TPM Vol. 32, No. S4, 2025
ISSN: 1972-6325
https://www.tpmap.org/

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# DEVELOPING A NOVEL IMAGING BIOMARKER FOR DIAGNOSING NEURODEGENERATIVE DISEASES

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**ABSTRACT**
A complex class of brain disorders known as neurodegenerative diseases is characterized by the progressive loss of neuronal structure and function in particular brain regions. Symptoms of these diseases include memory and cognitive impairment, as well as difficulties carrying out daily tasks. In elderly individuals, Alzheimer's disease usually starts as a slight reduction in cognitive function and develops into serious brain damage. The loss of nerve cells in the hippocampus, a region of the brain, is linked to the pathophysiology of AD. Parkinson's disease is a neurological condition brought on by the loss of nerve cells in the substantia nigra, a part of the brain that controls movement. When these nerve cells degenerate or die, they are unable to produce dopamine, a crucial neurotransmitter.Walking, balancing, speaking, and other coordinated movements are all impacted when dopamine neurons are lost. The disease's primary cause is the death of dopamine-producing neurons in the brain, which impacts bodily functions associated to movement. The proposed model's insights and additional research findings about protein characteristics could be a useful supplement to the current drug discovery process. Bioinformatics study that lowers the high dimensionality of data during disease classification and prediction challenges might benefit from the suggested feature selection techniques and classification procedures.The suggested method can be expanded in the future to categorize and forecast the classes of more brain illnesses brought on by gene changes. In another study, a new DNN-based model is put forth to differentiate AD and MCI patients from cognitively normal people. The network is built with 19 deep layers, drawing inspiration from the original VGG-19.

Keywords:Biomarker,Neurodegenerative, DiseasesMedical.

## 1. INTRODUCTION

Alzheimer's disease (AD) is a degenerative brain ailment that causes memory loss and intellectual impairment due to damage to brain cells. Dr. Alois Alzheimer inspired the name AD. Dr. Alois Alzheimer observed some striking changes in the brain tissues of a patient in 1906 who was afflicted with a rare psychological disorder, such as memory loss, trouble communicating, odd habits, etc. [1]. Dr. Alzheimer examined the patient's brain after she passed away and found several abnormalities [2]. Alzheimer's disease (AD) is an irreversible brain disorder that gradually impairs thinking and memory abilities, eventually making it difficult to do even the most fundamental tasks [11]. Around the middle of the 60s, AD symptoms start to show [3].Aside from memory loss, other symptoms of AD include: a) difficulty performing previously simple tasks; b) difficulty solving simple problems; c) mood or personality changes (such as avoiding friends and family); d) difficulties with written or spoken communication; e) confusion about typical places, people, and events; and f) visual changes, such as difficulty understanding images, etc. As per the National Institute on Aging's (NIH) research report, under U.S. Over 4 million people in India and 44 million people globally suffer from dementia, including AD, according to a survey conducted by Alzheimer's and Dementia Resources [16]. A individual with mild cognitive impairment (MCI) has cognitive abilities that fall somewhere between normal and AD [13]. MCI patients suffer from much greater memory loss than other people of their age, despite the fact that their symptoms are not as severe as those of AD [4]. Some of the signs of AD, like personality changes and difficulty doing daily tasks, are not experienced by those with MCI [10]. Although not all people with MCI go on to develop AD, the researchers found that the likelihood of developing AD from MCI is much higher [5]. A typical healthy individual over 65 has a nearly 3% probability of acquiring AD, whereas the likelihood of dementia advancing from MCI to AD (within seven years) is about 80% [12].

## 2. LITERATURE REVIEW

Three categories of feature selection strategies—filter techniques, wrapper methods, and embedding methods—were distinguished by the categorization context and issue type. Instead than employing a learning process, filter techniques assess the significance of features by examining the inherent characteristics of the data. Wrapper approaches, on the other hand, use a learning algorithm to assess particular feature subsets. The learning algorithm utilizes both wrappers and filters in the embedded methods [6]. It includes feature selection in the process of fitting and training the model. The embedded method learning algorithm enhances the model's objective function by evaluating the feature utility's worth. Effective machine learning techniques are now more important than ever because learning pertinent information is becoming more difficult due to the growing amount of input features (Garcia-Torres 2016). One of the fundamental ideas of machine learning is feature selection, which uses dimensionality reduction techniques to identify pertinent characteristics [8]. Subset creation, subset assessment, stopping criterion, and result confirmation are crucial phases in feature selection. Reducing overfitting, increasing accuracy, and cutting down on training time are all advantages of feature selection. Additionally, this procedure raises comprehensibility, boosts predictive accuracy, and expedites data mining techniques. (Aitken 2005; Peng et al. 2005). In order to improve the classification performance of supervised and unsupervised feature selection methods, feature selection aims to pick the appropriate set of features (Holte 1993; Peng et al. 2012) [6]. By simulating the relationships and dependencies between input and output variables, a supervised feature selection technique (Salvador et al. 2008; Dyer et al. 2011) identifies important characteristics throughout the assessment process. Using labeled training data, it creates a model and uses the relationships it has discovered from pre-existing datasets to predict the output values for target data. Unlabeled training data is used in the unsupervised feature selection technique to improve rule mining, pattern recognition, and data point summarization and classification.

## 3. METHODOLOGY

Manually diagnosing AD is a challenging task. Because significant cognitive decline is also typical in normal aging, it is challenging for a psychologist to diagnose AD based on cognitive tests. Moreover, the entire procedure is time-consuming, and after finishing the manual exams, psychiatrists can also want the assistance of neuro-imaging research. Therefore, one practical method of classifying AD is to employ biomarkers found in brain cells. Neuroimaging and feature extraction from each class can be used to successfully classify AD. [7].

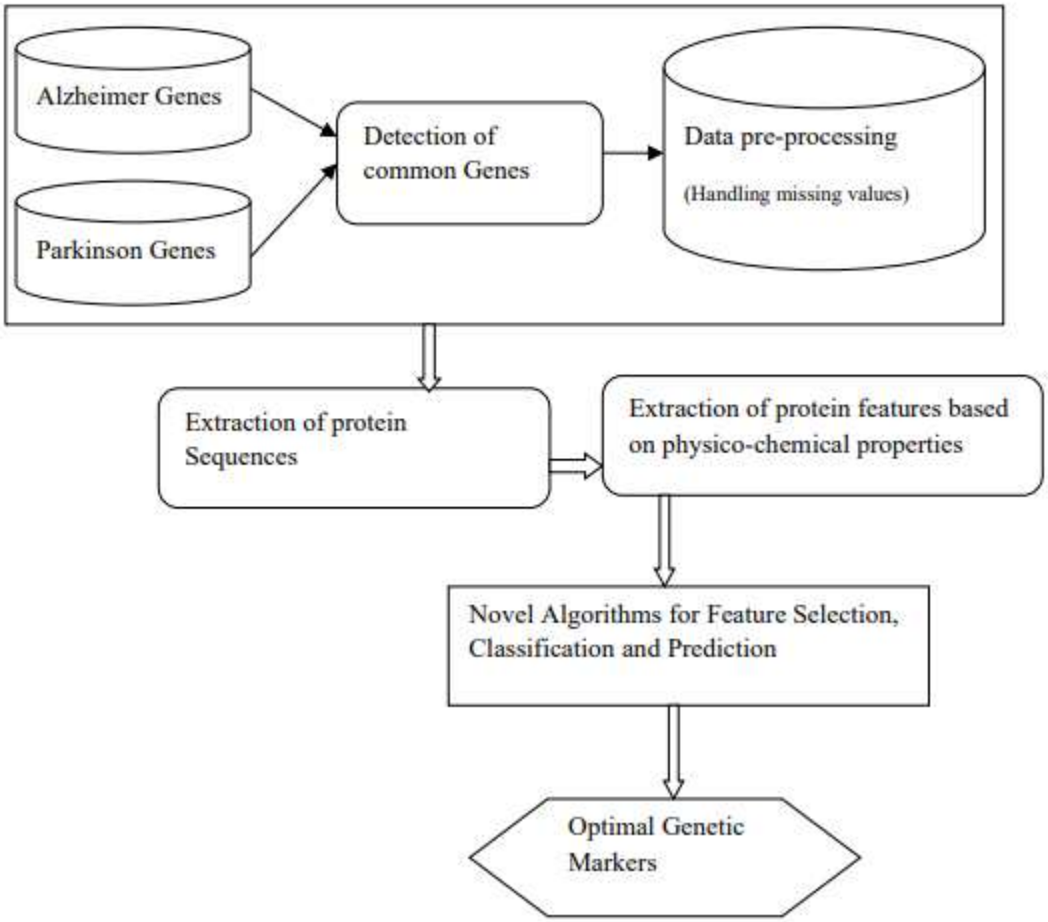

**Figure 1: Proposed flow**

One popular method for acquiring tissue-by-tissue information on the neurological system is magnetic resonance imaging (MRI). Numerous conditions, including as cancer and tumors, can be successfully diagnosed with MRI. With the right image processing technologies, it is possible to identify the differences in brain cells between those with AD, MCI, and Cognitively Normal (CN). However, researchers frequently encounter challenges when attempting to classify AD by examining tissue changes using traditional classifiers because of the complex pixel patterns. One of the most popular Machine Learning (ML) approaches in the field of medical image processing is the Artificial Neural Network (ANN). In order to comprehend input from the environment, ANNs construct a network of interconnected artificial neurons that mimic the biological processes of a human brain. An ANN component called a Deep Neural Network (DNN) interprets a group of hidden layers between input and output to help absorb important features for better model training [14]. A popular machine learning technique that has shown promise in a range of healthcare applications is DNN [38]. DNN's ability to process even the most complicated data, like brain pictures, is another factor contributing to its appeal [9]. DNN is therefore mostly used in this thesis for feature extraction and classification. In Figure 1, an example DNN architecture is displayed..

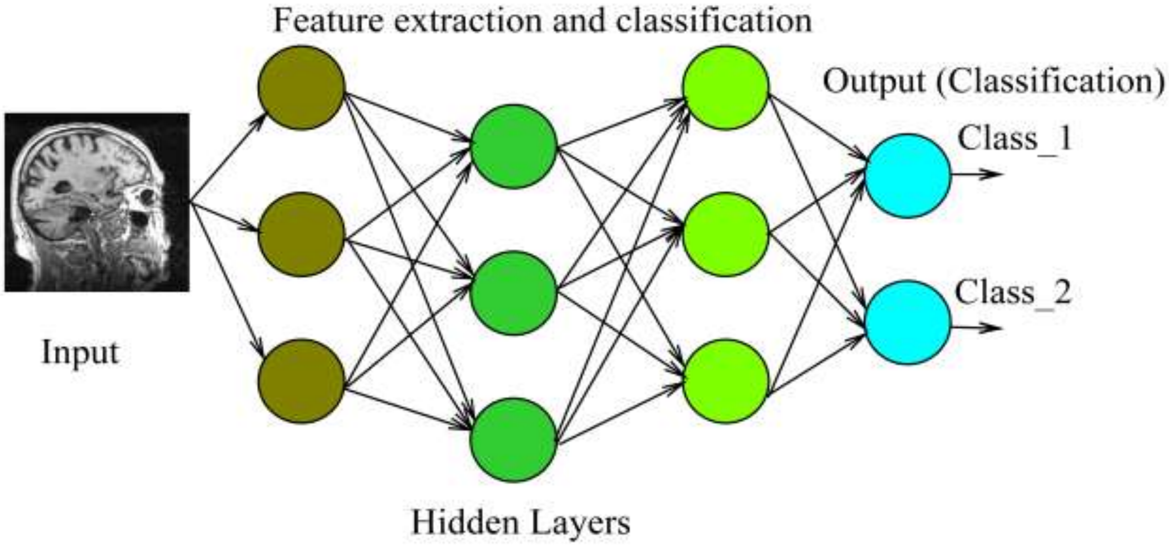

**Figure 2: DNN architecture**

According to one of our earlier studies, the DenseNet model performs better than the most widely used DNN models because of its Dense-block concept, which helps to minimize gradient and information loss throughout the network . The suggested model adopts the Dense-block concept. A model can learn more important features with the use of various convolutional filtering techniques, and feature representations can be enhanced by merging multiple features. Furthermore, compared to a single large-sized filter, a group of small-sized filters extracts far less convolutional parameters. [9]. It is evident that the suggested feature extraction model produced around 15856043 convolutional parameters, which are in charge of obtaining the salient characteristics from every classification class.The process of selecting only the elements that suit the data the best out of a vast number of created features is known as feature selection. In addition to minimizing dimensions, feature selection also includes choosing variables according to whether or not there is interaction between the attributes and the classification method. The right feature selection can help a model train more quickly and effectively. PCA is a widely used unsupervised feature selection method in image processing and computer vision.Because it creates a co-relation matrix from the original feature matrix and then provides the most practical elements needed to attain the highest classification accuracy based on the maximum co-relation measurements, PCA is quite popular. A PCA-based feature selection methodology is applied in this work.

## 4. STATISTICAL MEASURES

Even though some of the methods in the literature only selected a small number of variables, our suggested strategy outperforms them in terms of predicting the disease's class. Furthermore, every dataset taken into consideration in the study project is disease-based, and the presence or absence of the condition is determined by the appropriate feature selection. Therefore, the chosen feature set needs to accurately forecast the disease class. [15].

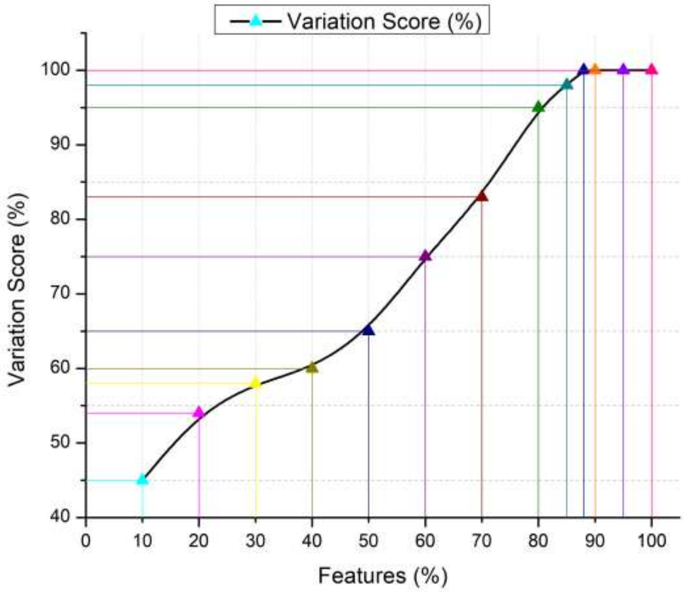

**Figure 3: Genderwise response**

In a variety of fields, including computer vision, natural language processing, automatic speech recognition, and medical data analysis, deep learning algorithms produce the best results. Because deep learning algorithms concentrate on layer-wise feature learning and make intelligent judgments on their own, they are distinct from traditional machine learning models. Based on structural and physicochemical protein features, this study used a deep learning approach to predict the class of shared Gene Alzheimer Parkinson data. The suggested method chooses the best feature subset from the CGAP data using the correlation feature selection based on rank search method, and then trains the selected feature with a deep neural network.. (figure 3).

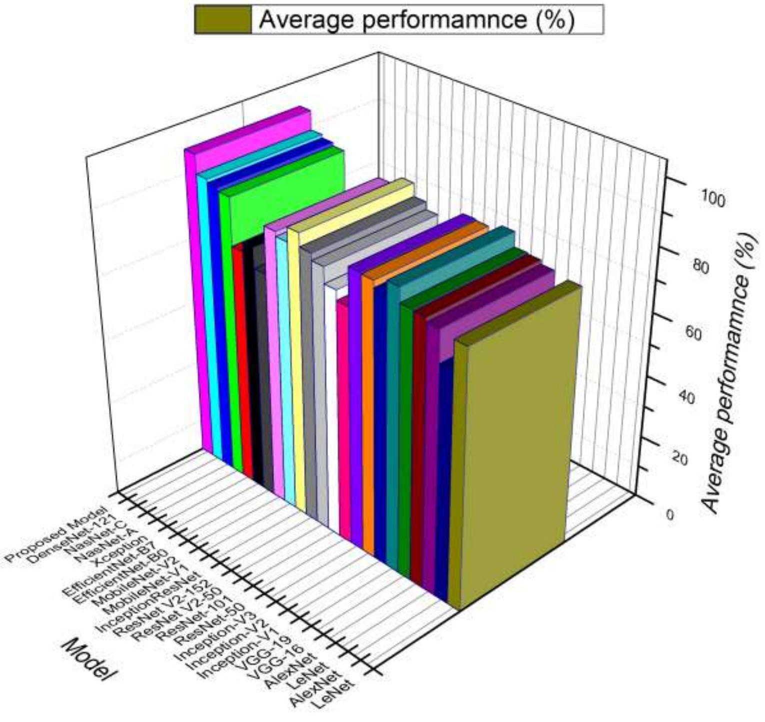

**Figure 4: Average performance comparison**

When compared to earlier techniques, the results confirmed that the DNN learns the characteristics with a high correlation coefficient more efficiently and predicts the disease class with the highest accuracy. In order to choose the best feature subset from the CGAP data, we used the CFS methodology, which is based on the rank method. A deep neural network was then used to train the chosen feature.. (figure 4).

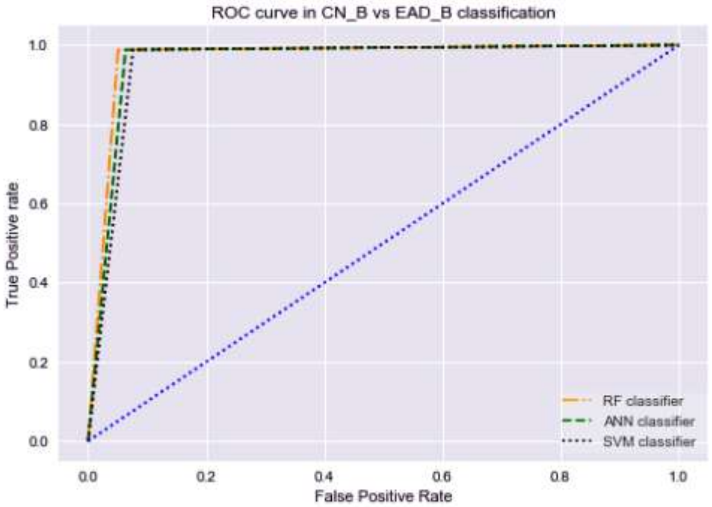

**Figure 5: ROC Curve**

Lately, deep neural networks have emerged as the go-to method for resolving a wide range of bioinformatics issues. Deep learning is particularly effective at handling challenging machine learning problems because of its capacity to analyze high dimensional information. On datasets with a maximum of a few feature columns, the majority of traditional models perform effectively. Deep neural network models, however, perform better on datasets with high feature dimensions. The data can pass through multiple dense layers in the deep neural network model, which then learns a simplified representation of the data and combines information from previous layers for categorization..

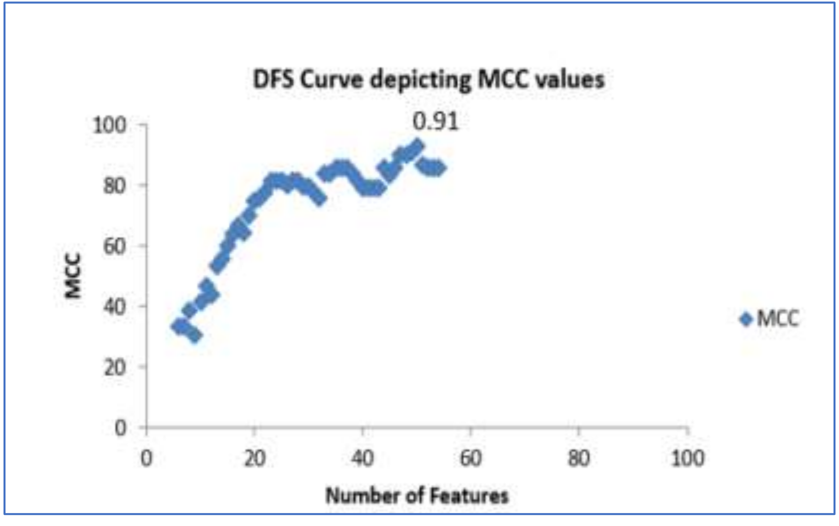

**Figure 6: DFS curves depicting MCC in Brain disorder categorization**

Selecting appropriate hyperparameters is a crucial step in the training of a DNN model since it directly regulates the behavior of the training algorithm, enhancing the model's performance. The network may be trained and learned more quickly and effectively with the help of optimization hyperparameters like learning rate, batch size, and number of epochs. As a result, hyperparameter optimization produces an ideal model that exhibits improved model accuracy and a reduced classification loss function.

## 5. CONCLUSION

In a variety of fields, including computer vision, natural language processing, automatic speech recognition, and medical data analysis, deep learning algorithms produce the best results. Because deep learning algorithms concentrate on layer-wise feature learning and make intelligent judgments on their own, they are distinct from traditional machine learning models. Based on structural and physicochemical protein features, this study used a deep learning approach to predict the class of shared Gene Alzheimer Parkinson data. To choose the best feature subset from the CGAP data, the suggested method employs correlation feature selection based on the rank search method. A deep neural network is then used to train the selected feature. The suggested strategy outperformed all other implemented segmentation techniques when the results were compared with some of the current segmentation methods.

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