Pertanika Proceedings 1 (5): 169 - 175 (2025)

PERTANIKA PROCEEDINGS

Journal homepage: http://www.pertanika.upm.edu.my/

Dense Net and Clustering Saliency Maps: A Novel Approach for Alzheimer's Diagnosis

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ABSTRACT

During the last few years, the use of biomarkers in the investigation of Alzheimer's disease (AD) has emerged as a strategy that has the potential to be beneficial. Recent research has led to the discovery of a cutting-edge biomarker for Alzheimer's disease. This biomarker was discovered via the visual examination of power modulation spectrograms, and it proposes using three "patches" or sections from the modulation spectrogram for AD diagnoses. To train these networks, spectrograms of power modulation are used as inputs. According to the findings of the experiments, the suggested biomarkers perform better than the state-of-the-art benchmark. This study presents a novel approach to the early detection of Alzheimer's disease. The proposed dense net architecture and the saliency map clustering approach may be used to develop a strategy for the early identification of AD. The suggested approach modifies the learning weights, and Adam's optimization is used in order to achieve higher levels of accuracy. This gives more evidence that it is feasible to use these biomarkers for the automated diagnosis of Alzheimer's disease. None of the suggested biomarkers revealed a significant association with age across any of the five activities.

Keywords: Alzheimer, deep learning, dense net architecture, saliency clustering

ARTICLE INFO

Article history:
Received: 29 August 2025
Published: 31 October 2025

DOI: https://doi.org/10.47836/pp.1.5.029

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e-ISSN: 3083-9475

INTRODUCTION

Alzheimer's disease is a kind of dementia that is defined by neurological symptoms and often affects people in their later years of life. It is generally diagnosed in people who are in their 60s and 70s. It may also have an impact on those who have not yet reached the age of 65. As a consequence of this, it targets a number of different brain areas in the central and frontal regions (Suk et al., 2013). The overall cost of treating Alzheimer's patients around the globe in 2015 was roughly $818 billion USD. At this time, it has achieved a total of one trillion dollars in US currency (Alberdi et al., 2016). Alzheimer's disease progresses via three distinct phases. Alzheimer's disease is the last stage. When a person reaches this stage in their life, it is more probable that they will struggle with both their behaviour and their intellect. At this point, a person is wholly reliant on the assistance of another party in order to carry out their day-to-day tasks (Richhariya et al., 2020). It is challenging to find a therapy for AD in its beginning stages (Richhariya et al., 2020), due to the fact that every person who has the disease has a unique set of symptoms. Researchers from Moon et al. (2007) found that persons with Alzheimer's disease often had brain ventricles that expand at a rate that is four times faster than the average.

RELATED WORK

When we do our analysis of the relevant literature, we concentrate primarily on the current techniques that are used to diagnose Alzheimer's disease in its early stages, as well as the developments that have been achieved in these areas by convolutional neural networks (Moon et al., 2007). In spite of the fact that they only had access to a small dataset, the researchers were able to reach a 93% accuracy rate for their experimental findings. They were successful in doing this by the use of a multi-model and multiscale neural network, which led to an accuracy rate of 82.4 percent (Rallabandi et al., 2020). As a consequence of their efforts, they were able to achieve an accuracy of 75%. An experiment was carried out on an MRI dataset. In this experiment, the completion of the categories resulted in this conclusion Rajendra Acharya and his colleagues were the ones who decided to develop this framework. There was a degree of accuracy that was obtained by the author, which was 94.54%. These neurons mimic the biological processes that occur in the human brain. Among the models that we have put into action are the following: LeNet, AlexNet, VGG-16 and VGG-19, Inception-V1/V2/V3, ResNet-50, MobileNet-V1, and all of these.

PROCESSED SYSTEM

ADNI dataset is used to test our experiment. The dataset is available in the following link https://www.kaggle.com/datasets/madhucharan/alzheimersdisease5classdatasetadni. Each of the following categories has been assigned to the information that has been received:

In the first case, "N" is made up of twenty healthy senior controls, in the second case, "AD1" refers to 19 patients who have been diagnosed with mild Alzheimer's disease, and in the third case, "AD2" refers to fifteen patients who have been recognised as having moderate-to-severe Alzheimer's disease (Thavavel & Karthiyayini, 2018). This group will be referred to as "AD" in any study that combines persons who have both kinds of Alzheimer's disease (AD1 and AD2) into a single group. The demographic information of the participants, including their MMSE scores, is shown in Table 1.

Table 1
Participant demographic information

Group Identifiers	Subjects (female)	Age (years)
N	20 (9)	68 nearby
AD1	19(11)	74 nearby
AD2	15(9)	75 nearby

Methodology

The method begins with the extraction of the features. The length of each segment is 8 seconds, and there is a 1-second gap between each pair of segments. This is done so that it is possible to make comparisons with the three visually acquired areas. The proposed block diagram is shown in Figure 1. Time-frequency transform (STFT) features were generated for each frequency band after the retrieval of all of the channels' microstate properties.

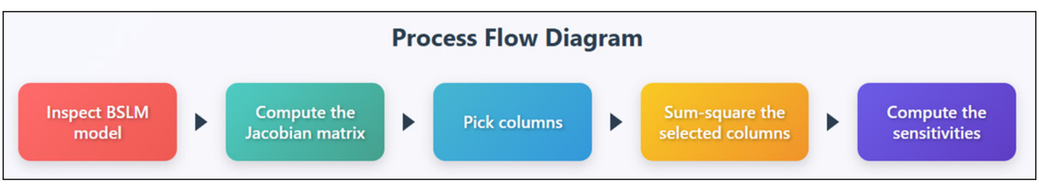

Figure 1. Proposed sensor-based system (Solano-Rojas et al., 2021)

Proposed Dense Net Compressed CNN Architecture

A convolutional DNN of the Dense Net Bottleneck-Compressed design is used since this specific sort of neural network structure offers an extraordinary degree of performance while also having a decreased amount of training parameters. As a result, it makes more efficient use of the resources at our disposal. The method only evaluated three channels, which are typically represented by the colours red, green, and blue; however, MRI images are monochromatic, so we added an additional channel parameter to the mix.

Batch size : On the basis of the findings of the experiment, we decided to use a batch size of five MRI pictures for the training.

Testing : The dataset for the test consisted of the remaining 75% of the data.

Classes	**:**	In the neural network, we started by establishing a number of classes equal to six. Despite this, we came to the conclusion that the SMC class was too subjective and boisterous; thus, we decided to withdraw from it. We have settled on five as the optimal number of classes.
Optimizer	**:**	The optimizer that we utilized was called Stochastic Gradient Descent, or SGD.
Learning	**:**	Within the SGD optimizer, we made use of a learning rate parameter with a value of 0.1.

Saliency Map Clustering

After the CNNs have been trained, the saliency maps are then retrieved from the final thick layer. When making the final map, saliency maps are created from all of the training inputs, and then they are averaged along with the training samples. They differ depending on which task the saliency map was produced from; for example, Lopes et al. (2023) Task 2's saliency map is more general, while Task 3's saliency map is more specialized. The following is a description of each of these four distinct experiments:

i. Experiment 1: In this experiment, we use the salience map. This map was gained through the aforementioned task. The general N vs. AD task serves as the basis for this experiment.

ii. Experiment 2: In the second experiment, certain subclasses are taken into consideration directly, although the most comprehensive saliency map is still used. As a direct consequence of this, the experiment in question is considerably more suited to the task at hand.

iii. The third experiment is the most specialized of the three since it locates the ideal clusters by making use of the saliency maps that are associated with each differential modulation spectrogram.

Biomarker Selection and AD Diagnosis

After the optimal number of clusters has been determined, these areas will be evaluated to see whether they are suitable candidates for each of the five tasks. Once the best number of clusters has been established, SVMs employ kernels to transform data from two classes into a higher-dimensional space. The classifier for all the individual subjects is trained by utilizing data from N minus 1 other people's data, which is then randomly selected and repeated 10 times.

RESULTS AND DISCUSSION

DenseNet CNN Accuracy

The patient identifies themselves as having Significant Memory Concern (SMC). Figures 2a and 2b illustrate the findings of this study. When compared to the confusion matrix, Figure 2a shows that the bulk of the values are placed along the diagonal, and as a consequence, Figure 2b demonstrates the predictive capacity of the classifier by illustrating the potential of each class as well as the potential of all classes combined.

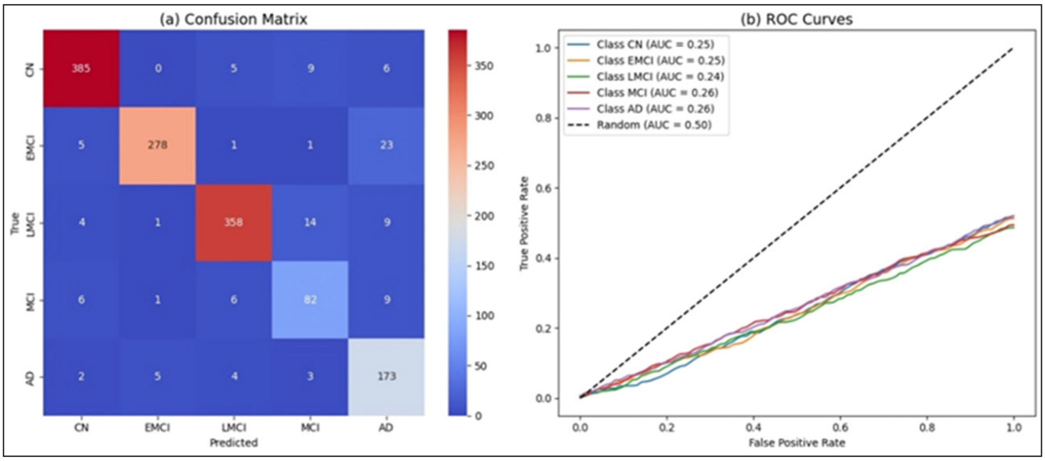

Figure 2. DenseNet-121 evaluation charts at 80 epochs (Solano-Rojas et al., 2021)

The model was enhanced even more, despite the fact that, based on Figure 2a, our classifier may have seemed to have a satisfactory level of performance previously. Following the elimination of the SMC class and the continuation of our training for a total of 80 iterations, we were successful in obtaining the confusion matrix that is shown in Figure 2a. The diagnostic skills of the classifier are shown to be true by the fact that the area under each curve tends to be equal to one, as shown in Figure 2b. Next, we continue to make improvements to this model. The indicators shown in Table 2 were included in the most recent prediction model.

Table 2
At 110 epochs, metrics for the obtained DNN are evaluated

	Specificity (precision)	**Sensitivity (Recall)**	**F1-Score**
Cognitive normal	0.92	0.93	0.92
Early MCI	0.94	0.90	0.92
Alzheimer Disease	0.59	0.99	0.73

Table 2 contains other classification metrics pertaining to this final model that have been presented by us. Because the AD class achieves approximately 100% sensitivity (recall), the poor specificity is not a critical issue.

Saliency Maps

Following the successful validation of the CNN technique, we will now continue to study the saliency maps that were created from the images. Study the usage of a single generic mask for all channels in order to keep things as simple as possible. Following that, we will investigate which of the four tested experiments has the optimal threshold as well as the number of clusters. The frequency ranges are shown in Figure 3. Each region (cluster) is identified as R1, R2 and R3.

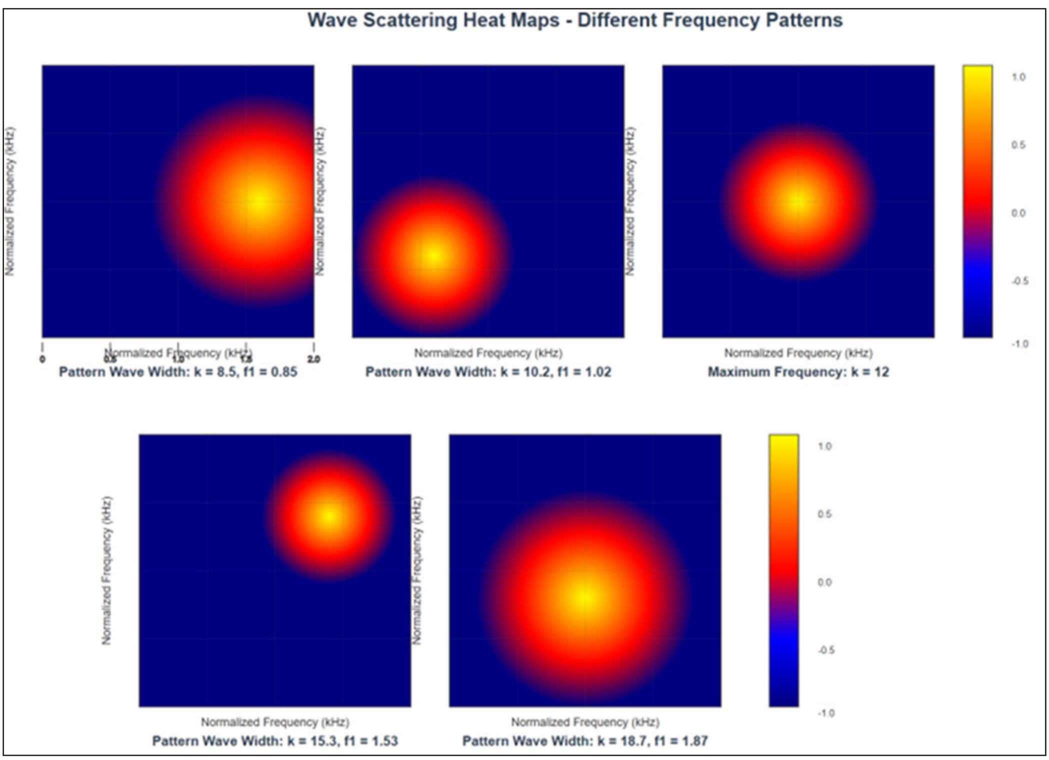

Figure 3. MQ2 gas sensor working

CONCLUSION

This paper aims to identify novel biomarkers for Alzheimer's disease by utilizing a DenseNet architecture in conjunction with saliency maps. Specifically, we investigated biomarkers across five distinct classification tasks: (1) distinguishing between healthy individuals (N) and those with mild Alzheimer's disease (AD1), compared to moderate-to-severe Alzheimer's disease (AD2); (2) differentiating between healthy individuals (N) and individuals with Alzheimer's disease (AD) (a combination of AD1 and AD2); (3) distinguishing between healthy individuals (N) and those with AD1; (4) differentiating between AD1 and AD2; and (5) distinguishing between healthy individuals (N) and those with AD2. The newly identified biomarkers were initially extracted for each available EEG channel before being input into a support vector machine for final classification.

ACKNOWLEDGEMENT

The authors would like to express sincere gratitude to everyone who supported us during the research process.

REFERENCES

Suk, H. I., & Shen, D. (2013). Deep learning-based feature representation for AD/MCI classification. In K. Mori, I. Sakuma, Y. Sato, C. Barillot & N. Navab (Eds.) *International Conference on Medical Image Computing and Computer-assisted Intervention* (pp. 583-590). Springer.

Alberdi, A., Aztiria, A., & Basarab, A. (2016). On the early diagnosis of Alzheimer's Disease from multimodal signals: A survey. *Artificial Intelligence in Medicine*, *71*, 1-29. https://doi.org/10.1016/j.artmed.2016.06.003

Richhariya, B., Tanveer, M., & Rashid, A. H. (2020). Diagnosis of Alzheimer's disease using universum support vector machine based recursive feature elimination (USVM-RFE). *Biomedical Signal Processing and Control*, *59*, Article 101903. https://doi.org/10.1016/j.bspc.2020.101903

Moon, H. J., Kim, S. D., Lee, J. B., Lim, D. J., & Park, J. Y. (2007). Clinical analysis of external ventricular drainage related ventriculitis. *Journal of Korean Neurosurgical Society*, *41*(4), 236-240.

Rallabandi, V. S., Tulpule, K., & Gattu, M. (2020). Automatic classification of cognitively normal, mild cognitive impairment and Alzheimer's disease using structural MRI analysis. *Informatics in Medicine Unlocked*, *18*, Article 100305. https://doi.org/10.1016/j.imu.2020.100305

Thavavel, V., & Karthiyayini, M. (2018). Hybrid feature selection framework for identification of Alzheimer's biomarkers. *Indian Journal of Science and Technology*, *11*(22), 1-10. https://doi.org/10.17485/ijst/2018/v11i22/123310

Lopes, M., Cassani, R., & Falk, T. H. (2023). Using CNN saliency maps and EEG modulation spectra for improved and more interpretable machine learning-based alzheimer's disease diagnosis. *Computational Intelligence and Neuroscience*, *2023*(1), Article 3198066. https://doi.org/10.1155/2023/3198066_

Solano-Rojas, B., & Villalón-Fonseca, R. (2021). A low-cost three-dimensional DenseNet neural network for Alzheimer's disease early discovery. *Sensors*, *21*(4), Article 1302. https://doi.org/10.3390/ s21041302