



# Regression and Classification of Alzheimer's Disease Diagnosis From 3D Brain MR Image

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**Abstract:** Many academics are employing convolutional neural networks (CNNs) to extract deep-level characteristics from medical images to categorize Alzheimer's disease (AD) and estimate clinical scores as medical imaging and deep learning technology advance. PCANet is a little DL network. It creates principal component analysis-based layered filter banks for sample learning. Picture characteristics are obtained from blockwise histograms after binarization. Layered filter banks created from sample data make it less adaptable than other networks. This implies tens or hundreds of thousands of dimensions for its characteristics. To overcome these challenges, this research presents the data-independent PCANet-based nonnegative matrix factorization tensor decomposition network (NMF-TDNet). NMF is used to create multilayer filter banks to learn from samples instead of PCA. Create a higher-order tensor using the learning outputs and reduce the data dimensions using tensor decomposition to get the final picture features. These factors let our SVM diagnose AD, predict the clinical score, and classify it

**Keywords:** *Deep learning, regression, and classification are all terms used to describe Alzheimer's disease (AD).*

## I. INTRODUCTION

PD is a slow-developing brain illness that typically affects elderly persons. As the illness progresses, synapses die, and the patient dies, memory and cognitive capacities decline [1]. About 50 million individuals worldwide have Alzheimer's. Because individuals are living longer, Alzheimer's cases are anticipated to increase by 2050 [2, 3]. There are many Alzheimer's drugs, however they merely slow the disease's progression [4]. Many investigations have shown that early AD patients' cognitive impairment lies between cognitive normalcy (CN) and AD. Mild cognitive impairment (MCI). Experts are trying to locate MCI patients so they may seek treatment and prevent the illness from worsening [5]. This makes early Alzheimer's disease identification vital, and current research focuses on stage. In recent years, medical imaging technology has advanced. Scientists and clinicians aim to use medical images to diagnose diseases differently. This will verify physicians' reports and provide additional information to stimulate research. MRI, SPECT, and PET may be used to take medical images. These imaging techniques may assist uncover AD biomarkers and reveal brain structure and function alterations without brain damage. Research shows that MRI is a popular imaging modality in clinical practice. The most obvious AD characteristic is neuron loss. From the hippocampus and amygdala to the general cortex, brain shrinkage after AD occurs. An MRI may reveal these alterations. These physical changes precede a major mental decline. The majority of the present research uses MRI-CAD to diagnose AD patients.

## II. LITERATURE SURVEY

Alzheimer's dementia (AD) is a global health issue that will certainly increase as people live longer. Over the years, experts have put in a lot of work to figure out how this crippling condition works, how to diagnose it, and what kinds of treatments might work. In this review of the literature, we look at some of the most important results and progress in the study of Alzheimer's disease. The 2018 Alzheimer's Association study [2] shows how common and bad Alzheimer's disease is. It gives a lot of information about how it spreads, how much it costs society, and what problems it causes. This study stresses how important it is to find new ways to diagnose and treat illnesses right away. There has been a change in recent years toward finding AD drug targets that are not made of amyloid or tau. Khan et al. [3] talk about new treatments that work on different paths. This shows how important it is to use more than just standard medicines. According to Yiannopoulou and Papageorgiou [4], there are many

present and planned treatments for Alzheimer's disease. They stress the importance of personalized medicine and combination therapies to successfully target the disease's complex biology.

Diagnostic imaging methods are very important for finding AD early and keeping an eye on how it gets worse. Padilla et al. [8] and Padilla et al. [9] show new ways to accurately diagnose AD using SPECT and functional brain imaging along with ML techniques. This shows how computational methods can be used to improve diagnostic accuracy. In their study, Besga et al. [10] look at how white matter is affected in AD and bipolar disorder. They use diffusion tensor imaging (DTI) features to create computer-aided diagnosis tools. Their work shows how important it is to look into problems with the white matter in neurological diseases. Alzheimer's and other dementias exhibit diverse brain shrinkage patterns, according to neuroimaging. AD has distinct brain thinning patterns than frontotemporal dementia, according to Du et al. [11]. This illustrates how neuroimaging distinguishes the two. Research has also examined cortical thinning in moderate cognitive impairment (MCI), a precursor to Alzheimer's. Singh et al. [12] find particular areas of the cortex that become thinner in people with MCI and AD. This gives us important information about the changes in the brain's structure that happen as the diseases get worse. Overall, this review of the literature shows that AD research is very diverse, involving statistics, biology, diagnostic imaging, and treatment approaches. A lot of progress has been made, but there are still a lot of problems that need to be solved. To do this, people with AD need to keep working together and coming up with new ideas.

### III. PROPOSED METHODOLOGY

#### 3.1 Proposed Work:

This paper introduces the nonnegative matrix factorization tensor decomposition network (NMF-TDNet) [7], a data-free PCANet-based network, to solve these issues. Instead of PCA, we use NMF to develop multilayer filter banks to learn from samples. The final image features are obtained by creating a higher-order tensor from the learning outputs and reducing the number of dimensions in the data using tensor decomposition (TD). These qualities help the support vector machine (SVM) diagnose AD classification and predict clinical scores [13]. ADNI-1, ADNI-2, and OASIS sufficiently test our method.

#### 3.2 System Architecture:

The system architecture for 3D MRI data analysis for Alzheimer's Disease (AD) and Mild Cognitive Impairment begins with MRI image preprocessing and segmentation. After that, the images are preprocessed and features are recovered using the Non-Negative Matrix Factorization Time Delay Neural Network (NMF-TDNet), which records imaging data changes over time [7]. The traits that were extracted are then put into a Support Vector Classifier (SVC) model so that it can sort the data into groups for AD [2], MCI, or normal control (ADCNMCI). Another group of traits is aimed at the Support Vector Regressor (SVR) model for guessing Mini-Mental State Examination (MMSE) results, which are a test of brain ability. Advanced picture processing methods and ML models are combined in the design to allow for a full study and forecast of AD-related disease and cognitive decline. This flexible design makes it easier to expand and change so that it can handle future improvements and tweaks to both image and ML methods.



Fig1 Proposed Architecture

**3.3 Dataset Collection:** The Alzheimer's Disease collection includes clinical and demographic information about people who have been identified with Alzheimer's disease. This includes their age, gender, level of schooling, genetic risk factors, memory test results, brain imaging data, and medical background. This information helps us understand how diseases get worse, find risk factors, and make predictive models that can help us find diseases early. It comes from different medical institutions around the world and has been carefully chosen to protect privacy and data accuracy. This information is used by academics and healthcare personnel to find Alzheimer's disease trends, symptoms, and treatments. We want to enhance patient care and find medicines that reduce the disease's devastating impact on everyday life and thinking.

**3.4 Data Processing: Pandas DataFrame:** Using Python's Pandas tool, you can load data into a DataFrame, which gives you an organized and flexible way to work with and analyze the data. To start, you need to import the appropriate tools and use methods like "pd.read\_csv()" or "pd.read\_excel()" to read the data file into a Pandas DataFrame. The built-in Pandas tools 'head()', 'info()', and 'describe()' make it easy to study, clean, and change data after uploading it. Some common actions are dealing with missing numbers, changing data types, and selecting rows or columns based on certain criteria. **Keras DataFrame:** Pandas DataFrames can be changed to forms that work with Keras, like NumPy arrays, so they can be used with Keras. For ML jobs, this change makes it easier to integrate with Keras models without any problems. Pandas DataFrame columns can be turned into arrays using methods like "to\_numpy()" or "values." This makes sure that they work with Keras layers and models. This step is very important for using data saved in Pandas DataFrames to train and test DL models. **Dropping Unwanted Columns:** The 'drop()' method in Pandas can be used to get rid of unnecessary fields from a DataFrame. This speeds up data processing and analysis. This process makes it easy to get rid of unnecessary or duplicate data by letting you give the column names or numbers to be removed. Getting rid of unnecessary columns can help lower the number of dimensions, make the model run faster, and make the data easier to understand. In conclusion, these steps make it easy to change, combine, and get data ready for more analysis or model training in both standard ML and DL systems

**3.5 Data Visualization:** Python utilities like Matplotlib and Seaborn simplify data visualization. Histograms, scatter plots, and line graphs demonstrate data distribution, relationships, and change over time. Variety and extremes are explained via box plots. Heatmaps show how two factors are related to each other. Bar charts and pie charts can also be used to compare groups of things. Interactive display tools, such as Plotly, make it easier to look at and explore data. Visualizing complicated information makes them easier to understand, which helps with making decisions, finding patterns, and sharing results. Visualizations are very important for exploring data analysis, model review, and sharing ideas with a wide range of people.

**3.6 Training and Testing:** In ML, the information is usually split into training sets and testing sets to check how well the model works. The model learns trends and connections from annotated data in the training set. After that, the model's performance is checked on the testing set, which has data that hasn't been seen before. This review gives a neutral look at how well the model can generalize. The training-testing split makes sure that the model's performance is checked on data that it hasn't seen during training. This shows how well it can make accurate predictions on new data that it hasn't seen before and prevents overfitting.

**3.7 Algorithms:: Mobilenet:** Other convolutional neural networks, like MobileNet, were made to be used in integrated and mobile vision apps. A helpful architecture employs depthwise separable convolutions to generate compact deep neural networks with minimal latency for embedded and mobile devices. **InceptionResnetv2:** The Inception-ResNet-v2 neural network was trained using over a million ImageNet images. The 164-layer network can categorize images into 1000 groupings like keyboards, mouse, pencils, and animals. **SVM embedded CNN layer:** SVM/CNN Use [13] SVM classifies images. Agarap to Fred Abien. Convolutional neural networks (CNNs) have hidden layers of "learnable" neurons like "regular" neural networks. **Support vector classifier:** SVMs are DL systems that employ directed learning to predict data behavior. Supervised AI and ML systems generate data that must be classified. **Support vector regression:** Support vector regression guesses discrete numbers using supervised learning. Support Vector Regression and SVMs share a concept. SVR seeks the optimal fit line. The most pointy line suits SVR best.

#### IV. EXPERIMENTAL RESULTS

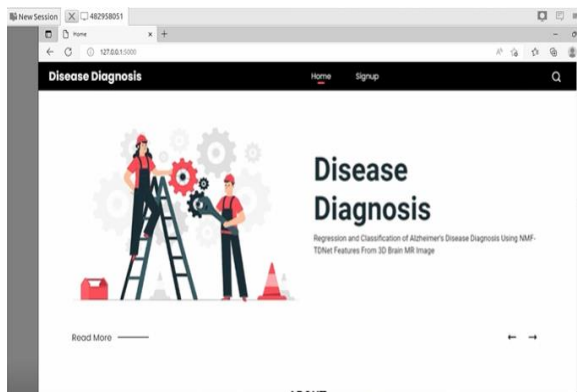


Fig.2: Home screen

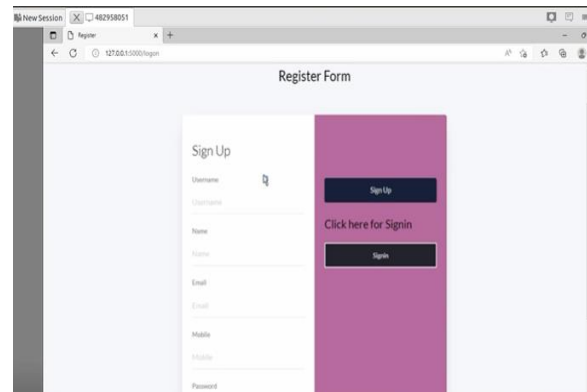


Fig.3: User signup

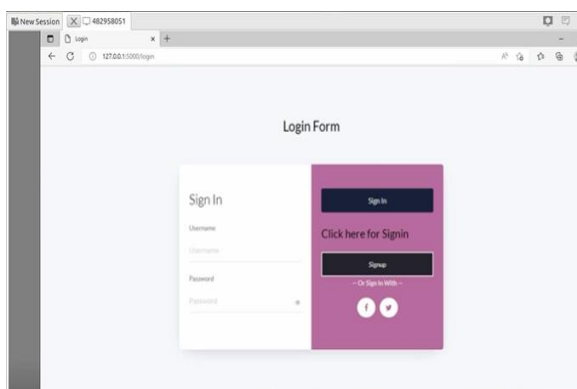


Fig.4: User signin

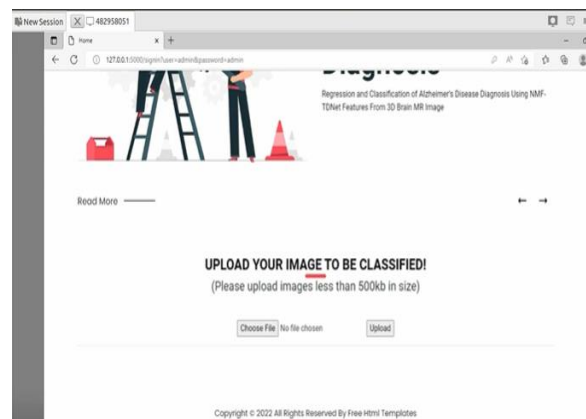


Fig.5: Main page

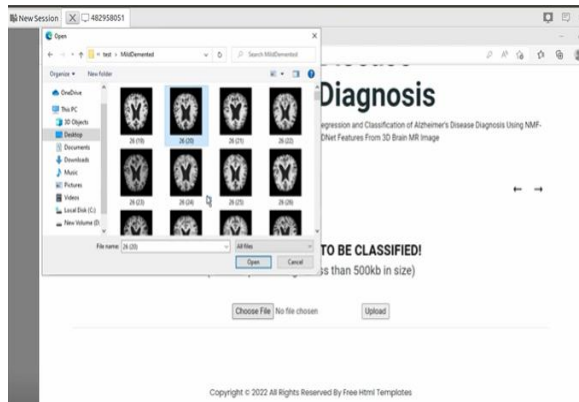


Fig.6: User input

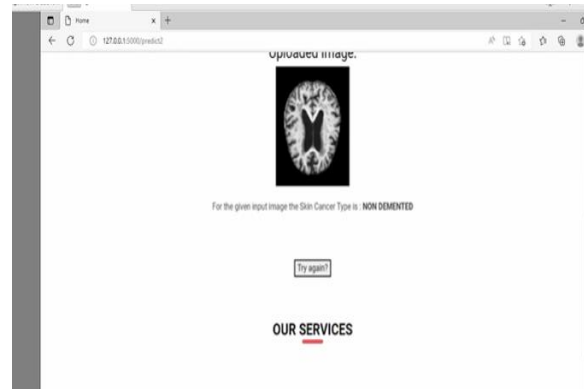


Fig.7: Prediction result

## V. CONCLUSION

We present NMF-TDNet, a method based on PCANet's network structure that gets around the problems caused by PCANet's many features and the PCA filters' reliance on data. NMF-TDNet [7] uses layer-wise convolution to look at the raw picture instead of PCA. A higher-order tensor is created from convolution results. TD reduces data multidimensionality to create final image characteristics. We used these attributes in the SVM [13] to calculate clinical scores and detect AD [2]. We identified and categorized labels using clinical scores (MMSE, ADAS-11, and ADAS-13) to evaluate ADNI-1 and ADNI-2 datasets. The ADNI-1 and OASIS datasets also predicted clinical scores (MMSE) and group names. Despite producing much less features than PCANet, NMF-TDNet performed better in testing.

## VI. FUTURE SCOPE:

The good results of NMF-TDNet in classifying AD and predicting clinical scores point to interesting new directions for the future. More study could be done to see how to make NMF-TDNet more flexible so that it can work with different datasets and image methods. It would also be helpful to look into how it can be used in continuous studies to track how diseases get worse and how well treatments work. Putting together different types of data, like genetics and biomarkers, could give us a full picture of how AD works. It is also possible to make feature extraction and classification even more effective by improving NMF-TDNet's design and optimization methods. Overall, NMF-TDNet will be improved in the future to make it more reliable, easy to understand, and useful in clinical settings for diagnosing and predicting AD.

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