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Research Article

SVM-Based Classifier For Early Detection Of Alzheimer's Disease

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ABSTRACT

Alzheimer's disease (AD) is a disorder affecting the brain and its functions that results in permanent damage to the brain. This multifaceted disease slowly destroys brain cells, reducing a person's ability to think, remember, and carry out even the most basic duties. Ultimately, this cognitive decline leads to dementia. A significant portion of the global population faces metabolic challenges like Alzheimer's disease and diabetes. Recent research has explored various machine learning approaches aimed at early disease detection. Early AD diagnosis is very important for a speedy recovery and minimizing damage to brain cells. In this proposed work, a machine learning model is developed using Support Vector Machine to detect individuals with dementia (AD) or without dementia (NC). Our model is trained using 2D Magnetic Resonance Imaging (MRI) brain scan images. We computed common performance measures like the F1-score and accuracy to assess the model. The 15-fold cross-validation technique was applied to cross-validate these results. Notably, our results demonstrate that Support Vector Machine (SVM) attained a remarkable accuracy of 99.06% in the detection of AD. Accurate Alzheimer's disease detection through machine learning algorithms can greatly reduce the annual mortality rates related to AD.

Keywords: Alzheimer's disease (AD), Binary Classification, Image Preprocessing, Machine Learning, Support Vector Machine

1. INTRODUCTION

Alzheimer's disease is a brain illness marked by a gradual degeneration of active cells in the brain that weakens memory and other cognitive abilities. This is the primary root cause of dementia, which has significant adverse effects on a person's mental and social capacities and, as it grows, eventually makes it more difficult for them to do daily duties [1], [2]. Alzheimer's is one of the more prevalent and life-threatening types of dementia, and the rapid progression of the disease can eventually take the life of the patient. This phenomenon arises due to the progressive loss of cells in the brain, the formation of neurofibrillary tangles and amyloid plaques, and the gradual deterioration of brain volume [3].

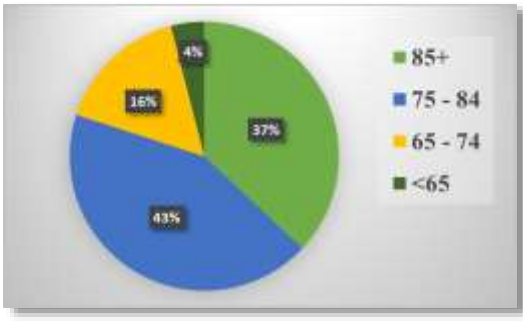


Figure 1. Age Distribution Of AD Patients in The United States

As per data from the WHO, in 2021, around 55 million people across the global were impacted by dementia. By 2030, this is anticipated to reach 78 million, and by 2050, it will reach an astounding 139 million. As Figure 1 illustrates, the risk of developing dementia is notably higher for individuals over the age of 65, while just 4% of younger people have young-onset dementia, which is typically caused by a variety of underlying disorders [4]. In the U.S., 5.7 million people suffer from AD. It has increased very rapidly by three times now, in the middle of the century. There were 110,561 official death certificates in 2015, making AD the sixth most common cause of death in the US. In India, around 7.4% of individuals aged 60 and above are estimated to have dementia, equating to approximately 8.8 million elderly Indians living with dementia [5].

People suffering from Alzheimer's disease undergo a progressive shift in symptoms over the years, mirroring the extent of neuronal damage across various brain regions. Symptoms of AD are shown in Figure 2, Most Alzheimer's patients can perform daily activities in the mild stage, but they may need assistance. In the severe stage, Alzheimer's severely damages physical health, increasing the risk of bed rest, blood clots, skin infections, and sepsis, which can lead to organ failure and is a factor in the death of many Alzheimer's patients.
It is therefore necessary to diagnose AD accurately at an early stage and to start medication at the right time to reduce substantial brain damage and mortality.

1.1 Early AD Identification

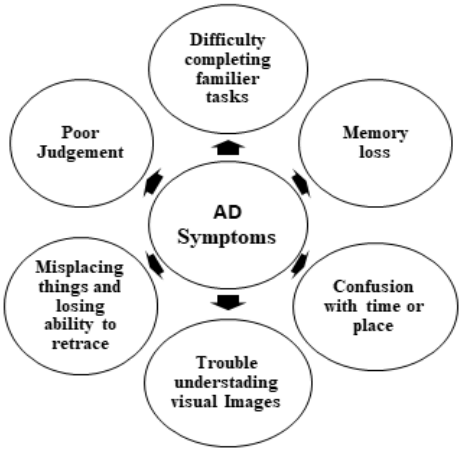


Figure 2. Shows Symptoms of AD

Early identification and accurate diagnosis of Alzheimer's disease require a comprehensive assessment conducted by a proficient medical specialist, which includes a thorough examination of the patient's medical background and extensive physical and neurological evaluations [MMSE][6],[7],[8]. Additionally, measures for treatment are more effective when implemented in the early phases of the AD [9]. Neuroimaging modalities such as functional MRI, structural MRI, and PET play a crucial role in providing evidence of structural brain changes associated with cognitive decline.These imaging modalities offer detailed insights into subcortical structure of brain such as cerebellum, amygdala, corpus callosum, cerebral cortex [10],[11] Magnetic Resonance Imaging (MRI) is a key diagnosis of Alzheimer's disease investigations because it is noninvasive and doesn't cause discomfort to patients[12].Figure 3 shows sMRI images of patient with Alzheimer's disease (AD) and patient without dementia (NC) consequently, researchers use structural MRI (sMRI) as biomarkers to characterize AD by observing the size of damaged tissues in the brain [13]. A machine-learning-based automated system is required to achieve greater accuracy compared to human assessments and can be integrated into medical decision support systems.

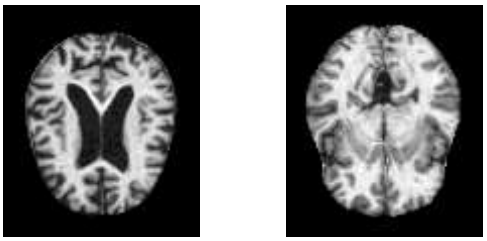


Figure 3. Shows AD and normal (NC) brain MR images.

2. RELATED WORK

In [14] focused on significance of early Alzheimer's disease (AD) detection and introduced a dense neural network approach for binary AD classification, contrasting it with conventional machine learning techniques. By utilizing MRI data sourced from the ADNI database and experimenting with various activation functions, their proposed model demonstrated remarkable accuracy, reaching an impressive 87.50%.In [15] highlighted the significance of early AD detection. This paper discussed about precise prediction and classification of AD using 3D MR scans. It employs a Multi - Layer Perceptron for feature extraction and classification in combination with a support vector machine.

In [16] introduced an innovative approach that utilizes graph kernels with texture features extracted from sMRI images to predict AD and MCI. This method showed promising outcomes, especially in distinguish AD and CN, CN vs. MCI classifications. In [17] discussed about ensemble technique using knowledge transfer between models to discriminate AD and MCI using brain MR images. The results show that ensemble transfer learning approach provides new insights for early AD diagnosis and prognosis.
In [18] significance of ML techniques in AD detection through the utilization of various imaging diagnostics like MRI, CT, EEG and PET. By processing neuroimaging data with machine learning algorithms like Neural Networks and Random Forest, the study aims to detect Alzheimer's in its early stages with high accuracy. In [19] concentrated on utilizing machine learning methods, namely Support Vector Machine (SVM), in conjunction with feature extraction from MRI axial brain slices employing Haralick features and Grey Level Co-occurrence Matrix (GLCM). This model achieves an 84% accuracy in classifying AD subjects from normal controls, demonstrating the potential of this approach for early detection.

In [20] the author(s) have proposed a model that utilizes AI techniques to predict the chances of transitioning from MCI to AD within a year, based on the analysis of MRI scans from ADNI database. This model uses CNN to extracts features and SVM as classifier. The results indicate that the model can achieve high classification accuracy (up to 92.3%).In [21] presented a combined approach using a three dimensional CNN with SVM for early Alzheimer's Disease detection .The model achieves promising results on ADNI data, with 91.85% accuracy, showing the superiority of SVM over other machine learning classifiers. The author introduced a new 3D MRI classifier, which combines Kernel Principal Component Analysis and SVM. It performs feature extraction through the Discrete Wavelet Transform categorizes brain MRI images as either normal or pathological. The study utilizes k-fold cross-validation, achieving high classification rates in terms of accuracy, specificity and sensitivity.

This [22] paper focused on early Alzheimer's disease prediction. This paper also highlights the use of support vector machine to classify AD into different stages. This model offers increased accuracy and potential alternative to conventional clinical diagnosis methods. In [23] introduced a new method aimed at enhancing feature selection process by particle swarm optimization and weighted SVM from brain MRIs. This method achieves a promising classification accuracy of 93%, marking its effectiveness in handling large datasets and classifying brain images, demonstrating its potential for Alzheimer's disease diagnosis.

After a thorough examination of existing methodologies, it is clear that these approaches require substantial computational resources for processing 3D MRI images and extracting features from 2D slices within these volumes. Certain approaches utilize advanced deep learning techniques, such as convolutional neural networks or transfer learning. Meanwhile, other methods employ complex procedures to extract features from MRI images, such as generating graph kernels using texture data. Furthermore, some methodologies rely on a limited number of images, thus rendering the model less adaptable to new data.

The proposed approach focuses on developing a simple machine learning model to achieve precise Alzheimer's disease (AD) detection. This method utilizes high-quality MRI images obtained from the Kaggle website. Unlike existing approaches, our method stands out by utilizing a dataset with good number of images sized at 128x128, leading to reduced computational requirements. Existing methods often employ high-dimensional images, contributing to increased computation time and complexity. In contrast to existing techniques that use separate feature selection methods applied to reduce complexity, which can result in decreased accuracy due to data loss, our proposed method abstains from applying any feature selection.

The model algorithm utilizes the entire image to construct a feature vector for image classification. This approach includes the application of appropriate image preprocessing techniques without compromising essential data. Moreover, we ensure a well-balanced dataset through data augmentation techniques suitable for binary classification. The chosen binary classification algorithm is the efficient and widely used Support Vector Machine (SVM) with a linear kernel. We conducted a comparative analysis with existing state-of-the-art techniques on the same dataset as shown in Table 1. The proposed model outperformed in terms of widely used classification performance measures.
The main highlights of this research work are outlined as follows:

- Utilizing various image preprocessing techniques to prepare MRI images for model design while reducing computational requirements.
- Training ML model using SVM Binary Classifier
- Achieving a remarkable 99% accuracy in AD prediction, surpassing the performance of alternative algorithms.

The remaining contents in this paper divided into sections in the following manner. Section-2 describes the proposed methodology. Section-3 presents the results and discussion. Section-4 provides the concluding remarks for this work.

3. MATERIALS AND METHODS

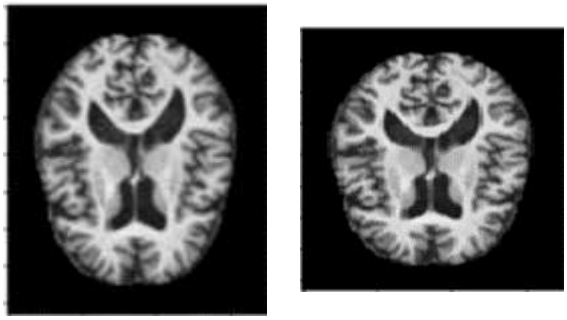
3.1 Dataset Description

The study utilizes a Kaggle dataset that focuses on the classification of Alzheimer's disease. The dataset consists of sMRI (structural MRI) images, classified into four distinct classes. Specifically, there are 717 images representing mild demented cases, 2,560 for non-demented cases, 52 for moderately demented cases, and 1,792 for very mild demented cases. Each MRI image within the dataset has dimensions of 176 × 208 and is in.jpg format. In the context of this research, the primary focus is on two categories: individuals with dementia and those without dementia. The above MR imaging data is available to access on the Kaggle website [24].

3.2 Preprocessing

Larger images have more pixels, and processing them requires more computational resources, memory, and time. By resizing images to a smaller dimension, we can significantly reduce the computational complexity of the model, making it more efficient and faster to train and evaluate. After normalization, the grayscale images are resized to 128x128 pixels, as shown in Figure 4.

3.3 Data Augmentation



(a)Original Image (176x208) (b)Resized Image (128x128)

Figure 4. Illustrates Resizing sMRI Images

In medical research, particularly in the field of neuroimaging, the significant challenge lies in obtaining a substantial number of scans due to privacy issues. Moreover, a limited and imbalanced dataset can lead to overfitting issues, adversely impacting model effectiveness. To overcome these issues, data augmentation techniques are applied to the original dataset. We applied the horizontal flipping augmentation technique to generate additional images, as illustrated in Figure 5. Although we attempted various data augmentation methods like brightness adjustment, zoom, and rotation range, they did not benefit our proposed model, so we settled for using only horizontal flipping [25].

We executed all preprocessing procedures using Python (version 3.9.17). Utilizing Keras libraries (https://keras.io/) and Scikit-learn (https://scikit-learn.org/stable/) to build ML models. After preprocessing, the dataset comprises two directories: "demented" and "non-demented," with each directory containing 3200 images, resulting in a well-balanced dataset conducive to designing an effective model.

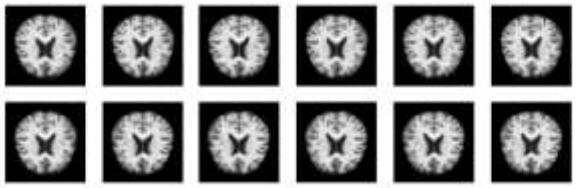


Figure 5. Sample Images Generated Using Data Augmentation

Table 1. Comparing the Proposed Method's Accuracy with Previous Research for AD vs. NC.

Author Name	Model	Dataset	Accuracy
Rukesh Prajapati & Goo-Rak Kwon, 2022	CNN	MRI Images	87.50%
Kongala et al., 2023	SVM	MRI Images	---
Lucas José Cruz de Mendonça & Ricardo José Ferrari .2023	SVM	MRI Images	92%
Loris et al., 2020	Fusion of Machine Learning	MRI Images	93.3%
Priyanka et al., 2018	SVM	ADNI	97.56%
Uma et al., 2021	SVM	MRI Images	84%
Ting et al., 2018	SVM	ADNI	92.3%
Shubham et al., 2021	3D CNN and SVM	ADNI	91.85%
Krishna Thulasi N P & Dany Varghese,	SVM	ADNI	---
Farzaneh Elahifasaee, 2022	Feature extraction with AdaBoost and PSO using SVM	MRI Images	93%
Proposed SVM classifier	SVM	MRI Images	99.06%

3.4 Proposed Algorithm

Various studies carried out by the researchers to diagnose AD are listed in Section 1. However, some research produced less accurate results, and other research produced good results, but at the expense of using a more complex and time-consuming methodology. In this paper, we propose a simple SVM model that enhances AD diagnosis performance. Its main goal is to create a hyperplane that accurately distinguishes a given data point between two output classes in a feature space, as depicted in Figure 6. SVM [26] classifies the data as a hyperplane, as in Eq. (1).

$$Wx^T + b = 0 \qquad (1)$$

In the above equation, w represents weight vector, b indicates bias, and the input feature vector is represented as x.

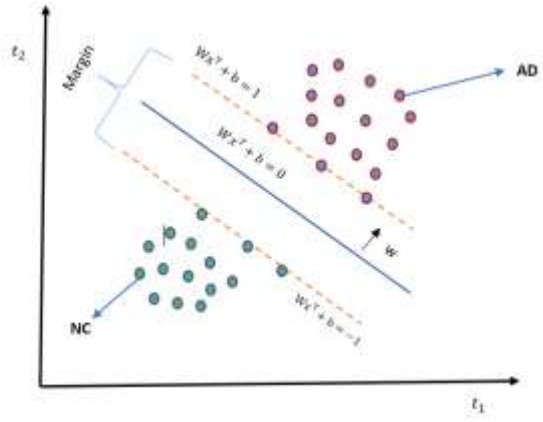


Figure 6. Shows Linear SVM model: Two classes AD vs NC

The hyperplane is strategically positioned to maximize the distance between the nearest data points belonging to each of the groups. These data points are generally known as support vectors.
The dataset used in training is represented as in Eq. (2).

$$(t_1, k_1) \ldots\ldots\ldots, (t_n, k_n), t_1 \in R_d \; and \; k_i \in (-1, +1) \quad (2)$$

In above equation, t_i represents feature vector and k_i is output class label of a training set i.
The parameters 'b' and 'w' must meet the inequalities described in Eq. (3) and Eq. (4) for every element within the training dataset.

$$Wx^T + b \geq +1 \; if \; y_i = 1 \quad (3)$$

$$Wx^T + b \leq -1 \; if \; y_i = -1 \quad (4)$$

Consider N training data samples, $\{\{(t_1,k_1),(t_2,k_2).....(t_N,k_N)\}$ are given $t_i \in R^d$ represents a set of feature vectors and $k_i \in \{-1,+1\}$ are output class label. The classification problem can be represented as defined in the following minimization problem in Eq. (5) and Eq. (6).

$$min_{w,b}\left(\frac{w^T w}{2}\right) \quad (5)$$

s. t.: $k_i(w^T.t_i) + b > 1, \quad i = 1, 2, \ldots. n \quad (6)$

The function defined in Eq. (7) can classify new data ob*ject x*.

$$g(x) = \sin\,(w^T t + b) \quad (7)$$

The objective of SVM algorithms during training is to find best hyperplane such that w and b parameters can group data points by maximizing the margin distance $\frac{1}{\|W\|^2}$.

In this study, we experimented with all other competitive classification algorithms using the same dataset, with the proposed SVM outperforming the others in terms of accuracy, precision, recall, and F1-score. Logistic Regression and Random Forest also perform well, while Decision Tree and XGBoost Classifier offer reasonable performance. The Naive Bayes classifier lags behind in terms of overall effectiveness. Table 2 presents the comparative performance analysis of various classifiers.
The Bar plot shows the accuracy comparison of various classification algorithms with proposed SVM classifier shown in Figure 7.

Table 2. Comparing the accuracy of various classification algorithms with the proposed SVM classifier.

Model	Prec	Rec	ACC	FS
Random Forest	0.95	0.95	94.53	0.95
Logistic Regression	0.99	0.99	98.67	0.99
Decision Tree Classifier	0.79	0.79	78.59	0.79
Naive Bayes Classifier	0.68	0.68	67.26	0.67
XGBoost	0.80	0.80	0.80	0.80
Proposed SVM	0.99	0.99	99.06	0.99

Here, "Prec" – Precision, "Rec"- Recall, "Acc"- Accuracy,"FS"- F1 - score

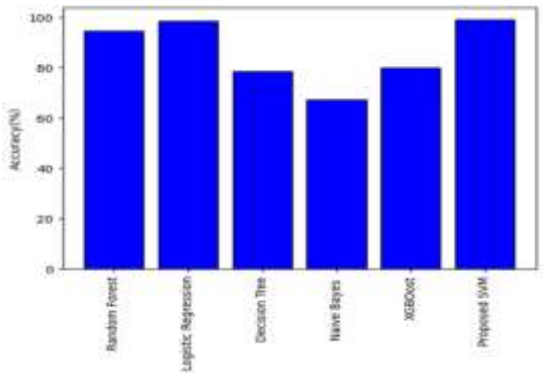


Figure 7. Shows Accuracy comparison of various classifiers with proposed method

3.5 SVM - Kernel Trick

The performance of SVM can be further improved with kernel function [23]. It allows to create higher-dimensional, non-linear models. In cases where the problem is not linear, a kernel adds new dimensions to the given data, thereby converting it into a linear problem within the resulting higher-dimensional space. Essentially, a kernel function, as illustrated in Eq. (8), allows for speeding up particular calculations that would otherwise require intricate computations in a high-dimensional space.

$$k(u, v) = < f(u), f(v) > \quad (8)$$

In the above equation, k represents the kernel function, where u and v are inputs with n dimensions. Function f transforms the input from an m-dimensional space to an n-dimensional space. The term (u, v) signifies the dot product between the inputs.

In this study, the linear kernel stands out with exceptional accuracy and performs well when the data supports linear separation. It achieves the highest accuracy, F1-score, precision, and recall, as shown in Table 3. When the data allows for a linear boundary, the linear kernel showcases outstanding performance, achieving the best accuracy, robust precision and sensitivity, and finally a good F1 score. On the other hand, the RBF kernel [27] is well-suited for complex, nonlinear data but achieves slightly lower accuracy when compared to the linear kernel. Nonetheless, it still delivers respectable precision, recall, and F1-score.

The polynomial kernel effectively captures moderate levels of nonlinearity, resulting in high accuracy alongside strong precision, recall, and F1-score. In stark contrast, the sigmoid kernel shows notably poorer performance compared to the other kernels, resulting in low accuracy, subpar precision, recall, and the F1-score. This suggests that it is not suitable for the given dataset.

3.6 Proposed Methodology Architecture

The proposed methodology, as illustrated in Figure 8, involves several key steps. Firstly, the data undergoes a pre-processing phase to clean and prepare it for analysis. Following this, the dataset is split into two sets: 80% of total data utilized for model training and the remaining 20% of data utilized for model testing, facilitating a rigorous testing process for model performance. For the training process, a Support Vector Machine (SVM) binary classifier is employed, utilizing a linear kernel for model construction.

This classifier is trained on the training dataset, learning patterns, and relationships within the data. Subsequently, model validation is carried out using a separate testing dataset. This step allows for a thorough assessment of the model's generalization performance, ensuring that it can make accurate predictions on unseen data.

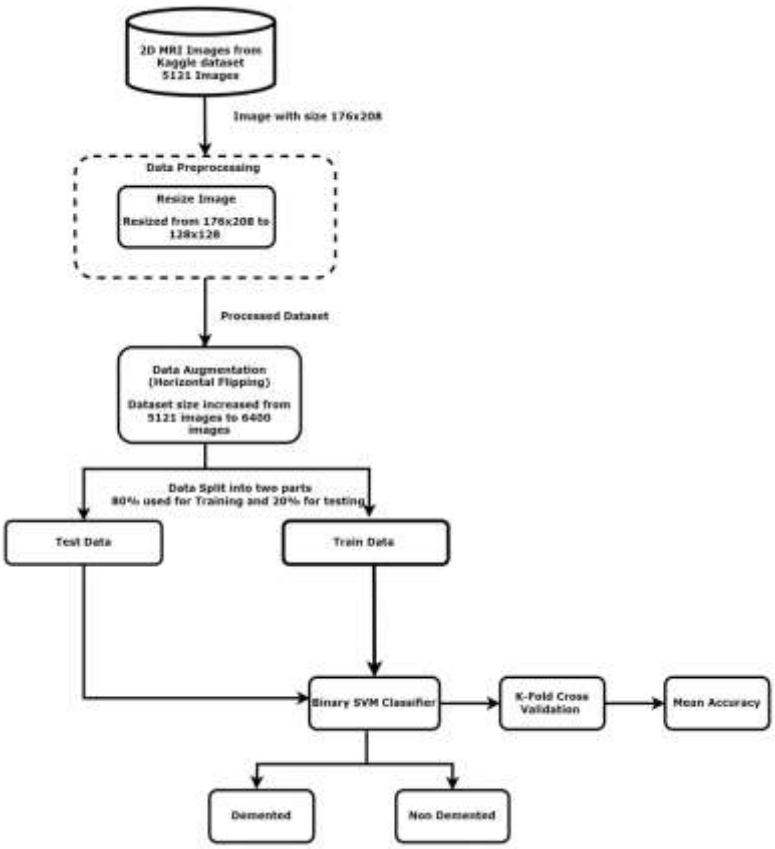


Figure 8. The Proposed Methodology Flowchart

3.7 Model Validation

To address the problem of overfitting in machine learning, a crucial technique is the implementation of cross-validation. Cross-validation plays a vital role in assessing the performance of a model and breaks the entire dataset into 'n' equally sized segments or folds. During each iteration, the model undergoes training using 'n-1' of these folds, while one fold is kept aside for testing. This process is reiterated 'n' times, with each of the 'n' folds taking on the role of the test set once. This iterative training and testing approach exposes the model to various subsets of the data, aiding it in generalizing effectively and preventing overfitting. To evaluate the model's performance, we compute the average of the results from all folds.

In this work, the model was trained and tested using 15-fold cross-validation, as shown in Table 3. By employing multiple folds, the study aims to comprehensively assess the model's performance under varying conditions, provide a robust model with good accuracy, and assess its capability in classifying new data by taking into account the variations across different subsets of the dataset.

Table 3. Accuracy validation using the 15-fold cross-validation approach.

Fold No.	AC	MAC
1	0. 99	
2	0. 99	
3	0. 99	
4	0. 98	
5	0. 99	
6	0. 98	
7	0. 96	
8	0. 97	0. 98
9	0. 99	
10	0. 98	
11	0. 98	
12	0. 98	
13	0. 98	
14	0. 97	
15	0. 97	

Here "AC" - Accuracy, "MAC" – Mean_Average

4. RESULTS AND DISCUSSION

The model's performance metrics include accuracy, sensitivity, specificity, and the F1-score, which are essential in evaluating its effectiveness. Accuracy alone may not be sufficient in healthcare diagnosis as it doesn't consider the consequences of false positives and false negatives. Sensitivity (also known as recall) measures the ability of the model to correctly identify positive cases (AD) out of all actual positive cases, ensuring early detection and treatment. In this case, the model achieves a high sensitivity of 99.02%, indicating that it rarely misses cases with AD.Specificity measures the ability of the model to correctly identify negative cases (non-AD) out of all actual negative cases, minimizing false alarms and unnecessary interventions. The specificity achieved by the model is 99.10%, indicating a high accuracy in identifying individuals without AD.

Table 4. Comparison of classification reports for proposed SVM classifier and other Classifiers.

	Prc	Rec	FS
Demanted	0. 99	0. 99	0. 99
Non_Demnated	0. 99	0. 99	0. 99
AC			99.06
Mavg	0. 99	0. 99	0. 99
Wavg	0. 99	0. 99	0. 99

Proposed SVM Classifier

	Prc	Rec	FS
Demanted	0. 80	0. 78	0. 79
Non_Demnated	0. 77	0. 79	0. 78
AC			0.79
Mavg	0. 79	0. 79	0. 79
Wavg	0. 79	0. 79	0. 79

Decision Tree Classifier

	Prc	Rec	FS
Demanted	0. 94	0. 95	0. 95
Non_Demnated	0. 95	0. 94	0. 94
AC			95.0
Mavg	0. 95	0. 94	0. 95
Wavg	0. 95	0. 95	0. 95

Random Forest Classifier

	Prc	Rec	FS
Demanted	0. 72	0. 60	0. 66
Non_Demnated	0. 63	0. 75	0. 69
AC			67
Mavg	0. 68	0.68	0. 67
Wavg	0. 68	0. 67	0. 67

Naïve Byes Classifier

	Prc	Rec	FS
Demanted	0. 99	0. 99	0. 99
Non_Demnated	0. 98	0. 99	0. 99
AC			98.6
Mavg	0. 99	0.99	0. 99
Wavg	0. 99	0. 99	0. 99

Logistic Regression

	Prc	Rec	FS
Demanted	0. 78	0. 81	0. 79
Non_Demnated	0. 82	0. 79	0. 80
AC			80
Mavg	0. 80	0.80	0. 80
Wavg	0. 80	0. 80	0. 80

XG Boost

Here "Prc"- Precision, "Rec"-Recall, "FS"- F1-score, "Supt"-Support," AC"-Accuracy, "Mavg" – Macro_Average, "Wavg"- Weighted_Average.

Precision measures the proportion of correctly identified positive cases out of all cases predicted as positive. The model's precision is 99.02%, indicating that very few cases predicted as positive are false positives. The F1-score, calculated by considering both precision and recall, provides a balanced assessment of the model's performance. The high F1-score of 99.0 suggests that the model maintains a good balance between precision and recall, crucial in healthcare diagnosis.In healthcare, finding the right balance between specificity and sensitivity is crucial. While sensitivity ensures early detection and treatment, specificity minimizes false alarms and unnecessary interventions. The model's high sensitivity and specificity, along with a balanced F1-score, indicate that it strikes an appropriate balance between minimizing missed diagnoses and false alarms, which is essential in healthcare settings.

The proposed model SVM with linear kernel achieved an accuracy of 99.06%, a sensitivity of 99.02, specificity of 99.10 and F1-score 99.0 when distinguishing between the AD and CN groups. The proposed model shows promising results in diagnosing AD, with high sensitivity, specificity, precision, and a balanced F1-score. These metrics collectively indicate the model's effectiveness in accurately identifying AD cases while minimizing false

alarms, demonstrating its potential utility in clinical practice. Consequently, our model yielded superior results that are on par with those of other models. Table 4 display the classification reports of various algorithms. Figure 9 displays the confusion matrix for our model and other classifiers.

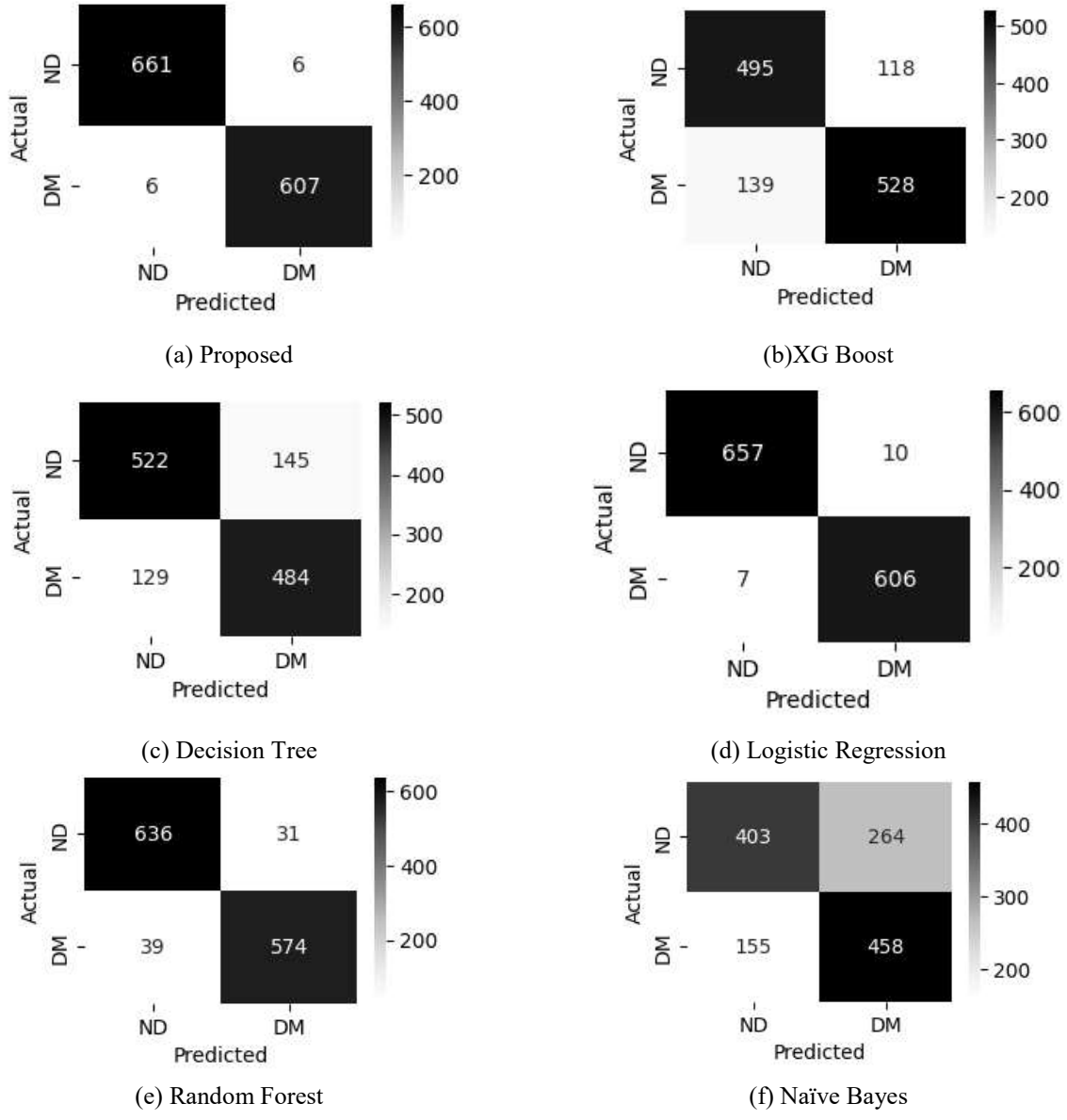


Figure. 10: from (a) to (f) shows confusion matrix for proposed and other classification algorithms

Here **ND – "Non_Demanted", DM - "Demanted"**

5. CONCLUSION

Alzheimer's disease represents a major health issue, and instead of primarily concentrating on discovering a cure, it is

crucial to prioritize risk reduction, early intervention, and precise symptom identification. Detecting AD at an early stage and initiating necessary treatment can significantly reduce the potential damage to brain cells in Alzheimer's patients. The literature review in this paper highlights the extensive efforts of authors in AD detection using ML techniques.

To address the challenge of early Alzheimer's detection, a binary classifier model using SVM with a linear kernel is proposed. When compared to contemporary machine learning techniques, the proposed model outperformed in terms of widely used classification performance measures, like sensitivity, specificity, accuracy, and F1-score, when distinguishing between individuals with Alzheimer's disease and those who are

cognitively normal (AD vs. CN). In our future research, we plan to implement a hybrid model that combines both traditional ML methods and neural networks to get more precise results.

REFERENCES

1. Kong, Z., Zhang, M., Zhu, W., Yi, Y., Wang, T., Zhang, B., 2022. Multi-modal data Alzheimer's disease detection based on 3D convolution. Biomedical Signal Processing and Control 75, 103565. https://doi.org/10.1016/j.bspc.2022.103565.
2. Arafa, D.A., Moustafa, H.E.-D., Ali, H.A., Ali-Eldin, A.M.T., Saraya, S.F., 2023. A deep learning framework for early diagnosis of Alzheimer's disease on MRI images. Multimedia Tools and Applications 83, 3767–3799. https://doi.org/10.1007/s11042-023-15738-7.
3. Mehmood, A., Maqsood, M., Bashir, M., Shuyuan, Y., 2020. A Deep Siamese Convolution Neural Network for Multi-Class Classification of Alzheimer Disease. Brain Sciences 10, 84. https://doi.org/10.3390/brainsci10020084.
4. 2018 Alzheimer's disease facts and figures, 2018. . Alzheimer's & Dementia 14, 367–429. https://doi.org/10.1016/j.jalz.2018.02.001.
5. Hebert, L.E., Weuve, J., Scherr, P.A., Evans, D.A., 2013. Alzheimer disease in the United States (2010–2050) estimated using the 2010 census. Neurology 80, 1778–1783. https://doi.org/10.1212/wnl.0b013e31828726f5.
6. Arevalo-Rodriguez, I., Smailagic, N., Roqué-Figuls, M., Ciapponi, A., Sanchez-Perez, E., Giannakou, A., Pedraza, O.L., Bonfill Cosp, X., Cullum, S., 2021. Mini-Mental State Examination (MMSE) for the early detection of dementia in people with mild cognitive impairment (MCI). Cochrane Database of Systematic Reviews 2021. https://doi.org/10.1002/14651858.cd010783.pub3.
7. Harrell, L.E., Marson, D., Chatterjee, A., Parrish, J.A., 2000. The Severe Mini-Mental State Examination: A New Neuropsychologic Instrument for the Bedside Assessment of Severely Impaired Patients With Alzheimer Disease. Alzheimer Disease and Associated Disorders 14, 168–175. https://doi.org/10.1097/00002093-200007000-00008.
8. Pangman, V.C., Sloan, J., Guse, L., 2000. An examination of psychometric properties of the Mini-Mental State Examination and the Standardized Mini-Mental State Examination: Implications for clinical practice. Applied Nursing Research 13, 209–213. https://doi.org/10.1053/apnr.2000.9231.
9. Leifer, B.P., 2003. Early Diagnosis of Alzheimer's Disease: Clinical and Economic Benefits. Journal of the American Geriatrics Society 51. https://doi.org/10.1046/j.1532-5415.5153.x.
10. Kavitha, C., Mani, V., Srividhya, S.R., Khalaf, O.I., Tavera Romero, C.A., 2022. Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models. Frontiers in Public Health 10. https://doi.org/10.3389/fpubh.2022.853294.
11. Tufail, A.B., Ma, Y.-K., Zhang, Q.-N., 2020. Binary Classification of Alzheimer's Disease Using sMRI Imaging Modality and Deep Learning. Journal of Digital Imaging 33, 1073–1090. https://doi.org/10.1007/s10278-019-00265-5.
12. EL-Geneedy, M., Moustafa, H.E.-D., Khalifa, F., Khater, H., AbdElhalim, E., 2023. An MRI-based deep learning approach for accurate detection of Alzheimer's disease. Alexandria Engineering Journal 63, 211–221. https://doi.org/10.1016/j.aej.2022.07.062.
13. Herrera, L.J., Rojas, I., Pomares, H., Guillen, A., Valenzuela, O., Banos, O., 2013. Classification of MRI Images for Alzheimer's disease Detection. 2013 International Conference on Social Computing. https://doi.org/10.1109/socialcom.2013.127.
14. Prajapati, R., Kwon, G.-R., 2022. A Binary Classifier Using Fully Connected Neural Network for Alzheimer's disease Classification. Journal of Multimedia Information System 9, 21–32. https://doi.org/10.33851/jmis.2022.9.1.21.
15. Rao, K.N., Gandhi, B.R., Rao, M.V., Javvadi, S., Vellela, S.S., Khader Basha, S., 2023. Prediction and Classification of Alzheimer's Disease using Machine Learning Techniques in 3D MR Images. 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS). https://doi.org/10.1109/icscss57650.2023.10169550.
16. de Mendonça, L.J.C., Ferrari, R.J., 2023. Alzheimer's disease classification based on graph kernel SVMs constructed with 3D texture features extracted from MR images. Expert Systems with Applications 211, 118633. https://doi.org/10.1016/j.eswa.2022.118633.
17. Nanni, L., Interlenghi, M., Brahnam, S., Salvatore, C., Papa, S., Nemni, R., Castiglioni, I., 2020. Comparison of Transfer Learning and Conventional Machine Learning Applied to Structural Brain MRI for the Early Diagnosis and Prognosis of Alzheimer's Disease. Frontiers in Neurology 11. https://doi.org/10.3389/fneur.2020.576194.
18. Lodha, P., Talele, A., Degaonkar, K., 2018. Diagnosis of Alzheimer's Disease Using Machine Learning. 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). https://doi.org/10.1109/iccubea.2018.8697386.
19. K, U.R., S, Sharvari.S., G, Umesh.M., C, Vinay.B., 2021. Binary Classification of Alzheimer's disease using MRI images and Support Vector Machine. 2021 IEEE Mysore Sub Section International Conference (MysuruCon). https://doi.org/10.1109/mysurucon52639.2021.9641661.

20. Shen, T., Jiang, J., Li, Y., Wu, P., Zuo, C., Yan, Z., 2018. Decision Supporting Model for One-year Conversion Probability from MCI to AD using CNN and SVM. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). https://doi.org/10.1109/embc.2018.8512398.
21. Dwivedi, S., Goel, T., Sharma, R., Murugan, R., 2021. Structural MRI based Alzheimer's Disease prognosis using 3D Convolutional Neural Network and Support Vector Machine. 2021 Advanced Communication Technologies and Signal Processing (ACTS). https://doi.org/10.1109/acts53447.2021.9708107.
22. Thulasi N.P., K., Varghese, D., 2018. A Novel Approach for Diagnosing Alzheimer's Disease Using SVM. 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI). https://doi.org/10.1109/icoei.2018.8553789.
23. Elahifasaee, F., 2022. Optimized SVM using AdaBoost and PSO to Classify Brain Images of MR. 2022 International Conference on Machine Vision and Image Processing (MVIP). https://doi.org/10.1109/mvip53647.2022.9738549.
24. Alzheimer's Dataset (4 class of Images) [WWW Document], 2019. . Kaggle. URL https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images.
25. Mehmood, A., Maqsood, M., Bashir, M., Shuyuan, Y., 2020. A Deep Siamese Convolution Neural Network for Multi-Class Classification of Alzheimer Disease. Brain Sciences 10, 84. https://doi.org/10.3390/brainsci10020084.
26. Applications of Support Vector Machine (SVM) Learning in Cancer Genomics, 2018. . Cancer Genomics & Proteomics 15. https://doi.org/10.21873/cgp.20063.
27. Neffati, S., Taouali, O., 2017. An MR brain images classification technique via the Gaussian radial basis kernel and SVM. 2017 18th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA). https://doi.org/10.1109/sta.2017.8314948.