



# INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

## DEEP LEARNING TECHNIQUES FOR THE CLASSIFICATION OF ALZHEIMER'S DISEASE

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**Abstract:** This project aims to address the crucial task of Alzheimer's disease (AD) classification through the implementation of two distinct deep learning models: Convolutional Neural Network (CNN) and Transfer Learning using Densenet201. Leveraging a diverse dataset comprising four classes – Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented – sourced from open-access repositories, our study seeks to compare the efficacy of these models in accurately diagnosing different stages of Alzheimer's. The CNN model will be developed from scratch, while Densenet201, a pre-trained model, will be fine-tuned for optimal performance. Evaluating and comparing these models will provide insights into their respective strengths and weaknesses, aiding in the determination of the superior approach for AD classification. This research contributes to the advancement of diagnostic methodologies, potentially enhancing the early detection of Alzheimer's Disease.

**Keywords:** Alzheimer's Disease, Deep Learning, CNN, DenseNet201.

### I INTRODUCTION

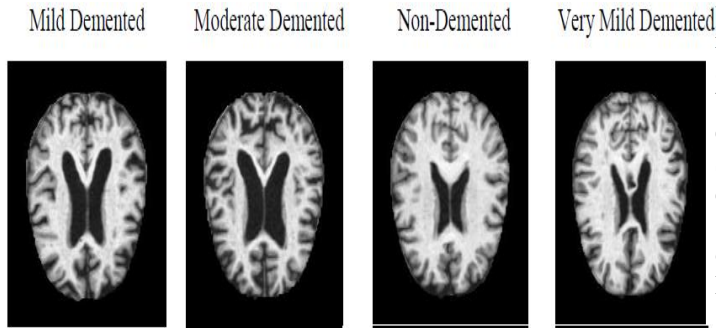
The Alzheimer's Disease (AD) stands as a formidable global health challenge, affecting millions of individuals worldwide. As a progressive neurodegenerative disorder, its impact on cognitive function is profound, leading to memory loss, impaired reasoning, and altered behavior. Early and accurate diagnosis is crucial for effective intervention and patient care. Leveraging the power of deep learning, this project addresses the imperative need for robust classification models to discern different stages of Alzheimer's, facilitating

timely and targeted treatment. The primary focus of this research is the development and comparison of two advanced deep learning models: Convolutional Neural Network (CNN) and Transfer Learning utilizing Densenet201. The choice of these models is grounded in their proven capabilities in image classification tasks, making them well-suited for analyzing neuroimaging data associated with Alzheimer's Disease.

The dataset employed in this study is sourced from reputable open-access repositories, ensuring diversity and relevance in capturing the intricate variations across four distinct classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. These classes represent different stages of Alzheimer's, encompassing the spectrum from mild cognitive impairment to severe dementia. The CNN model is designed from scratch, allowing for the extraction of hierarchical features directly from the input images. In contrast, Transfer Learning using Densenet201 involves fine-tuning a pre-trained model, capitalizing on the wealth of knowledge it has acquired from extensive prior training on large datasets. This approach can potentially expedite the learning process and enhance the model's ability to generalize across diverse image patterns.

The ultimate objective of this research is to rigorously compare the performance of these two models, gauging their accuracy, precision, recall, and F1 score in classifying Alzheimer's Disease stages. By identifying the strengths and weaknesses of each model, this study contributes valuable insights into the selection of optimal methodologies for AD classification. The overarching goal is to advance the state-of-the-art in Alzheimer's diagnostics, potentially paving the way for more reliable and early detection methods that can positively impact patient outcomes and contribute to ongoing

efforts in understanding and managing this debilitating disease.



*Fig 1: Four Stages of the Alzheimer's Disease Classification*

## II LITERATURE SURVEY

In this research The majority of research on Alzheimer's disease (AD) classification employs supervised deep learning, with the Support Vector Machine (SVM) emerging as a prevalent tool for AD diagnosis [1]. SVM is a computer program that utilizes training data to establish a hyperplane, essentially a line, for distinguishing between different subject groups. This hyperplane is then employed to predict outcomes for new, unseen datasets [2]. Conceptually, this process involves finding an optimal line to effectively separate diverse groups, showcasing the versatility of SVM applications. The literature also explores alternative methods serving the same purpose.

Linear SVM exhibits sensitivity to the nature of input data, leading to varying classification outcomes based on the dataset employed [2]. Decisions made by the program are influenced by how data is selected for training and testing. Intriguingly, linear SVM performs well whether specific features are identified prior to utilization or not [3]. Comparisons with the radial basis function (RBF) kernel SVM, another method frequently evaluated, reveal that the RBF SVM necessitates adjustments in  $C$  and  $\gamma$  for optimal functioning.  $C$  regulates regularization, while  $\gamma$  controls kernel expansion using training data.

Studies, such as that by Khedher et al. [4], suggest superior results with linear SVM compared to RBF SVM. Beheshti & Demirel's 2016 research, combining data from various brain regions affected by bronchitis, implemented data fusion for a more accurate depiction. They employed majority voting, combining initial classifications from diverse brain regions. Remarkably, RBF SVM demonstrated strong performance without data fusion, indicating its success is more reliant on feature selection, whereas linear SVM tends to outperform overall.

While SVM is primarily designed for binary classification, sorting more than two groups led to the development of Kernel Support Vector Machine Decision Tree (kSVM-DT) [5]. Utilizing the RBF kernel, kSVM-DT incorporates Canonical Quadratic Programming (QP) and Particle Swarm Optimization (PSO) to determine optimal settings. PSO

mimics the behavior of birds flocking, where each "particle" is tested against the best past position, and updates are made to find optimal settings. Comparative analyses between randomly selected settings and PSO reveal improved accuracy with the latter, preventing the program from becoming overly simplistic or complex, thereby enhancing efficiency.

Similar to the methodology employed in [5], Demirhan and collaborators [6] utilized Gaussian radial basis function (RBF) kernels along with the sequential minimum optimization (SMO) technique to train their Support Vector Machine (SVM). SMO, introduced in 1998 to address significant challenges in SVM training processes [7], excels in breaking down large problems into more manageable components. The claim is that SMO is over 1000 times faster than conventional SVM methods, and its efficiency extends to handling substantial sets of training data without demanding excessive memory resources.

In addition to SVM, a spectrum of classification techniques exists, including K-means clustering, fuzzy clustering method (FCM), orthogonal partial least squares hidden structures (OPLS), decision trees (Trees), artificial neural networks (ANN), elastic net (EN) regular regression, and discriminant classification analysis. In a study conducted by Farzan et al. [8], four classification techniques—K-means clustering, FCM, linear SVM, and RBF-SVM—were compared.

While K-means and FCM demonstrated proficiency in specificity, accurately identifying non-Alzheimer's disease (AD) cases, their sensitivity, particularly in correctly identifying AD cases, was lacking. Potential issues with incorrect initial starting points might have caused overlapping features between classes. Despite the similarities between K-means and FCM, the iterative nature of FCM led to increased time consumption [9].

Another study comparing OPLS, Trees, ANN, and SVM in the classification of healthy controls (HC), Alzheimer's disease (AD), stable myocardial cognitive impairment (sMCI), and progressive MCI (pMCI) [10] revealed that all methods effectively distinguished AD from HC and pMCI from AD. However, classification efficacy was less pronounced when discriminating between HC and sMCI.

OPLS, a variant of partial least squares (PLS), constructs a model tailored for class separation, defining a predictive component that facilitates data interpretation [11]. The findings align with Westman et al.'s research [11], indicating the proximity of MCI subjects to HC subjects, posing challenges in their differentiation. This proximity likely contributes to the less accurate classification of HC and sMCI, even across diverse techniques.

## III. SYSTEMS ARCHITECTURE

Alzheimer's disease classification relies on a systematic system architecture encompassing data collection, preprocessing, feature engineering, model training, evaluation, and deployment stages. This holistic framework ensures the efficient flow of information, enabling the

creation of robust models for accurate disease classification. The structured approach enhances the reliability and effectiveness of the overall system in addressing the complexities associated with Alzheimer's diagnosis.

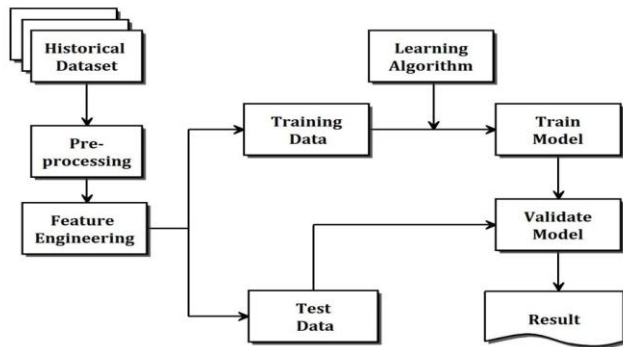


Figure No 3.1: System Architecture

The system architecture diagram is as follows:

- **Collect data:** This data can come from a variety of sources, such as historical medical records, clinical trials, and research studies. The data should include both patient characteristics (e.g., age, gender, medical history) and neuroimaging data (e.g., MRI scans, PET scans).
- **Preprocess the data:** This may involve cleaning the data, removing outliers, and normalizing the data.
- **Engineer features:** This involves extracting relevant features from the data that can be used by the deep learning model to make predictions. For example, features may be extracted from the neuroimaging data to measure brain atrophy, plaque accumulation, or tangle formation.
- **Train the model:** This involves feeding the preprocessed data and features to the deep learning model and allowing it to learn the relationship between the features and the target variable (i.e., Alzheimer's disease diagnosis).
- **Validate the model:** Once the model is trained, it is important to validate it on a held-out test set to assess its performance on unseen data. This helps to ensure that the model is not overfitting the training data.
- **Deploy the model:** Once the model is validated, it can be deployed to production so that it can be used to classify new patients.

The following is explanation of each step in the system architecture diagram:

1. **Training Data:** This is the data that will be used to train the deep learning model. The training data should be representative of the population that you want to use the model on. For example, if you want to use the model to classify Alzheimer's disease in the elderly population, then the training data should include data from elderly patients with and without Alzheimer's disease.

2. **Learning Algorithm:** The learning algorithm is the type of deep learning model that you will use to classify Alzheimer's disease. There are many different types of deep learning algorithms that can be used for classification, such as support vector machine, random

forests, and deep learning models. The best learning algorithm to use will depend on the specific nature of your data.

3. **Historical Data:** This is data that has been collected in the past. Historical data can be used to train the deep learning model, but it is important to be aware that the model may not perform well on new data if the historical data is not representative of the current population.

4. **Feature Engineering:** This is the process of extracting relevant features from the data. Features are the inputs to the deep learning model, and they should be chosen carefully to maximize the model's performance. For example, if you are using MRI data to classify Alzheimer's disease, then you may want to extract features such as brain volume, atrophy, and plaque accumulation.

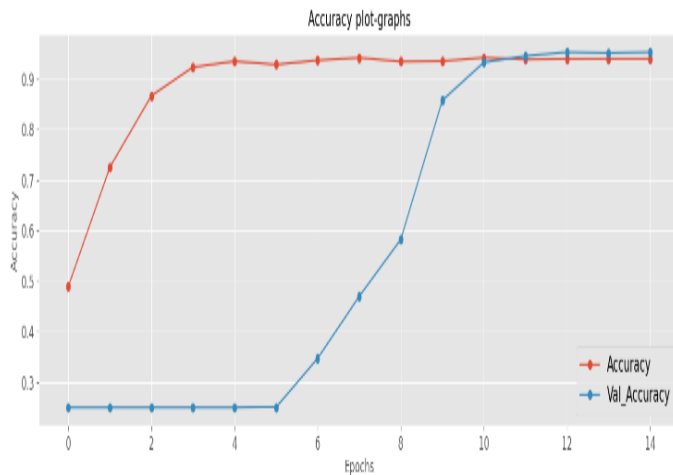
5. **Data Preprocessing:** This is the process of cleaning and preparing the data for training. Data preprocessing may involve removing outliers, normalizing the data, and converting categorical variables to numerical variables.

6. **Test Data:** This is the data that will be used to evaluate the performance of the deep learning model. The test data should be held out from the training data to ensure that the model is not overfitting the training data.

7. **Predicted Result:** This is the output of the deep learning model. The predicted result is a classification label, such as "Alzheimer's disease" or "No Alzheimer's disease."

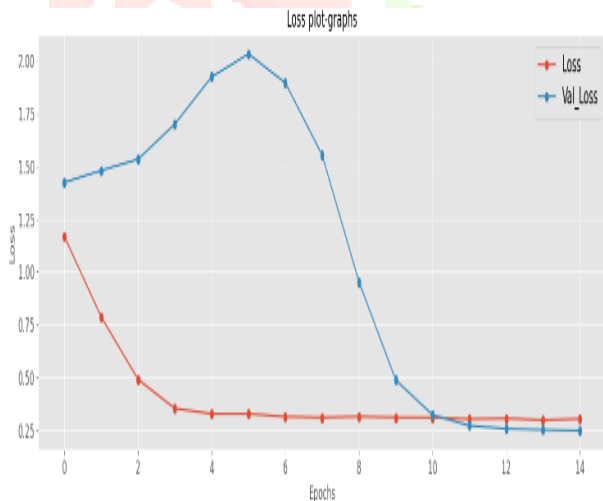
## IV EXPERIMENTAL RESULTS

The graph provided in Fig. illustrates the performance of a convolutional neural network (CNN) model designed to classify Alzheimer's disease. On the horizontal axis, we track the number of training iterations or epochs, while the vertical axis represents the accuracy of the model. The red line depicts how accurately the model predicts the training data, while the blue line represents its performance on unseen validation data. Initially, both lines show improvement, indicating the model is learning. However, while the training accuracy continues to rise steadily, the validation accuracy begins to plateau after a few epochs, hinting at potential overfitting. Overfitting occurs when the model becomes too fixated on the training data and struggles with new data.



**Figure No 4.1: Accuracy plot graph of CNN**

The loss plot graph provided in Fig 22 tracks the performance of a CNN model aimed at classifying Alzheimer's disease. It illustrates how well the model learns to distinguish between Alzheimer's and healthy patients over training epochs. The x-axis represents training iterations (epochs), while the y-axis indicates loss, with lower values signaling better alignment between model predictions and actual labels. The red line shows decreasing training loss, indicating effective learning from the training data. However, the blue line, representing validation loss, decreases at a slower rate, suggesting potential overfitting as the model struggles to generalize beyond the training set.



**Figure No 4.2: Loss plot graph of CNN**

## V CONCLUSION

This project represents a significant step forward in addressing the global health challenge of Alzheimer's Disease (AD). Through the integration of Python, Convolutional Neural Networks (CNN), and deep learning

algorithms, the developed diagnostic tool demonstrates high accuracy in AD classification. By leveraging neuroimaging data, particularly MRI scans, the system effectively extracts relevant features and employs deep learning to automatically discern subtle abnormalities associated with Alzheimer's. This synergistic approach not only enhances the model's predictive capabilities but also offers interpretability through feature importance analysis. The results underscore the efficacy of its potential as a valuable asset for clinicians in the early detection and intervention of Alzheimer's disease, ultimately contributing to advancements in the ongoing battle against this pervasive neurodegenerative condition.

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