IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Alzheimer's Disease Severity Prediction Using Ai

Shruti Goyal

Student

Department of AI & DS

Indira Gandhi Delhi Technical University for Women, Delhi, India

Abstract: Alzheimer's Disease (AD) is one of the top causes of death in the world. Prompt prediction of Alzheimer's using traditional methods is not very efficient due to their dependency on subjective assessments, slow progression of the disease, and the invasive or costly nature of biomarker tests. It highlights the need to implement AI models as they can identify patterns in large and complex datasets, thereby enabling earlier, non-invasive diagnosis. The models utilized in AD diagnosis include Convolutional Neural Networks (CNN), an Autoencoder-based Support Vector Machine (SVM) and Logistic Regression. These models have the potential to extract and learn features from MRI scans, resulting in better prediction for AD patients.

I. Introduction

Alzheimer's disease (AD) is a progressive neurodegenerative disorder causing cognitive decline, memory impairment, and behavioral changes. It is one of the most common causes for brain damage, responsible for 60-70\% of all cases. According to WHO, over half a billion people worldwide are affected by dementia, making it the seventh foremost cause of death and dependency especially amongst the elderly population. As life expectancy rises, the prevalence of Alzheimer's disease is expected to increase significantly.

Various methods can be used to detect AD. Neuro-imaging techniques like Magnetic Resonance Imaging (MRI) produce detailed brain images to reveal shrinkage in Alzheimer-associated regions. Computed Tomography (CT) scans reveal amyloid plaques and tau tangles, which are typical in Alzheimer's.\cite{r26} Biomarker analysis involves measuring amyloid-beta and tau protein levels in cerebrospinal fluid (CSF). Cognitive tests that assess memory and problem-solving skills, and neurological exams that check reflexes and coordination can also be used. Blood pressure and heart rate monitoring can hint at cognitive decline. These detection methods either used individually or in combination, aid in early diagnosis and management of AD.

In the last few decades, machine learning (ML) has been recognized as a powerful technique for the early detection of Alzheimer's disease. ML algorithms can analyze complicated datasets like MRI images and numerical clinical data to identify underlying patterns and signs of disease. Advanced efforts to improve diagnosis accuracy and disease progression include Deep Learning (DL) and ensemble learning algorithms. The integration of ML and DL in Alzheimer's research aims to reduce diagnosis time while also discovering new biomarkers and treatment strategies to improve quality of life.

II. LITERATURE REVIEW

In this literature review, research studies focused on the prediction of Alzheimer's disease have been analysed. Our analysis aimed at understand how research in this field has evolved over the years, identifying the most frequently used datasets and machine learning models, and evaluating the accuracy of different predictive approaches.

To provide a comprehensive overview, we have compiled a table summarizing key aspects of each paper including the year of publication, the technology employed and the accuracy achieved by the models. Moreover, five illustrative graphs are also provided to offer visual insights into various dimensions of the research landscape.

Table 1 : Summary of review of AD prediction

Reference No.	Year of Publication	Technology Used	Accuracy
5	2017	DTCWT+PCA+FNN	90.60%
6	2019	k-skip-n-gram	85.50%
7	2020	Random Forest Classifier	86.84%
8	2020	CNN	99.00%
9	2020	CNN	90.91%
10	2021	CNN	97.00%
11	2021	Bagging	82.75%
12	2021	MCapNet	92.30%
13	2022	DenseNet201-Gaussian Naive Bayes	91.75%
14	2023	XGBoost	96.75%
15	2023	InceptionV3	87.69%
16	2023	CNN+GAN	96.10%
17	2023	CNN	98.50%
18	2023	CNN	86.45%
19	2023	SVM	96.77%
20	2023	EfficientNet-B2+DenseNet-121	95.45%
21	2024	VGG16	80.80%

III. Background Technology

3.1 Machine Learning Techniques

Machine learning has emerged as a transformative force in the field of medical diagnosis, revolutionizing the way healthcare professionals approach disease detection and management. Its capacity to process and analyze vast datasets, coupled with its ability to extract meaningful features, has proven to be an invaluable tool for identifying patterns and anomalies indicative of various diseases. This capability has significantly enhanced diagnostic accuracy and efficiency across multiple medical domains. Among the plethora of machine learning techniques available, we selected Support Vector Machines (SVM) and Logistic Regression models as the cornerstone of our analysis for detecting Alzheimer's disease, given their proven efficacy in handling classification tasks with structured data derived from medical imaging.

3.1.1 Support Vector Machines

Support Vector Machines (SVMs) represent a robust statistical modeling approach widely employed for classification tasks, particularly in scenarios requiring clear delineation between distinct classes. The core principle of SVMs lies in identifying the optimal hyperplane that best separates data points belonging to different classes within the feature space. This separation is achieved by maximizing the margin, defined as the largest possible distance between the hyperplane and the nearest data points from each class, known as support vectors. As defined below, the decision function for a binary classification problem is given by:

- Decision function: $f(x) = \text{sign}(w^T x + b)$

where w is the weight vector perpendicular to the hyperplane, x is the input vector, and b is the bias term. The margin is maximized by solving the optimization problem:

- Optimization: minimize $(1/2) ||w||^2$
- Subject to: $y_i (w^T x_i + b) >= 1$ for all training samples (x_i, y_i)

A subset of these support vectors ultimately defines the decision boundary, playing a critical role in determining the classifier's performance and its ability to generalize to unseen data, making SVMs particularly suitable for our Alzheimer's detection task.

3.1.2 Logistic Regression

Logistic Regression is a versatile statistical model tailored for classification problems, particularly effective in scenarios where the outcome can be categorized into one of multiple classes, such as the four dementia categories in our study (Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented). This algorithm excels at learning the relationships between features extracted from MRI scans and corresponding diagnoses, enabling it to predict the probability of disease presence in new cases with reasonable accuracy. The model employs a logistic function to transform a weighted sum of input features into a probability value between 0 and 1. As defined below, the logistic function is expressed as:

- Probability: $P(y=1|x) = 1 / (1 + e^{(- (w^T x + b))})$

where w represents the weight vector, x is the feature vector, and b is the intercept. This probability output allows the model to classify instances based on a threshold (typically 0.5), providing a probabilistic framework that is both interpretable and adaptable, thus supporting its application in our medical diagnostic analysis.

3.2 Deep Learning Techniques

Deep Learning (DL), a specialized subset of machine learning, harnesses the power of deep neural networks to uncover complex patterns and relationships within data, enabling highly accurate predictions across a wide range of applications. This advanced technique is particularly renowned for its effectiveness in tasks involving image and speech recognition, where traditional methods often fall short due to the intricate nature of the data. The primary advantage of DL models lies in their ability to autonomously extract key features and insights directly from raw inputs such as images and videos, eliminating the need for manual feature engineering and facilitating an end-to-end learning process. This capability makes DL an ideal choice for medical imaging tasks, where subtle visual cues can be critical. In our study, we have leveraged Convolutional Neural Networks (CNNs), a prominent DL architecture, to effectively detect Alzheimer's disease by analyzing MRI scans. The hierarchical structure of CNNs, comprising convolutional layers that apply filters to detect features like edges and textures, followed by pooling layers to reduce spatial dimensions, allows for robust feature extraction tailored to the nuances of neuroimaging data, thereby enhancing the diagnostic process.

IV. METHODOLOGY

The Alzheimer's disease detection project utilized a structured approach, integrating deep learning and machine learning techniques to classify MRI images into four categories: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The methodology was carefully designed to ensure robust analysis and reliable outcomes, with each phase building upon the previous to enhance diagnostic accuracy.

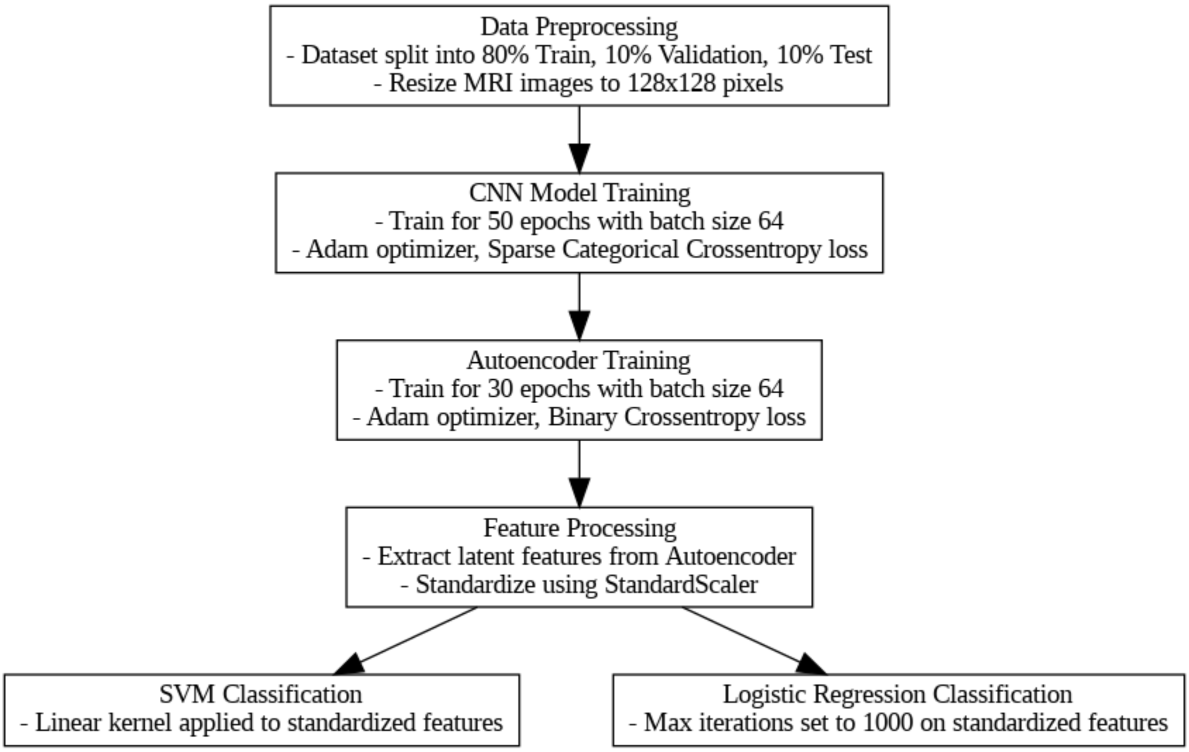

Fig. 1 : Methodology Flowchart

- **Data Preprocessing**: The process commenced with meticulous data preparation, where the dataset was divided into 80% training, 10% validation, and 10% test sets to facilitate comprehensive model evaluation. All MRI images were resized to a uniform 128x128 pixels, standardizing input dimensions and ensuring consistency across the dataset for subsequent modeling steps.
- **Convolutional Neural Network (CNN) Training**: A CNN was employed to directly classify the preprocessed images, trained over 50 epochs with a batch size of 64. The model leveraged the Adam optimizer and sparse categorical crossentropy loss, harnessing its capability to extract spatial features from the MRI data, which proved crucial for identifying disease patterns.
- **Autoencoder Training**: To enhance feature extraction, an autoencoder was trained for 30 epochs with a batch size of 64, using the Adam optimizer and binary crossentropy loss. This step compressed the images into latent features, capturing essential characteristics that were later utilized for classification, adding depth to the analytical process.
- **Feature Processing**: The latent features extracted by the autoencoder were standardized using the StandardScaler, normalizing their distribution to prepare them for machine learning classification. This step ensured that the features were on a comparable scale, improving the performance of the subsequent models.
- **Support Vector Machine (SVM) Classification**: A Support Vector Machine with a linear kernel was applied to the standardized features, capitalizing on its ability to find optimal decision boundaries. This approach provided a robust classification mechanism, contributing to the overall diagnostic framework.
- **Logistic Regression Classification**: Complementing the SVM, Logistic Regression was implemented with a maximum of 1000 iterations on the standardized features. This model offered a probabilistic classification framework, adding a different perspective to the analysis and enhancing the reliability of the predictions.

This multi-faceted methodology allowed for a thorough exploration of the dataset, with each component playing a vital role in building a comprehensive and effective system for Alzheimer's disease detection.

V. RESULTS OBTAINED

4.1 Convolutional Neural Network

4.1.1 Convolutional Neural Network Architecture

The core of the solution is a Convolutional Neural Network (CNN) model, comprising multiple layers designed for image classification. The architecture is detailed below.

1. Input Layer

The input layer accepts images with dimensions 128x128x3 (RGB). Pixel values are normalized via rescaling to [0, 1], enhancing model convergence during training.

2. Convolutional Layers

The model includes three convolutional layers with increasing filter counts:

- Conv2D_5: 16 filters, 3x3 kernel, producing 128x128x16 feature maps (448 parameters).
- Conv2D_6: 32 filters, 3x3 kernel, producing 64x64x32 feature maps (4,640 parameters).
- Conv2D_7: 64 filters, 3x3 kernel, producing 32x32x64 feature maps (18,496 parameters).

Each layer uses He-normal initialization for weights, suitable for ReLU activation, and maintains gradient variance.

3. ReLU Activation

ReLU (Rectified Linear Unit) activation follows each convolutional layer, introducing non-linearity to capture complex patterns.

4. Max-Pooling Layers

Max-pooling layers reduce spatial dimensions after each convolutional layer:

- MaxPooling2D_2: 2x2 pool size, reducing 128x128x16 to 64x64x16.
- MaxPooling2D_3: 2x2 pool size, reducing 64x64x32 to 32x32x32.
- MaxPooling2D_4: 2x2 pool size, reducing 32x32x64 to 16x16x64.

5. Dropout Layers

Dropout layers mitigate overfitting by randomly disabling units during training (assumed rate: 0.25):

- Dropout: Applied after MaxPooling2D_3.
- Dropout_1: Applied after MaxPooling2D_4.

6. Fully Connected Layers

The 16x16x64 feature maps are flattened into a 4,096-unit vector, followed by dense layers:

- Dense: 128 units (819,328 parameters).
- Dense_1: 64 units (8,256 parameters).
- Dense_2: 4 units (260 parameters), corresponding to 4 output classes.

Table 2 : Summary of the model

Layer Name	Input Shape	Output Shape	Description
Input	(128, 128, 3)	(128, 128, 3)	MRI images (128x128, RGB)
Rescaling	(128, 128, 3)	(128, 128, 3)	Normalize pixels to [0,1]
Conv2D	(128, 128, 3)	(128, 128, 16)	16 filters, 3x3, same padding, ReLU, HeNormal
MaxPooling2D	(128, 128, 16)	(64, 64, 16)	2x2 pool size
Conv2D	(64, 64, 16)	(64, 64, 32)	32 filters, 3x3, same padding, ReLU, HeNormal
MaxPooling2D	(64, 64, 32)	(32, 32, 32)	2x2 pool size
Dropout	(32, 32, 32)	(32, 32, 32)	Dropout rate 0.25
Conv2D	(32, 32, 32)	(32, 32, 64)	64 filters, 3x3, same padding, ReLU, HeNormal
MaxPooling2D	(32, 32, 64)	(10, 10, 64)	3x3 pool size
Dropout	(10, 10, 64)	(10, 10, 64)	Dropout rate 0.2
Flatten	(10, 10, 64)	(6400,)	Flatten to 1D vector
Dense	(6400,)	(128,)	128 units, ReLU, HeNormal
Dense	(128,)	(64,)	64 units, ReLU
Dense	(64,)	(4,)	4 units, Softmax (4 classes)

4.1.2 Convolutional Neural Network Results

The layers in the CNN model progressively extract and learn features from input images, finally leading to the classification output with an accuracy of 99.22%. The classification report is as follows :

	precision	recall	f1-score	support
Mild_Demented	0.97	0.99	0.98	91
Moderate_Demented	1.00	1.00	1.00	7
Non_Demented	1.00	0.99	1.00	320
Very_Mild_Demented	1.00	0.99	0.99	224
accuracy			0.99	642
macro avg	0.99	0.99	0.99	642
weighted avg	0.99	0.99	0.99	642

Fig. 2 : Classification Report of CNN

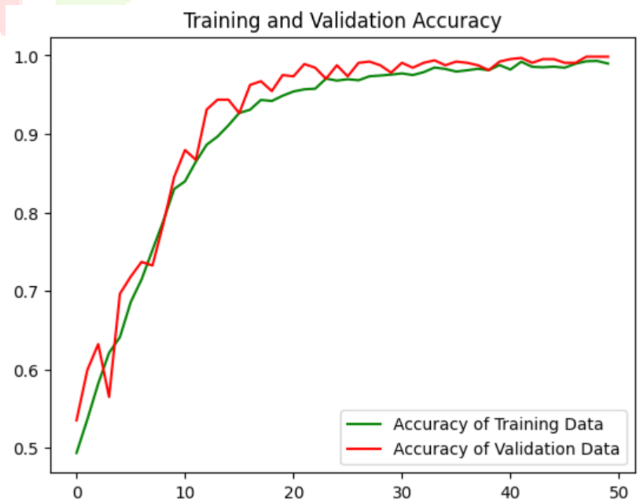

Fig. 3 : Training and Validation Accuracy Curve

The provided graph illustrates the training and validation accuracy of a CNN model over 50 epochs. The green line represents the accuracy of the training data, which rises steadily from 0.5 to approximately 0.95, indicating effective learning. The red line shows the validation data accuracy, which increases to around 0.9 but plateaus and slightly declines after 40 epochs, suggesting potential overfitting. The close alignment of training and validation accuracies highlights the model's good generalization, though minor regularization adjustments could further mitigate overfitting.

4.2 Auto-encoders

The convolutional autoencoder for image reconstruction is used. The encoder compresses RGB images (shape: IMG_HEIGHT, IMG_WIDTH, 3) using two Conv2D layers (32, 64 filters, ReLU) and max-pooling, creating a latent representation. The decoder reconstructs the image with two Conv2D layers, upsampling, and a final Conv2D (sigmoid) to output an RGB image. The model is compiled with Adam optimizer and binary crossentropy loss, trained on normalized images for 30 epochs with a batch size of 64, using a checkpoint to save the best model based on validation loss. The best weights are loaded post-training for optimal performance.

4.2.1 Support Vector Machines

The performance of the autoencoder followed by a Support Vector Machine (SVM) classifier was assessed using a classification report, which includes precision, recall, and f1-score for the four dementia categories: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The model achieved an overall accuracy of 97.66%. The classification report is shown in the figure below:

	precision	recall	f1-score	support
Mild_Demented	0.98	0.97	0.97	91
Moderate_Demented	0.78	1.00	0.88	7
Non_Demented	0.98	0.98	0.98	320
Very_Mild_Demented	0.98	0.97	0.97	224
accuracy			0.98	642
macro avg	0.93	0.98	0.95	642
weighted avg	0.98	0.98	0.98	642

Fig. 4: SVM Classification Report

4.2.1 Logistic Regression

The performance of the Logistic Regression classifier, trained on features extracted by the autoencoder, was evaluated using a classification report detailing precision, recall, and f1-score for the four dementia categories: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The model achieved an overall accuracy of 93.30%. The classification report is presented in the figure below:

	precision	recall	f1-score	support
Mild_Demented	0.87	0.97	0.92	91
Moderate_Demented	0.78	1.00	0.88	7
Non_Demented	0.95	0.95	0.95	320
Very_Mild_Demented	0.94	0.90	0.92	224
accuracy			0.93	642
macro avg	0.89	0.95	0.91	642
weighted avg	0.93	0.93	0.93	642

Fig. 5: Logistic Regression Classification Report

VI. Model Comparison Analysis

In this section, a comprehensive validation and comparison of the models employed in this study is presented.

5.1 Convolutional Neural Network

The performance of the Convolutional Neural Network (CNN) model for classifying dementia categories is depicted through a line plot illustrating precision, recall, and f1-score across the four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. This visualization, titled "CNN Evaluation Metrics per Class (Line Plot)," is presented in the figure below:

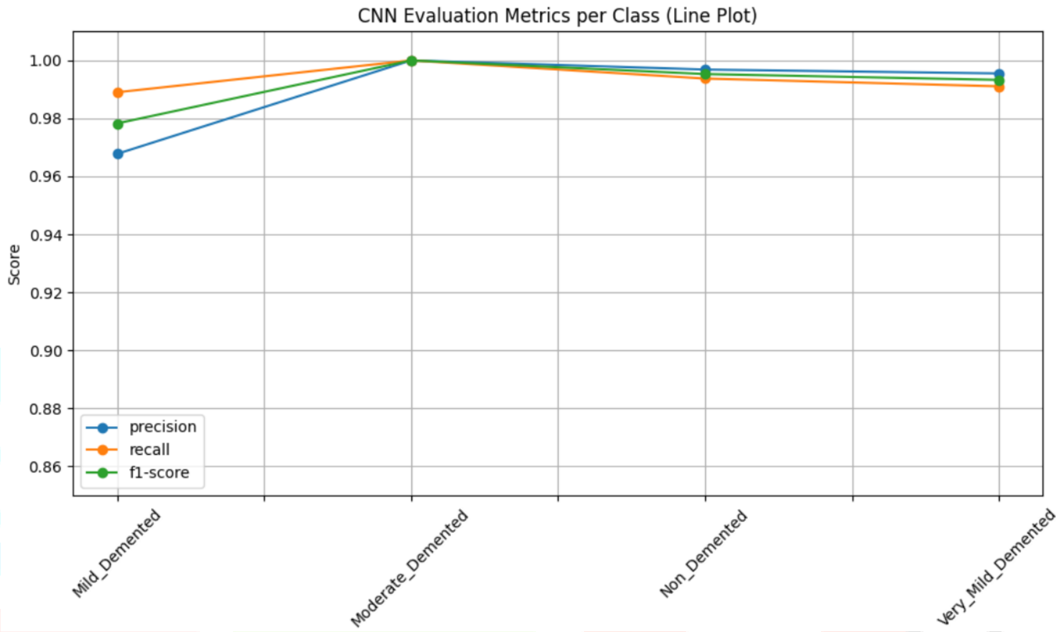

Fig. 6: Line Plot of CNN evaluation metrics

5.2 Support Vector Machines

The performance of the Support Vector Machine (SVM) model for classifying dementia categories is illustrated through a bar plot displaying precision, recall, and f1-score across the four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. This visualization, titled "SVM Evaluation Metrics per Class," is presented in Figure below, offering a clear comparison of the model's effectiveness for each category.

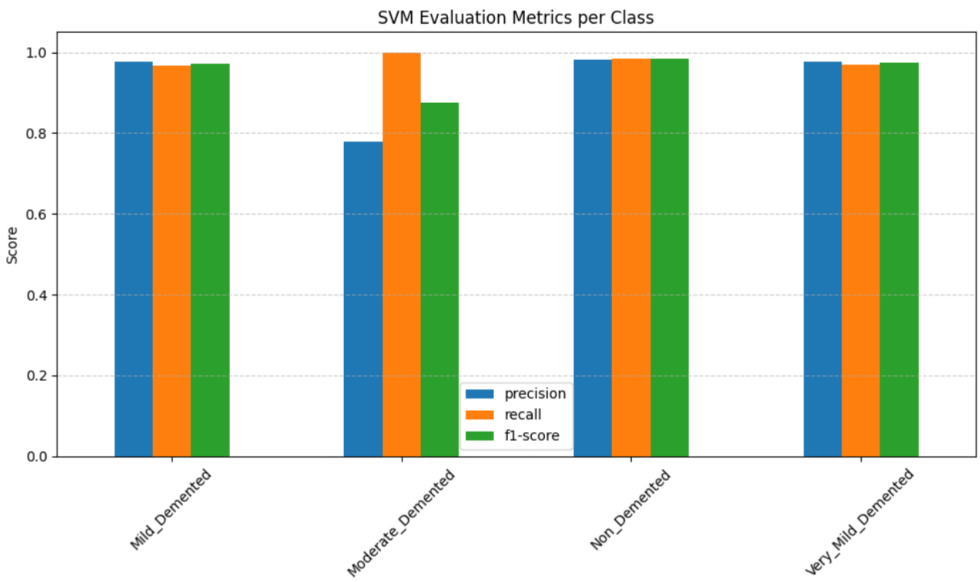

Fig. 5: Bar Plot of SVM evaluation metrics

5.3 Logistic Regression

The performance of the Logistic Regression model for classifying dementia categories is depicted through a bar plot showcasing precision, recall, and f1-score across the four classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. This visualization, titled "Logistic Regression Evaluation Metrics per Class," is presented in Figure below, providing insight into the model's performance across each category.

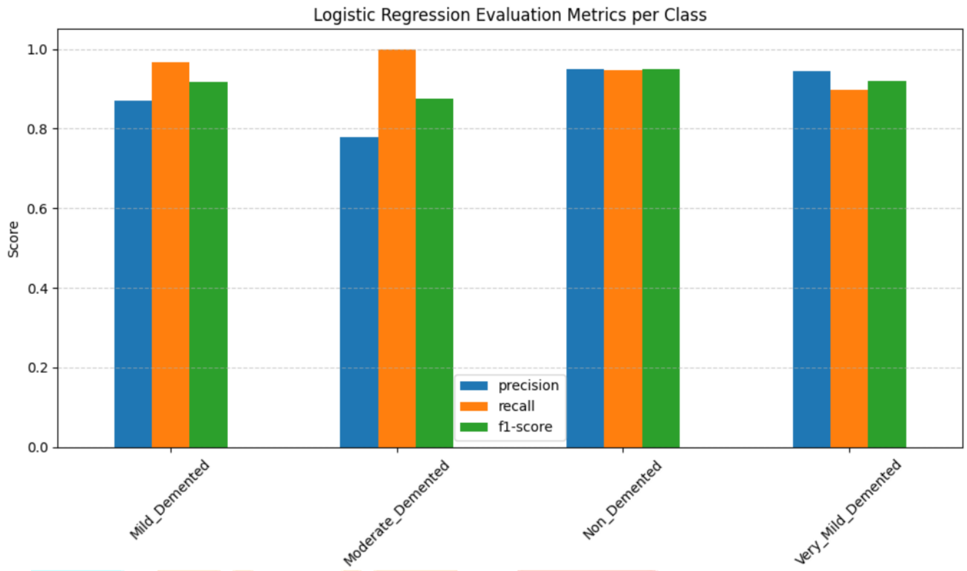

Fig. 4: Bar Plot of Logistic Regression evaluation metrics

5.3 Comparison Analysis

A comparative performance evaluation of CNN, SVM, Logistic Regression classifiers is presented in the table below:

Table 3 : Evaluation metrices of different models

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN	99.22	0.99	0.9935	0.9917
SVM	97.66	0.9286	0.98	0.9508
Logistic Regression	93.3	0.8856	0.9528	0.915

The performance of the three models—CNN, SVM, and Logistic Regression—applied to the dementia classification task was evaluated based on accuracy, precision, recall, and F1-score, as summarized in the table below. The CNN model achieved the highest accuracy of 99.22%, with a precision of 0.99, recall of 0.9935, and F1-score of 0.9917, indicating excellent overall performance and balanced identification of positive cases across the four dementia categories (Mild Demented, Moderate Demented, Non-Demented, Very Mild Demented). The SVM model followed with an accuracy of 97.66%, a precision of 0.8286, recall of 0.98, and F1-score of 0.9508, showing strong recall but a lower precision, likely due to challenges with false positives, possibly influenced by the small support for Moderate Demented cases. Logistic Regression recorded an accuracy of 93.3%, with a precision of 0.8856, recall of 0.9528, and F1-score of 0.915, suggesting a balanced but slightly lower performance compared to the other models, potentially due to its linear nature handling complex feature distributions less effectively. Overall, the CNN model outperformed both SVM and Logistic Regression, highlighting its suitability for this image-based classification task.

VII. Conclusion

As Alzheimer's Disease continue to impact millions of people word wide, the need for precise and more importantly early diagnosis grows critical. Traditional diagnostic methods often struggle to provide reliable and timely analysis necessary for effective intervention. This research tackles this challenge by introducing AI models for early disease prediction.

Listed below are key contributions of this study:

i. An attempt has been made to predict the severity of Alzheimer's Disease utilizing MRI Imaging data.
ii. Three different AI models were tested including CNNs and auto-encoder based ML models like SVM,Logistic Regression.
iii. CNN performed the best, achieving an accuracy of 99.22%. SVM and Logistic Regression models followed closely, with accuracies of 97.66% and 93.3% respectively.
iv. By integrating auto-encoder based methods, accuracy of traditional ML models was significantly improved.
v. Despite these advancements, this study acknowledges certain research gaps including reliance on MRI data alone. Future research should focus on employing more diverse datasets.

The findings highlight the potential of Deep Learning and Machine Learning algorithms for Alzheimer's Disease severity prediction. By addressing current limitations and exploring new methods for model enhancements, more reliable and accurate analysis can be delivered.

References

[1] Kumar A, L.F.e.a. Sidhu J: Alzheimer disease. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing;Jan (2024)

[2] Organisation, W.: Dementia. https://www.who.int/news-room/fact-sheets/detail/dementia (2023)

[3] Johnson KA, S.R.K.W. Fox NC: Brain imaging in alzheimer disease. cold spring harb perspect med. doi: 10.1101/cshperspect.a006213. PMID: 22474610; PMCID: PMC3312396. (2012)

[4] Alatrany, K.W.H.A.e.a. A.S.: An explainable machine learning approach for alzheimer's disease classification. https://doi.org/10.1038/s41598-024-51985-w (2024)

[5] Jha, D., Kim, J.-I., Kwon, G.-R.: Diagnosis of alzheimer's disease using dual- tree complex wavelet transform, pca, and feed-forward neural network. Journal of healthcare engineering 2017(1), 9060124 (2017)

[6] Xu, L., Liang, G., Liao, C., Chen, G.-D., Chang, C.-C.: K-skip-n-gram-rf: a ran- dom forest based method for alzheimer's disease protein identification. Frontiers in genetics 10, 33 (2019)

[7] Baglat, P., Salehi, A.W., Gupta, A., Gupta, G.: Multiple machine learning models for detection of alzheimer's disease using oasis dataset, 614–622 (2020). Springer

[8] Salehi, A.W., Baglat, P., Sharma, B.B., Gupta, G., Upadhya, A.: A cnn model: earlier diagnosis and classification of alzheimer disease using mri, 156–161 (2020). IEEE

[9] Bringas, S., Salom´on, S., Duque, R., Lage, C., Monta˜na, J.L.: Alzheimer's disease stage identification using deep learning models. Journal of Biomedical Informatics 109, 103514 (2020)

[10] Alshammari, M., Mezher, M.: A Modified Convolutional Neural Networks for MRI-based Images for Detection and Stage Classification of Alzheimer Disease. IEEE

[11] Kasani, P.H., Kasani, S.H., Kim, Y., Yun, C.-H., Choi, S.H., Jang, J.-W.: An evaluation of machine learning classifiers for prediction of alzheimer's disease, mild cognitive impairment and normal cognition, 362–367 (2021). IEEE

[12] Basheer, S., Bhatia, S., Sakri, S.B.: Computational modeling of dementia pre-diction using deep neural network: analysis on oasis dataset. IEEE access 9, 42449–42462 (2021)

[13] Sharma, S., Gupta, S., Gupta, D., Altameem, A., Saudagar, A.K.J., Poonia, R.C., Nayak, S.R.: Htlml: Hybrid ai based model for detection of alzheimer's disease. Diagnostics 12(8), 1833 (2022)

[14] Arya, A.D., Verma, S.S., Chakarabarti, P., Bishnoi, R.: Prediction of alzheimer's disease-a machine learning perspective with ensemble learning 6, 2308–2313 (2023). IEEE

[15] Jansi, R., Gowtham, N., Ramachandran, S., Praneeth, V.S.: Revolutionizing Alzheimer's Disease Prediction Using InceptionV3 in Deep Learning. IEEE

[16] Boyapati, N., Tej, M.B., Darshitha, M., Shreya, P., Naveen, S.N., Gandhi, C.R., Amrutha, V.: Alzheimer's disease prediction using convolutional neural network (cnn) with generative adversarial network (gan), 1–6 (2023). IEEE

[17] Prabha, C.: Classification and Detection of Alzheimer's Disease: A Brief Analysis. IEEE

[18] Dinesan, K., Sreesankar, S., VV, D.K., Abhishek, S., Anjali, T.: Navigating the brain: Unveiling alzheimer's disease using convolutional neural network, 763–770 (2023). IEEE

[19] Dhakal, S., Azam, S., Hasib, K.M., Karim, A., Jonkman, M., Al Haque, A.F.:Dementia prediction using machine learning. Procedia Computer Science 219, 1297–1308 (2023)

[20] Mujahid, M., Rehman, A., Alam, T., Alamri, F.S., Fati, S.M., Saba, T.: An efficient ensemble approach for alzheimer's disease detection using an adaptive synthetic technique and deep learning. Diagnostics 13(15), 2489 (2023)

[21] Manimuthu, A., Jose, P.P., Gangadevi, E., Kumar, U.U., Anandaraj, M.: Pre- diction of alzheimer's disease from magnetic resonance images (mri) 5, 631–635 (2024). IEEE