ISSN: 2278-4632
Vol-13, Issue-05, May 2023

# DETECTION OF ALZHEIMERS DISEASE USING RF SIGNALS

1. Mr. S. Praveen Kumar, Assistant Professor, Department of ECE, JNTUH University College of Engineering Jagtial, Telangana, India, praveenkumar_00019@yahoo.com

2. K. Neelima, Department of ECE, JNTUH University College of Engineering Jagtial, Telangana, India, neelimakoutam@gmail.com

3. T. Sai Prasad , Department of ECE, JNTUH University College of Engineering Jagtial, Telangana, India, saiprasadtokala1969@gmail.com

4. E. Samatha , Department of ECE, JNTUH University College of Engineering Jagtial, Telangana, India, naveen98899@gmail.com

**ABSTRACT:** Alzheimer's disease is one of the most fastest growing and costly diseases in the world today. It affects the livelihood of not just patients, but those who take care of them, including care givers, nurses, and close family members. Current progression monitoring techniques are based on MRI and PET scans which are inconvenient for patients to use. In addition, more intelligent and efficient methods are needed to predict what the current stage of the disease is and strategies on how to slow down its progress over time. Technology or Method: In this paper, machine learning was used with S-parameter data obtained from 6 antennas that were placed around the head to noninvasively capture changes in the brain in the presence of Alzheimer's disease pathology. Measurements were conducted for 9 different human models that varied in head sizes. The data was processed in several machine learning algorithms. Each algorithm's prediction and accuracy score were generated, and the results were compared to determine which machine learning algorithm could be used to efficiently classify different stages of Alzheimer's disease. Results: Results from the study showed that overall, the logistic regression model had the best accuracy of 98.97% and efficiency in differentiating between 4 different stages of Alzheimer's disease. Clinical or Biological Impact: The results obtained here provide a transformative approach to clinics and monitoring systems where machine learning can be integrated with noninvasive microwave medical sensors and systems to intelligently predict the stage of Alzheimer's disease in the brain.

***Keywords*** *– Machine learning, RF, alzheimer's disease, predictive diagnostics, microwave medical diagnostics.*

## 1. INTRODUCTION

ALZHEIMER'S disease (AD) is quickly becoming a global challenge that is affecting not just elderly people, but their caregivers, nurses, and close family members close. With the current rapid increase in the ageing population, AD is also becoming not only a fast-growing disease, in terms of the number of people affected, but an even faster, larger, and costlier burden to society that imposes a social and economic threat for the next 30 to 40 years [1]. In addition, the disruption in ongoing care and research for AD due to ongoing pandemic is likely to impact and increase these numbers [2]. It is therefore of paramount importance to investigate, develop, and deploy solutions to detect and monitor the progression of AD in patients intelligently, quickly, and noninvasively. This will enable doctors and caregivers to predict the course of the disease and determine which treatment strategies are effective. Machine learning (ML) techniques combined

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

with advanced sensing technology is an important field to provide contributions in the automatic prediction, monitoring, and early detection of AD progression.

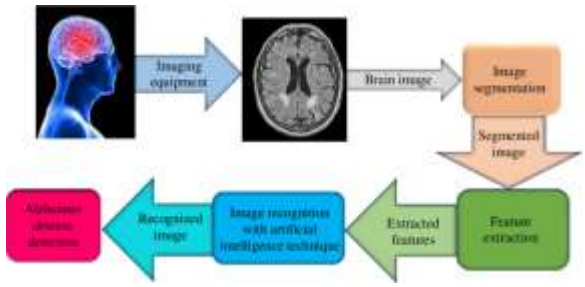


Fig.1: Example figure

ML has been used in the past decade to detect certain biomarkers in MRI scans for AD. Many ML methods are currently utilised to improve the determination and prediction of AD. In [3], a proof-of-concept personalized classifier for AD dementia and mild cognitive impairment (MCI) patients was presented based on biomarkers provided from [4]–[6]. In [7], precise categorisation of stable MCI versus progressive MCI was achieved by analysing 35 cases of normal controls and 67 cases of MCI with a support vector machine (SVM) [7]. Segmentation has been emphasised in most ML processes for bio-image classification, whereas the retrieval of strong texture descriptions has generally been neglected [8]. A review of several SVM-based research showed that SVM is a widely utilised method to distinguish between AD cases and cognitively normal cases and between stable forms and progressive forms of MCI [9]. Microwave sensing and imaging for medical diagnostics has developed into a lucrative area of research for several decades, due to its non-ionising technology and ability to develop devices and sensors that are portable and wearable. This technology has been used extensively in the detection of breast cancer, stroke, and most recently, neurodegenerative diseases [10]–[12]. Recently,ML has been utilised to efficiently process the captured RF signals from such devices and classify different diseases in the heart and breast using received RF signals [13], [14].

## 2. LITERATURE REVIEW

**Machine learning-based method for personalized and cost-effective detection of Alzheimer's Disease:**

Diagnosis of Alzheimer's disease (AD) is often difficult, especially early in the disease process at the stage of mild cognitive impairment (MCI). Yet, it is at this stage that treatment is most likely to be effective, so there would be great advantages in improving the diagnosis process. We describe and test a machine learning approach for personalized and cost-effective diagnosis of AD. It uses locally weighted learning to tailor a classifier model to each patient and computes the sequence of biomarkers most informative or cost-effective to diagnose patients. Using ADNI data, we classified AD versus controls and MCI patients who progressed to AD within a year, against those who did not. The approach performed similarly to considering all data at once, while significantly reducing the number (and cost) of the biomarkers needed to achieve a confident diagnosis for each patient. Thus, it may contribute to a personalized and effective detection of AD, and may prove useful in clinical settings.

**Subregional neuroanatomical change as a biomarker for Alzheimer's disease:**

Regions of the temporal and parietal lobes are particularly damaged in Alzheimer's disease (AD), and this leads to a predictable pattern of brain atrophy. In vivo quantification of subregional atrophy, such as changes in cortical thickness or structure volume, could lead to improved diagnosis and better assessment of the neuroprotective effects of a therapy. Toward this end, we have developed a fast and robust method for accurately quantifying cerebral structural changes in several cortical and

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

subcortical regions using serial MRI scans. In 169 healthy controls, 299 subjects with mild cognitive impairment (MCI), and 129 subjects with AD, we measured rates of subregional cerebral volume change for each cohort and performed power calculations to identify regions that would provide the most sensitive outcome measures in clinical trials of disease-modifying agents. Consistent with regional specificity of AD, temporal-lobe cortical regions showed the greatest disease-related changes and significantly outperformed any of the clinical or cognitive measures examined for both AD and MCI. Global measures of change in brain structure, including whole-brain and ventricular volumes, were also elevated in AD and MCI, but were less salient when compared to changes in normal subjects. Therefore, these biomarkers are less powerful for quantifying disease-modifying effects of compounds that target AD pathology. The findings indicate that regional temporal lobe cortical changes would have great utility as outcome measures in clinical trials and may also have utility in clinical practice for aiding early diagnosis of neurodegenerative disease.

**Associations between cognitive, functional, and FDG-PET measures of decline in AD and MCI:**

The Functional Activities Questionnaire (FAQ) and Alzheimer's Disease Assessment Scale – cognitive subscale (ADAS-cog) are frequently-used indices of cognitive decline in Alzheimer's disease (AD). The goal of this study was to compare FDG-PET and clinical measurements in a large sample of elderly subjects with memory disturbance. We examined relationships between glucose metabolism in FDG-PET regions of interest (FDG-ROIs), and ADAS-cog and FAQ scores in AD and mild cognitive impairment (MCI) patients enrolled in the Alzheimer's Disease Neuroimaging Initiative (ADNI). Low glucose metabolism at baseline predicted subsequent ADAS-cog and FAQ decline. In addition, longitudinal glucose metabolism decline was associated with concurrent ADAS-cog and FAQ decline. Additionally, a power analysis revealed that FDG-ROI values have greater statistical power than ADAS-cog to detect attenuation of cognitive decline in AD and MCI patients. Glucose metabolism is a sensitive measure of change in cognition and functional ability in AD and MCI, and has value in predicting future cognitive decline.

**Update on biomarker core of the Alzheimer's disease neuroimaging initiative subjects:**

Here, we review progress by the Penn Biomarker Core in the Alzheimer's Disease Neuroimaging Initiative (ADNI) toward developing a pathological cerebrospinal fluid (CSF) and plasma biomarker signature for mild Alzheimer's disease (AD) as well as a biomarker profile that predicts conversion of mild cognitive impairment (MCI) and/or normal control subjects to AD. The Penn Biomarker Core also collaborated with other ADNI Cores to integrate data across ADNI to temporally order changes in clinical measures, imaging data, and chemical biomarkers that serve as mileposts and predictors of the conversion of normal control to MCI as well as MCI to AD, and the progression of AD. Initial CSF studies by the ADNI Biomarker Core revealed a pathological CSF biomarker signature of AD defined by the combination of Ab1-42 and total tau (T-tau) that effectively delineates mild AD in the large multisite prospective clinical investigation conducted in ADNI. This signature appears to predict conversion from MCI to AD. Data fusion efforts across ADNI Cores generated a model for the temporal ordering of AD biomarkers which suggests that Ab amyloid biomarkers become abnormal first, followed by changes in neurodegenerative biomarkers (CSF tau, F-18 fluorodeoxyglucose-positron emission tomography, magnetic resonance imaging) with the onset of clinical symptoms. The timing of these changes varies in

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

individual patients due to genetic and environmental factors that increase or decrease an individual's resilience in response to progressive accumulations of AD pathologies.

**Individual prediction of cognitive decline in mild cognitive impairment using support vector machine based analysis of diffusion tensor imaging data:**

Although cross-sectional diffusion tensor imaging (DTI) studies revealed significant white matter changes in mild cognitive impairment (MCI), the utility of this technique in predicting further cognitive decline is debated. Thirty-five healthy controls (HC) and 67 MCI subjects with DTI baseline data were neuropsychologically assessed at one year. Among them, there were 40 stable (sMCI; 9 single domain amnestic, 7 single domain frontal, 24 multiple domain) and 27 were progressive (pMCI; 7 single domain amnestic, 4 single domain frontal, 16 multiple domain). Fractional anisotropy (FA) and longitudinal, radial, and mean diffusivity were measured using Tract-Based Spatial Statistics. Statistics included group comparisons and individual classification of MCI cases using support vector machines (SVM). FA was significantly higher in HC compared to MCI in a distributed network including the ventral part of the corpus callosum, right temporal and frontal pathways. There were no significant group-level differences between sMCI versus pMCI or between MCI subtypes after correction for multiple comparisons. However, SVM analysis allowed for an individual classification with accuracies up to 91.4% (HC versus MCI) and 98.4% (sMCI versus pMCI). When considering the MCI subgroups separately, the minimum SVM classification accuracy for stable versus progressive cognitive decline was 97.5% in the multiple domain MCI group. SVM analysis of DTI data provided highly accurate individual classification of stable versus progressive MCI regardless of MCI subtype, indicating that this method may become an easily applicable tool for early individual detection of MCI subjects evolving to dementia.

## 3. METHODOLOGY

Although there are no studies that investigate ML with RF data for AD detection, there have been recent studies that utilised this approach to classify stroke in the brain. In support vector machine (SVM) classifier is used with simulation data to detect the presence of stroke in the brain. While the use of SVM made the overall performance of the system to be more effective, the algorithm still needs to be validated with experimental data. Authors in investigated 5 different ML algorithms, SVM, K-Nearest Neighbours (KNN), linear discriminant analysis (LDA), Naïve-Bayes (NB), and classification trees, to classify the presence of ischemic versus hemorrhagic stroke using experimental data. It was found that SVM and LDA algorithms had the best accuracy in differentiating ischemic and hemorrhagic stroke, while KNN had the fastest learning and classification time. However, while the study is promising, a limitation of the study is the lack of data that will help in training the algorithms better. Finally, a recent paper presented a novel graph degree mutual information (GDMI) approach along with SVM in order to identify between ischemic and hemorrhagic stroke. The algorithm could obtain an accuracy of 88% and obtain results in under a minute. Although the algorithm is promising, it requires further validation on experimental data to verify its effectiveness.

**Disadvantages:**

1. The algorithm still needs to be validated with experimental data.
2. A limitation of the study is the lack of data that will help in training the algorithms better.

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

This paper aims to build upon the previous work by investigating and applying ML algorithms to the captured RF signals in order to predict and classify the current stage of AD. The study conducted in this paper, to the authors' knowledge, has not been done before, and serves as a novel and transformative validation of ML techniques with RF data for medical diagnostic and predictive analytics.

**Advantages:**

1. Machine learning algorithm could be used to efficiently classify different stages of Alzheimer's disease.
2. Here provide a transformative approach to clinics and monitoring systems where machine learning can be integrated with noninvasive microwave medical sensors and systems to intelligently predict the stage of Alzheimer's disease in the brain.

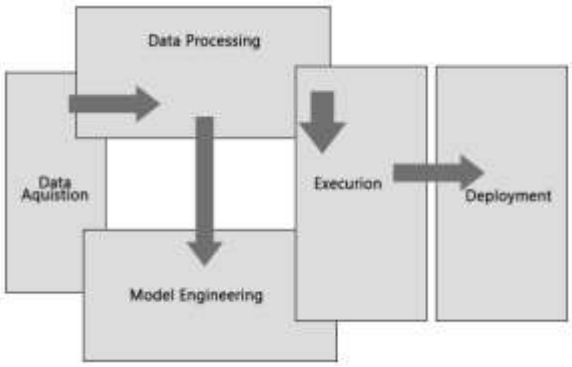


Fig.2: System architecture

**MODULES:**

In this project we have designed following modules

- Data exploration: using this module we will load data into system
- Processing: Using the module we will read data for processing
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: building the model - Logistic regression - LDA Sixcriminant Analysis - KNN - Decision Tree (CART) - Gaussian Naive Bayes - Support Vector Machine - SGD Booste - XGBoost - Random Forest - J48 Decision Tree - Voting Classifier.Algorithms accuracy calculated.
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

## 4. IMPLEMENTATION

Logistic regression:

Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables.

LDA Sixcriminant Analysis:

Linear discriminant analysis (LDA) is used here to reduce the number of features to a more manageable number before the process of classification. Each of the new dimensions generated is a linear combination of pixel values, which form a template.

KNN:

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples (K) closest to the query, then votes for the most frequent label (in the case of classification) or averages the labels (in the case of regression).

Decision Tree (CART):

It is a decision tree where each fork is split into a predictor variable and each node has a prediction for the target variable at the end. In the decision tree, nodes are split into sub-nodes on the basis of a threshold value of an attribute.

Gaussian Naive Bayes:

Naive Bayes is a generative model. (Gaussian) Naive Bayes assumes that each class follow a Gaussian distribution. The difference between QDA and (Gaussian) Naive Bayes is that Naive Bayes assumes independence of the features, which means the covariance matrices are diagonal matrices.

Support Vector Machine:

Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection.

SGD Booster :

Gradient boosting is a machine learning technique used in regression and classification tasks, among others.

XGBoost :

The XGBoost (eXtreme Gradient Boosting) is a popular and efficient open-source implementation of the gradient boosted trees algorithm. Gradient boosting is a supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models.

Random Forest:

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression.

J48 Decision Tree:

J48 is based on a top-down strategy, a recursive divide and conquer strategy. You select which attribute to split on at the root node, and then you create a branch for each possible attribute value, and that splits the instances into subsets, one for each branch that extends from the root node.

Voting Classifier:

A voting classifier is a machine learning estimator that trains various base models or estimators and predicts on the basis of aggregating the findings of each base estimator. The aggregating criteria can be combined decision of voting for each estimator output.

## 5. EXPERIMENTAL RESULTS


Fig.3: Home screen

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

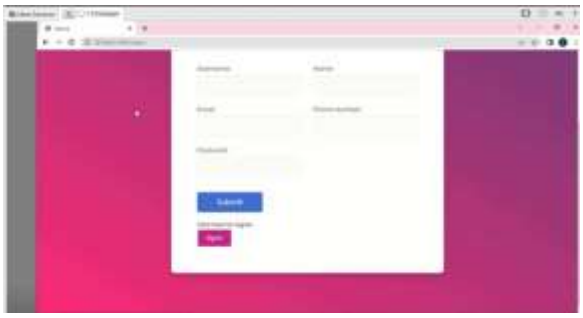

Fig.4: User registration

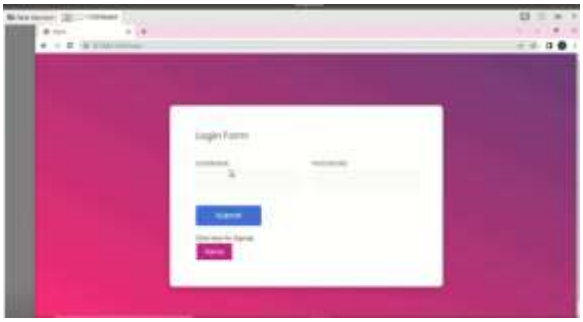

Fig.5: User login

Fig.6: Main page

Fig.7: User input


Fig.8: Prediction result

## 6. CONCLUSION

This study investigated whether stages of AD could be classified with ML algorithms that were trained using RF data that noninvasively captured measurements of dielectric changes in the brain. Results indicate that LR is an accurate and efficient ML model that can be used for RF sensing and classification of AD noninvasively. The results obtained here provides a transformative approach to AD diagnostics and monitoring systems where ML can be integrated with RF sensing systems to intelligently predict the stage of AD in the brain. As a next step, ML algorithms will be investigated and evaluated on a much larger number of simulation cases in order to validate its performance on a larger group.

## 7. FUTURE SCOPE

This works serves as a foundation for future work in the investigation of ML and DL techniques to RF imaging. Future research will focus on investigating DL techniques to classify AD traits from image data generated from the authors' previous work in [19]. In addition, the authors also plan to utiluse ML to classify AD based on other physiological changes in the brain that can be detected by RF sensors [32], [33]. Depending on these results, the next and final goal is to combine the different studies together to develop an AI solution that will take the captured RF data and predict the progression rate of AD

ISSN: 2278-4632
Vol-13, Issue-05, May 2023

in a patient. This, in turn, will be used to determine the different treatment strategies to slow down its progression. This would lead to a transformative and effective solution for future systems and techniques for AD monitoring and treatment delivery.

**REFERENCES**

[1] Alzheimer's Association, "2020 Alzheimer's disease facts and figures," Alzheimer's Dement., vol. 16, pp. 391–460, 2020.

[2] Alzheimer's Association, "The impact of COVID-19 and the global pandemic on Alzheimer's research, long-term care and the brain," in Proc. Alzheimer's Assoc. Int. Conf., 2020. [Online]. Available: https: //www.alz.org/aaic/releases_2020/covid-19-cognition-media-panel.asp

[3] J. Escudero, E. Ifeachor, J. P. Zajicek, C. Green, J. Shearer, and S. Pearson, "Machine learning-based method for personalized and cost-effective detection of Alzheimer's Disease," IEEE Trans. Biomed. Eng., vol. 60, no. 1, pp. 164–168, Jan. 2013.

[4] D. Holland, J. B. Brewer, D. J. Hagler, C. Fennema-Notestine, A. M. Dale, and the Alzheimer's Disease Neuroimaging Initiative, "Subregional neuroanatomical change as a biomarker for Alzheimer's disease," in Proc. Nat. Acad. Sci. U.S.A., vol. 106, no. 49, pp. 20954–20959, Dec. 2009.

[5] S. M. Landau et al., "Associations between cognitive, functional, and FDG-PET measures of decline in AD and MCI,"Neurobiol. Aging, vol. 32, no. 7, pp. 1207–1218, Jul. 2011.

[6] J. Q. Trojanowski et al., "Update on biomarker core of the Alzheimer's disease neuroimaging initiative subjects," Alzheimer's Dement., vol. 7, no. 3, pp. 257–262, May 2011.

[7] S. Haller et al., "Individual prediction of cognitive decline in mild cognitive impairment using support vector machine based analysis of diffusion tensor imaging data," J. Alzheimer's Disease, vol. 22, no. 1, pp. 315–327, Sep. 2010.

[8] S. Al-Shoukry, T. H. Rassem, and N. M. Makbol, "Alzheimer's diseases detection by using deep learning algorithms: A mini-review," IEEE Access, vol. 8, pp. 77131–77141, 2020.

[9] C. Saraiva, C. Praça, R. Ferreira, T. Santos, L. Ferreira, and L. Bernardino, "Nanoparticle-mediated brain drug delivery: Overcoming blood-brain barrier to treat neurodegenerative diseases," J. Controlled Release, vol. 235, pp. 34–47, Aug. 2016.

[10] E. C. Fear and M. A. Stuchly, "Microwave detection of breast cancer," IEEE Trans. Microw. Theory Techn., vol. 48, no. 11, pp. 1854–1863, Nov. 2000, doi: 10.1109/22.883862.