International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 12 | Dec 2022 www.irjet.net p-ISSN: 2395-0072

Alzheimer Disease Prediction using Machine Learning Algorithms

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Abstract - *In this study, machine learning techniques are used to forecast Alzheimer's. Among neurodegenerative illnesses Although the symptoms are first mild, they worsen over time. A typical dementia is Alzheimer's disease. Psychological factors like as age, the frequency of visits, the MMSE, and education can be used to predict the AD*

Key words**: **Alzheimer disease, mild cognitive impairment Machine learning algorithms, psychological parameters

1. INTRODUCTION

Short-term memory loss, paranoia, and delusional thoughts are symptoms of Alzheimer's Disease (AD), a degenerative neurological disorder that is often misdiagnosed as stress or aging-related symptoms. About 5.1 million Americans are afflicted by this disease. AD does not receive adequate medical care. AD must be treated with medication consistently. Because AD (1) is chronic, it might last for a long time or for the rest of your life. Therefore, in order to prevent significant brain damage, it is crucial to prescribe medication at the right time. Since we need to gather a lot of data, apply advanced methods for prediction, and consult an experienced doctor, early detection of this disease is a time-consuming and expensive process.

1.1 Motivation

Innovative approaches such as machine learning are increasingly being used to offer prescient and customized prescriptions. Viewing medical reports may lead radiologists to miss other disease conditions because it only considers a few causes and conditions. The goal here is to identify the knowledge gaps and potential opportunities associated with ML and EHR derived data.

1.2 Objectives

This project is being put forth to forecast Alzheimer's disease prediction and to acquire better and accurate results.

It will use a CNN algorithm and SVM algorithm Python programming language is employed for machine learning in order to complete this operation.

1.3 Problem Statement

There is no proper awareness about Alzheimer Disease. As they age, they may experience changes in your physical abilities and walking, sitting, and eventually swallowing. Individuals may need substantial assistance with daily activities as their memory, and cognitive skills continue to decline. At this stage, individuals may need 24/7 assistance for personal care and daily activities. When people suffer from dementia, their ability to communicate, adapt to their environment, and eventually move is lost. It becomes much more difficult for them to communicate pain through words or phrases.

1.4 Machine Learning Using Python

Python is a sophisticated, widely used programming language. In 1991, "GUIDO VAN ROSSUM" invented it. Numerous libraries, including pandas, numpy, SciPy, matplotlib, etc., are supported by Python. It supports Xlsx, Writer, and X1Rd, among other packages. Complex performed extremely effectively using it. There are numerous functional Python frameworks. Machine learning is a branch of artificial intelligence that allows computer frameworks to pick up new skill and enhance their performance with the help of data. It is employed to research the development of computer-based algorithms for making predictions about data. Providing data is the first step in the machine learning process, after which the computers are trained by using a variety of algorithms to create machine learning models. Software engineering's branch of machine learning has significantly altered how people analyses data.

2. RELATED WORKS

According to research [1] The most prevalent and common type of dementia is Alzheimer's disease (AD). AD can be clinically diagnosed by physical and neurological examination, so there is an need for developing better diagnostic tools for AD. MRI (Magnetic resonance imaging) scans were processed by Free Surfer, a powerful tool suitable for processing and normalizing brain MRI images. The multistage classifier used in this thesis produced a good performance for AD detection as compared with previous individual machine learning approaches, such as SVM and KNN.

Based on [2] In this paper, we have proposed a new classification framework based on combination of CNN and RNN to perform the longitudinal analysis of structural MR images for AD diagnosis. CNN model was proposed to extract the spatial features of each time point and generates single-time classification result, while RNN based on cascaded

BGRU was used to model the temporal variations an extract the longitudinal features for improving disease classification. Experimental results on the ADNI dataset demonstrate the effectiveness of the proposed classification algorithm. In the future works, we will include other imaging features such as structural and functional connection networks of brain for RNN based longitudinal analysis. In addition, our work can be Experimental results show that the proposed method achieves classification accuracy of 91.33% for AD vs. NC and 71.71% for pMCI vs. sMCI, demonstrating the promising performance for longitudinal MR image analysis.

The [3] Alzheimer's disease seriously affects the lives of the elderly and their families. Mild cognitive impairment (MCI) is a transitional state between normal aging and Alzheimer's disease. MCI is often misdiagnosed as the symptoms of normal aging, which results to miss the best opportunity of treatment. In this paper, the neuroimaging diagnosis and the clinical psychological diagnosis are combined. The experimental results show that the proposed multi-modal auxiliary diagnosis can achieve an excellent diagnostic efficiency. The consistency of the output of two convolutional neural networks is judged by correlation analysis. If the results of the two CNN models are similar, it is intuitive that the diagnosis for the same patient are consistent with the difference modality diagnosis. The accuracy rates achieves 95.9% (CN vs. AD), 85.0%(CN vs. MCI), and 75.8% (MCI vs. AD), respectively .

As in [7] The accurate diagnosis of Alzheimer's disease (AD) is essential for timely treatment and possible delay of AD. Fusion of multimodal neuroimaging data, such as MRI and PET, has shown its effectiveness for AD diagnosis. The proposed MM-SDPN algorithm is applied to the ADNI dataset to conduct both binary classification and multiclass classification tasks. Deep learning and deep polynomial networks. It can be found that MM-SDPN algorithm achieves the best performance with mean classification accuracy of 97.13%.

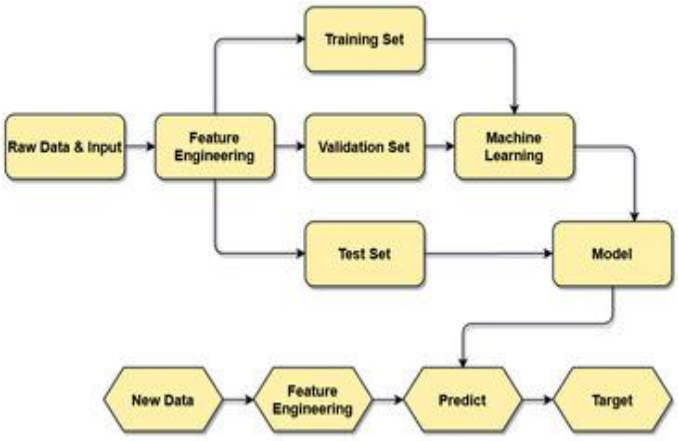
In [10] 15 metabolites associated with cognition including sub fractions of high-density lipoprotein, docosahexaenoic acid, ornithine, glutamine, and glycoprotein acetyls. Six of the metabolites were related to the risk of dementia and lifestyle factors independent of classical risk factors such as diet and exercise. Measurements of cognitive function and blood drawn for metabolite measurements were concurrent in all metabolite measurements from our discovery and 73.6% of the samples in the replication.

As with reference [8] "View aligned hypergraph learning for Alzheimer's disease diagnosis with incomplete multi-modality data", Med. Image Anal., 2017. View-aligned hypergraph learning (VAHL) method to explicitly model the coherence among views. We evaluate our method on the baseline ADNI-1 database with 807 subjects and three modalities. Experimental results show that our method outperforms state-of-the-art methods for AD/MCI diagnosis. We develop a view-aligned hypergraph classification model to explicitly capture the underlying coherence among views, as well as automatically learn the optimal weights of different views from data. Results on the baseline ADNI-1 database with MRI, PET, and CSF modalities demonstrate the efficacy of our method in AD/MCI diagnosis. this paper, they propose a view-aligned hypergraph learning (VAHL). By using VAHL accuracy of 78.9%.

According to [10] In this paper, the authors developed a system to improve the prediction of progression to Alzheimer's Disease (AD) among older individuals with mild cognitive impairment. The dataset used was the ADNI dataset for predicting the progression of AD. PHS, Atropy score and MMSE predictor algorithm were used for the prediction of the progression, highest accuracy of 78.9% along with a sensitivity of 79.9% was found when all three predictor algorithms were used together.

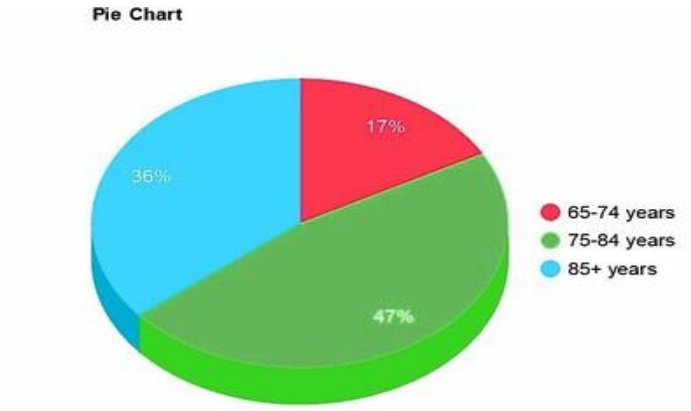
3. IMPLEMENTATION AND WORKING

3.1 Architectural Diagram



The structural basic working methodology is based on the flowchart given above.

3.2 Data Collection and Data Cleaning



A decision tree is a supervised learning model that uses a set of rules to find a solution. A proportion of people affected by AD according to ages in the United States. Of course, the image search process requires two processes.

step: In the first stage we generate the features and then reproduces the query image and subsequent steps correlate these characteristics with those already recorded in the database [2]. The selection uses the PSO algorithm to create the best biomarker indicative of AD or MCI. Data is Acquired from Alzheimer's Disease Neuroimaging Initiative (ADNI) Database. Control Based Image Retrieval was used for retrieving images from the database feature selection includes volume and thickness measurement. Then the best feature list is obtained from the PSO algorithm [2]. control-based image search was used to retrieve images from the database. Then use 3D Convolutional neural network to perform feature learning. CNN is followed via the pooling layer there are many ways to pool or otherwise collect the maximum value, or a specific sequence of neurons within a section.

3.3 Data Preprocessing and Analysis of Data

First pre-processed MRI images are created after recording the database. Ruoxuan Cuia et al. provided a model that performs longitudinal analysis which is performed sequentially and is required for IRM design and calculation. Disease progression over time for: more accurate diagnosis [3]. actual process used

Features of brain morphological abnormalities and longitudinal differences in MRI and a classifier is built to distinguish between different groups. The classification model consists of the early diagnosis, initially preprocessing of raw R-fMRI is done.

3.4 Data Visualization

Data visualization is the representation of data through use of common graphics, such as charts, plots, infographics, and even animations. Data visualization is used in many high-quality visual representations.

3.5 Cross Validation and Training the Model

To train a machine learning model using a subset of the dataset, cross-validation is performed. training is important to achieve accuracy when dividing the data set into set of "N" for the evaluation of the model has been built. We need to train the model first because the data is divided in two modules: a test set and a training set. The Target variable is part of the training set. The training dataset is according to the decision tree regression method. Using one decision tree to generate regression model. When finite amount of data cases is taken, k-fold cross verification was implemented mainly to avoid the over fitting complication.

3.5 Testing and Integration with UI

A web framework like Flask provides us with technology, tools, and the libraries needed to create web application. The bottle is one framework mainly used to integrate Python models because it is easy to build routes together. Alzheimer's disease is predicted using training model and test data set. The front is then connected to the model which is trained using Python's Flask framework. After creating the model and successfully creating the desired results, followed by integration with the user interface (UI) phase, then flask is used.

4.CONCLUSION

The current study demonstrates that the age-sensitive PHS and structural neuroimaging can be combined to more accurately predict the clinical progression to AD in MCI patients and basic mental capacity. Improved individual assessments of AD risk among elderly patients presenting with subjective memory complaints may be useful in clinical practice to guide treatment plans. These assessments are also extremely important for intervention studies, where recruiting high-risk subjects at an early stage of the disease process is crucial for evaluating the efficacy of novel disease-altering intervention.

5. ACKNOWLEGEMENT

We thank, Dr. Thomas P John (Chairman), Dr. Suresh Venugopal P (Principal), Dr Srinivasa H P (Vice-principal), Ms. Suma R (HOD – CSE Department), Dr. John T Mesia Dhas (Associate Professor & Project Coordinator), Ms. Kiranashree B.K (Assistant Professor & Project Guide), Teaching & Non-Teaching Staffs of

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