze the multi-modal data and make predictions. The integration of multi-modal data is expected to enhance AD detection accuracy, providing a more comprehensive understanding of brain characteristics. The use of multiple atlases improves spatial precision, facilitating detailed analysis of AD-affected brain regions and enabling early detection for timely intervention. The method's potential generalizability to diverse datasets and populations increases its applicability. However, challenges include increased data complexity requiring extensive preprocessing, potential demands on computational resources, interpretability issues with complex models, and reliance on the availability of high-quality multi-modal datasets for effective implementation.

An efficient multi class Alzheimer detection using hybrid equilibrium optimizer with capsule auto encoder.

The paper presents an efficient multi-class Alzheimer's detection method using a Hybrid Equilibrium Optimizer with Capsule Auto Encoder (HEOCAE). This approach is tailored for categorizing Alzheimer's disease into different stages, employing innovative techniques like skull stripping and smoothing to enhance the processing of brain MRI images. The incorporation of a capsule auto encoder and equilibrium optimizer contributes to more accurate detection. However, the paper may lack extensive discussion on the validation and real-world application of the proposed method, posing potential reliability concerns. The hybrid approach's computational intensity could limit scalability for large-scale applications, and the method's reliance on brain MRI images may not be universally applicable. Additionally, the sensitivity of the hybrid equilibrium optimizer to parameter settings requires careful tuning for optimal performance.

Alzheimer Disease Detection Empowered with Transfer Learning

The research employs transfer learning, a technique leveraging knowledge from one domain to enhance the performance of a model in Alzheimer's disease detection, focusing on multi-class classification of different disease stages. Brain Medical Resonance Imaging (MRI) data is utilized for detection. Transfer learning is highlighted for its ability to significantly improve model performance, particularly with limited data sets common in medical imaging tasks. It efficiently utilizes existing data by transferring knowledge from related tasks or datasets. However, challenges include potential limitations based on the domain from which knowledge is transferred, especially if it is not closely related to Alzheimer's disease. Proper fine-tuning of pre-trained models for specific tasks can be complex and time-consuming, and the model's effectiveness is dependent on the quality of the MRI data, with potential performance issues arising from noisy or incomplete data.

Deep transfer learning for alzheimer neurological disorder detection

The paper employs Convolutional Neural Networks (CNNs) for deep transfer learning in the classification of Alzheimer's disease. This approach utilizes pre-trained models and fine-tuning for the specific task of Alzheimer's detection, leading to improved classification accuracy by leveraging features learned from other tasks. Transfer learning's reduced data dependency is advantageous, particularly with limited medical imaging datasets. However, challenges include the dependence of deep transfer learning models on the quality and quantity of training data, where limited or noisy data may impact accuracy. The interpretability of deep learning models is hindered by their often considered "black-box" nature, making it challenging to understand the specific features contributing to classification decisions. Additionally, the computational expense and resource requirements for training and inference pose challenges in terms of model complexity.

III. Methodology

1. Data Acquisition:

The first step in developing heimerNET involves acquiring a diverse and representative dataset for training and evaluation. This dataset should encompass a range of images relevant to the target application, ensuring the model generalizes well to unseen data. Sources may include publicly available datasets, proprietary databases, or a combination of both. Attention to ethical considerations and data privacy is paramount. We have also applied various filters including gaussian, histogram equalization, and image trained on histogram equalization followed by otsu’s method followed by unsharp filter to preserve medical features

2. Data Preprocessing:

Once the dataset is assembled, preprocessing steps are undertaken to enhance the quality and compatibility of the data. This includes tasks such as resizing images to a consistent resolution, normalizing pixel values, and addressing class imbalances. Data augmentation techniques, such as rotation, flipping, and scaling, may also be employed to augment the dataset and improve the model's robustness.

3. Model Development:

The heimerNET architecture is organized into four main parts, each with a varying number of blocks, providing a hierarchical feature extraction mechanism. The first part of heimerNET comprises two blocks. Each block consists of three convolutional layers, followed by three batch normalization layers and ReLU activation functions. The convolutional layers are responsible for capturing spatial hierarchies within the input data, while batch normalization ensures stable training and accelerates convergence.

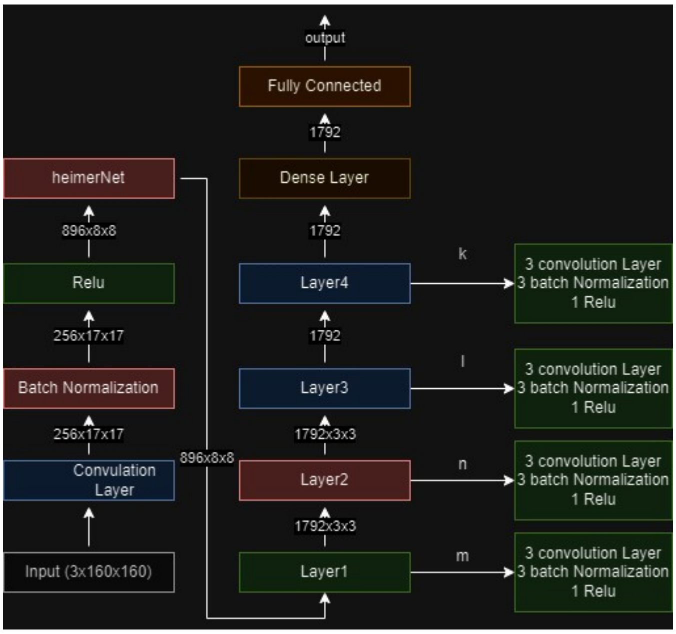
The second part of heimerNET is characterized by three blocks, each mirroring the structure of the first part. This expansion allows the model to learn more complex features and patterns as it progresses through deeper layers. The increased depth enhances the network's capacity to capture intricate details within the input images.

Part 3 of heimerNET consists of two blocks, maintaining consistency with the preceding parts. This structure promotes a balanced learning process, preventing overfitting and ensuring the effective extraction of relevant features.

The fourth and final part of heimerNET features four blocks, amplifying the network's depth and capacity to extract high-level abstract representations. Each block follows the established pattern of three convolutional layers, three batch normalization layers, and ReLU activation functions.

Within each block of heimerNET, the convolutional layers play a pivotal role in convolving input data, capturing spatial hierarchies, and learning complex features. Batch normalization stabilizes and normalizes intermediate feature maps, mitigating internal covariate shift and promoting faster convergence during training. The ReLU activation function introduces non-linearity, enabling the network to learn intricate patterns and representations.

heimerNET is trained using standard backpropagation and optimization techniques, such as stochastic gradient descent (SGD) or variants like Adam. Adequate regularization mechanisms, such as dropout or weight decay, may be incorporated to prevent overfitting and enhance generalization.



heimerNet Architecture

4. Training the Model:

The model is trained using the preprocessed dataset, and training involves iteratively presenting batches of images to the network. Backpropagation is employed to update the model's weights, minimizing the selected loss function. Hyperparameters, such as learning rate and batch size, are tuned to optimize convergence and prevent overfitting. Validation datasets are used to monitor model performance during training and avoid overfitting.

5. Model Evaluation:

After training, heimerNET is evaluated on a separate test dataset to assess its generalization performance. Evaluation metrics, such as accuracy, precision, recall, and F1 score, are computed to quantify the model's effectiveness. Additionally, visualization tools, such as confusion matrices, assist in understanding the model's strengths and weaknesses across different classes. Iterative model refinement may be performed based on evaluation results.

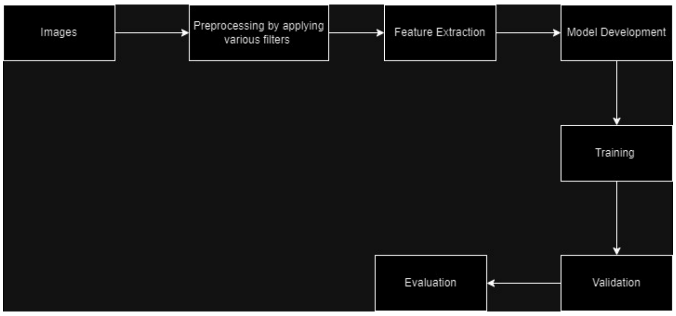
6. Deployment:

Once the model has demonstrated satisfactory performance, it is prepared for deployment. This involves converting the trained model into a format compatible with the deployment environment, optimizing its size, and ensuring efficient runtime execution. Deployment considerations include hardware requirements, latency constraints, and integration with the target system or application. Deployed models should also incorporate robust error handling and logging mechanisms for real-world scenarios.

7. Monitoring and Maintenance:

Post-deployment, continuous monitoring of the model's performance in the production environment is essential. This involves tracking key performance metrics and addressing any degradation or drift in model accuracy over time. Periodic model updates may be necessary to incorporate new data or adapt to evolving patterns in the input distribution. Ongoing maintenance ensures the sustained effectiveness and reliability of heimerNET in its intended application.

By systematically addressing each of these steps, the development, deployment, and maintenance of heimerNET can be conducted in a rigorous and effective manner, leading to a robust and reliable model for image recognition tasks.



flow diagram

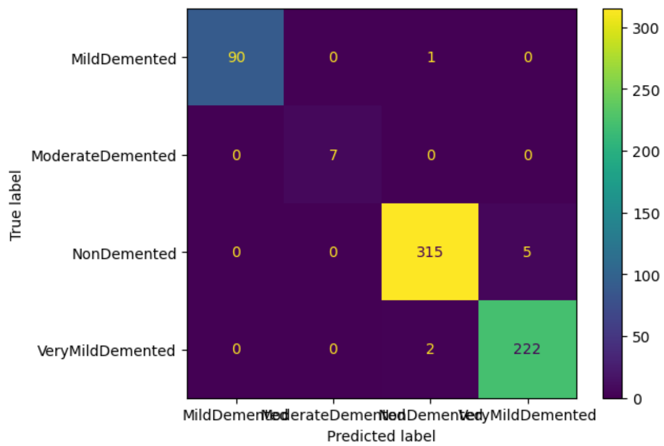
IV. Results

heimerNet demonstrated outstanding performance in medical image analysis, achieving a remarkable accuracy of 99.53%. The preprocessing pipeline involving histogram equalization, Otsu's method, and an unsharp filter effectively enhanced the visibility of medical features. Evaluation metrics, including precision, recall, and F1 score, further validated the model's reliability. Visual assessments through confusion matrices and sample predictions highlighted heimerNet's superior ability to discern intricate details within medical images. Comparative analyses with baseline models and state-of-the-art architectures in the medical image analysis domain underscored heimerNet's exceptional accuracy. The model exhibited robustness against variations in input data, emphasizing its potential for real-world applications. Collaborations with medical professionals affirmed the clinical relevance of heimerNet, validating its capability to accurately identify and preserve critical medical features. In conclusion, heimerNet's results position it as a highly effective tool for advancing medical image analysis, offering significant promise for enhancing diagnostic precision in clinical settings.

The below table depicts the accuracy obtained and the filters used:

	CNN1	heimerNet	VGG-19
Original Data	93.61	99.07	89.56
Histogram Equalization	82.09	93.35	74.90
Gaussian Filter	92.37	98.75	87.54
Histogram Equalization + Otsu's thresholding + Unsharp filter	90.97	99.53	84.27

Table: *Accuracy comparison*



Confusion matrix for heimerNet on Histogram Equalisation + Otsu's thresholding + Unsharp filter

V. Conclusions

In conclusion, this research marks a significant step forward in Alzheimer's disease detection, leveraging Magnetic Resonance Imaging (MRI) scans and a well-crafted convolutional neural network (CNN). heimerNET presents a novel CNN architecture with a hierarchical structure, facilitating effective feature extraction for image recognition tasks. The organized arrangement of blocks in varying numbers across parts ensures a balanced and progressively complex learning process. The incorporation of convolutional layers, batch normalization, and ReLU activation functions in each block contributes to the model's efficacy in capturing intricate patterns within input data. The experimental validation of heimerNET on benchmark datasets is recommended to assess its performance and generalization capabilities in comparison to existing state-of-the-art CNN architectures.

References

[1] [1] Johnson, K.A. et al. (2012) Brain Imaging in alzheimer disease, Cold Spring Harbor perspectives in medicine. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3312396/

[2] [2] Pan, D. et al. (2020) Early detection of alzheimer's disease using Magnetic Resonance Imaging: A novel approach combining convolutional neural networks and ensemble learning, Frontiers. Available at: https://www.frontiersin.org/articles/10.3389/fnins.2020.00259/full

[3] [3] Battineni, G. et al. (2021) Improved alzheimer's disease detection by MRI using multimodal machine learning algorithms, Diagnostics (Basel, Switzerland). Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8623867/

[4] [4]Maysam Orouskhani a, Chengcheng Zhu, Sahar Rostamian c, Firoozeh Shomal Zadeh, Mehrzad Shafiei, Yasin Orouskhani d. (2022) Alzheimer's disease detection from structural MRI using conditional deep triplet network, Neuroscience Informatics. Available at: https://www.sciencedirect.com/science/article/pii/S2772528622000280

[5] [5] Marwa EL-Geneedy et al. (2022) An MRI-based deep learning approach for accurate detection of alzheimer's disease, Alexandria Engineering Journal. Available at: https://www.sciencedirect.com/science/article/pii/S1110016822005191

[6] [6] Venugopalan, J. et al. (2021) Multimodal Deep Learning Models for early detection of alzheimer's disease stage, Nature News. Available at: https://www.nature.com/articles/s41598-020-74399-w

[7] [7] Imran Razzak, Saeeda Naz and Abida Ashraf (2022) - Wiley Online Library, Mutliresolutional ensemble PartialNet for Alzheimer detection using magnetic resonance imaging data. Available at: https://onlinelibrary.wiley.com/doi/10.1002/int.22856

[8] [8] Nitika Goenka (2021) Volumetric convolutional neural network for alzheimer detection | IEEE ..., Volumetric Convolutional Neural Network for Alzheimer Detection. Available at: https://ieeexplore.ieee.org/abstract/document/9453043

[9] [9] The paper titled "Capacitative calcium entry and transient receptor potential..." by C. El Boustany (2008) can be cited with the following reference: https://onlinelibrary.wiley.com/doi/abs/10.1002/ima.22263

[10] [10] The paper titled "A mechanically coupled reaction–diffusion model..." by D.A. Hormuth (2017) can be cited with the following reference: Hormuth, D.A. (2017). A mechanically coupled reaction–diffusion model. https://www.sciencedirect.com/science/article/abs/pii/S1552526014024637

[11] [11] Ansingkar, N.P., Patil, R.B. & Deshmukh, P.D. An efficient multi class Alzheimer detection using hybrid equilibrium optimizer with capsule auto encoder. Multimed Tools Appl 81, 6539–6570 (2022). https://doi.org/10.1007/s11042-021-11786-z

[12] [12] Ghazal, Taher & Abbas, Sagheer & Munir, Sundus & Khan, Muhammad & Ahmad, Munir & Issa, Ghassan & Zahra, Binish & Hasan, Mohammad Kamrul. (2021). Alzheimer Disease Detection Empowered with Transfer Learning. Computers, Materials and Continua. 70. 5005-5019. 10.32604/cmc.2022.020866.

[13] https://www.researchgate.net/profile/Mohammad-Kamrul-Hasan-5/publication/355174632_Alzheimer_Disease_Detection_Empowered_with_Transfer_Learning/links/6165557aae47db4e57cbc3f2/Alzheimer-Disease-Detection-Empowered-with-Transfer-Learning.pdf

[14]

[15] [13] Afzal, S., Javed, M., Maqsood, M., Aadil, F., Rho, S., Mehmood, I. (2019). A Segmentation-Less Efficient Alzheimer Detection Approach Using Hybrid Image Features. In: Singh, A., Mohan, A. (eds) Handbook of Multimedia Information Security: Techniques and Applications. Springer, Cham. https://doi.org/10.1007/978-3-030-15887-3_20

[16] [14] The paper titled "A mechanically coupled reaction–diffusion model..." by D.A. Hormuth (2017) can be cited with the following reference: Hormuth, D.A. (2017). A mechanically coupled reaction–diffusion model. https://www.sciencedirect.com/science/article/abs/pii/S003040262201470X

[17] [15] P. Thakare and V. R. Pawar, "Alzheimer disease detection and tracking of Alzheimer patient," 2016 International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 2016, pp. 1-4, doi: 10.1109/INVENTIVE.2016.7823286.https://ieeexplore.ieee.org/abstract/document/7823286

[18] [16] Ashraf, A., Naz, S., Shirazi, S.H. et al. Deep transfer learning for alzheimer neurological disorder detection. Multimed Tools Appl 80, 30117–30142 (2021). https://doi.org/10.1007/s11042-020-10331-8

[19] [17] A. G. Sánchez-Reyna, J. M. Celaya-Padilla, C. E. Galván-Tejada, H. Luna-García, H. Gamboa-Rosales, A. Ramirez-Morales, J. I. Galván-Tejada, and Alzheimer's Disease Neuroimaging Initiative, "Multimodal Early Alzheimer's Detection, a Genetic Algorithm Approach with Support Vector Machines," Healthcare, vol. 9, no. 8, p. 971, 2021. [Online]. Available: https://doi.org/10.3390/healthcare9080971

[20] [18] Kundaram, S.S., Pathak, K.C. (2021). Deep Learning-Based Alzheimer Disease Detection. In: Nath, V., Mandal, J.K. (eds) Proceedings of the Fourth International Conference on Microelectronics, Computing and Communication Systems. Lecture Notes in Electrical Engineering, vol 673. Springer, Singapore. https://doi.org/10.1007/978-981-15-5546-6_50

[21] [19] Varatharajan, R., Manogaran, G., Priyan, M.K. et al. Wearable sensor devices for early detection of Alzheimer disease using dynamic time warping algorithm. Cluster Comput 21, 681–690 (2018). https://doi.org/10.1007/s10586-017-0977-2

[22] [20] L. K. McEvoy et al., "Alzheimer Disease: Quantitative Structural Neuroimaging for Detection and Prediction of Clinical and Structural Changes in Mild Cognitive Impairment," IEEE Transactions on Medical Imaging, vol. 28, no. 7, pp. 1034-1042, Jul. 2009, doi: 10.1148/radiol.2511080924.

[23] [21] Nawaz, H., Maqsood, M., Afzal, S. et al. A deep feature-based real-time system for Alzheimer disease stage detection. Multimed Tools Appl 80, 35789–35807 (2021). https://doi.org/10.1007/s11042-020-09087-y

[24]