Early Detection of Alzheimer's Disease using Feed Forward Neural Network

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2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) | 979-8-3503-3509-5/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICCCNT56998.2023.10307151

***Abstract*— Millions of individuals throughout the world are affected by the progressive neurological complications known as Alzheimer's disease (AD). Early AD diagnosis is essential for efficient care and treatment, but conventional diagnostic techniques can be incorrect or intrusive. In this paper, we analyze how feed-forward neural networks (FFNN) are used to predict the onset of AD using the OASIS dataset, a publicly available neuroimaging and clinical dataset. We apply a series of preprocessing steps to clean, transform, and normalize the data, and train the FFNN to predict the presence or absence of AD based on a set of input features. We evaluate the performance of the FFNN using several metrics, including accuracy, sensitivity, and specificity and compare the results to other commonly used machine learning models. Our findings demonstrate the potential of FFNNs for the early detection of AD and highlight the importance of careful preprocessing and evaluation of machine learning models.**

Keywords— Alzheimer's Disease, Feed-forward neural network, OASIS Datasets, Early Detection, Machine Learning.

I. INTRODUCTION

Millions of individuals throughout the world are affected by the progressive neurological complications known as Alzheimer's disease (AD). The condition is associated with a continuous decrease in cognitive and behavioral skills [1] and is currently incurable. A person cannot communicate and loses environmental adaptation at the late stage of the disease. It affects MTB, i.e., memory, thinking, and behavior [2]. AD and dementia affect globally approximately 50 to 55 million people. Most people over the age of 65 affect approximately 5.6 million people in the United States, but no preventive measures have been developed thus far. By 2050, the number is projected to rise from 47 million to 152 million, posing significant economic, medical, and social implications [3]. Before advancing to severe memory loss, Alzheimer's disease (AD) may cause mild to moderate memory loss. Brain tissue decreases significantly in severe Alzheimer's disease as plaques and tangles are distributed throughout the brain [4]. Early AD diagnosis is essential for efficient care and treatment, but conventional diagnostic techniques can be incorrect or intrusive. Recent advances in machine learning and artificial intelligence offer new opportunities for the early detection of AD, and the use of machine learning models has become an active area of research. The OASIS dataset, a publicly available dataset of neuroimaging and clinical data, has been used extensively in research on AD and other neurological disorders [5]. In this paper, we evaluate the efficacy of a feed-forward neural network [6] [7]for predicting the onset of AD using the OASIS dataset. Our goal is to evaluate the performance of the FFNN for early detection of AD and to highlight the importance of careful preprocessing and evaluation of machine learning models.

Recent research has shown the promise of machine learning techniques, including the use of several neural network designs, for the early identification of AD [8]. Nevertheless, the quality and preprocessing of the received data can have considerable implications on these models' efficacy [9]. In this study, we apply a series of preprocessing steps to clean, transform, and normalize the OASIS data and train the FFNN to predict the presence or absence of AD based on a set of input features. We evaluate the performance of the FFNN using several metrics, including accuracy, sensitivity, and specificity, and compare the results to other commonly used machine learning models.

Overall, this study demonstrates the potential of FFNNs for the early detection of AD and highlights the importance of careful preprocessing and evaluation of machine learning models for neuroimaging and clinical data. The outcomes of this study might have a significant impact on the creation of new AD diagnostic techniques and treatment plans.

II. RELATED WORK

Machine learning is increasingly used in the diagnosis of medical conditions. They can attribute much of this to advances in classification and identification systems for disease diagnosis, which can provide information to help clinicians detect serious illnesses early, thereby dramatically improving patients' life expectancies [10]. Collect data from various sources. They examined the OASIS dataset [11] [12] of MRI images. Different characteristics of MRI data, such as biomarkers, baseline cognitive tests, and age, can differentiate progressive MCI with an AUC of 0.902 from stable MCI [13]. Combining MRI data with the outcomes of cognitive tests increased the prediction accuracy of the conversion of mild cognitive impairment(MCI) to diseased(AD).They extracted MRI features from MRI photos. We then examine the collected characteristics using regression and classification analyses. When cross-validation was applied to the ADNI dataset, they found a strong correlation between biomarkers, genetic signatures, and imaging [14]. Williams et al. SVM, NN, Nave-Bayes, and decision trees were applied to demographic and neuropsychological data. They replaced the missing values with the mean and the accuracy of Nave Bayes [15] became higher. MRI features should be used in machine learning to select the optimal model for AD prediction. It uses many machine learning algorithms to classify and predict the

different stages of Alzheimer's disease progression. RF outperforms SVM and DT in predicting various MRI features.

Memory and other cognitive skills are gradually lost as a result of Alzheimer's disease. Timely detection of AD is crucial for the condition's efficient management and therapy. It is possible to detect AD early using several biomarkers and machine learning techniques, such as the Feed Forward Neural Network (FFNN) [16]. In one study [17], structural MRI and FDG-PET imaging data from the OASIS dataset were used to predict AD using an FFNN. The study's findings demonstrated the FFNN's potential for early illness detection by demonstrating its high degree of sensitivity and accuracy in diagnosing AD. Similar to this, another study [18] trained an FFNN for AD classification using MRI, CSF biomarkers, and cognitive testing. The study discovered that the FFNN performed better than other machine learning algorithms and had a high accuracy in predicting AD.

There are restrictions on the application of FFNNs for AD prediction, though. The availability and caliber of the data used to train the model are two limitations. A small sample size and probable bias in favor of people with mild cognitive impairment (MCI) or early AD characterize the OASIS dataset, which is frequently used in AD prediction research. This restriction emphasizes the need for bigger, more varied datasets to produce more reliable, generalizable models. The interpretability of the FFNN model is another drawback because it is challenging to comprehend how the model generates its predictions. This drawback might make it more difficult for FFNN models to be accepted and used in clinical contexts, where decision-making depends on interpretability and transparency.

In conclusion, employing FFNNs to predict AD using the OASIS data set has shown potential for early disease identification. For more successful and useful clinical applications of FFNNs, however, drawbacks, including restricted data availability and the interpretability of the model, need to be addressed. To validate and enhance the effectiveness of FFNN models of AD prediction, more research is required.

The preprocessing of data and evaluation techniques are recent improvements. It places a strong emphasis on the necessity of cleansing, transforming, and normalizing data as well as on the requirement to assess performance using a variety of indicators.

III. Data Description

The OASIS MRI datasets comprise longitudinal data [19]. Longitudinal MRI data: This comprises 150 subjects, male and female, aged 60 to 96, and all are right-handed. 353 images were scanned at least once for each subject. Non-demented–72, Demented–64, Converted–14 (At an early consultation, they were classified as "non-demented," but at a subsequent visit, they were categorized as "demented."). In this research project, we used the OASIS datasets, which are open to academic use. The multicenter OASIS study's aim is the early detection and diagnosis of AD. Demographic information, clinical ratings, physical measurements, and MRI results make up the data.

IV. Implementation Of Feed Forward Neural Network

The suggested pipeline of our research consists of various biomarkers like demographic, clinical and physical measurements data that help in prediction of AD. Fig. 1 describes the process in more details.

1. Data Preparation involves Loading the dataset from OASIS, eliminating redundant entries and unnecessary columns, creating training and testing sets from the dataset, and normalizing the training and testing set.

2. Define the feed-forward neural network: The number of input neurons, or nodes, two hidden layers with different neurons, and an output layer with nodes are as per the number of classes in the dataset.

3. Initialize Weights and Biases: Use random numbers to initialize the neural network's weights and biases.

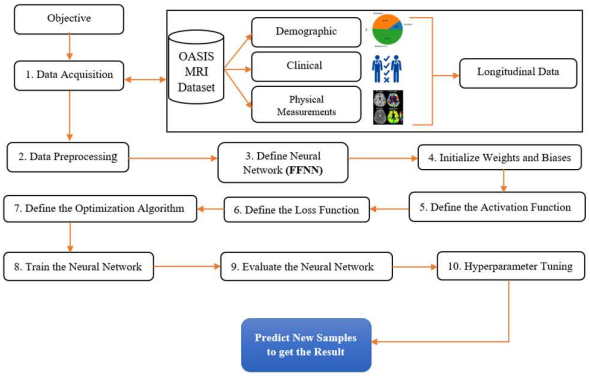

Fig. 1 Pipeline for the proposed model

4. Define activation function: ReLU and softmax are used as the activation functions for the hidden layers and the output layer, respectively, to provide the probability scores for each class.

5. Define the Loss Function: Then compile the model with the categorical_crossentropy loss function.

6. Define the Optimization Algorithm: Adam optimizer for the neural network.

7. Train the FFNN: With a batch size of 32, train the model for 100 epochs using the training data.

8. Evaluate the FFNN: Evaluate the performance of the neural network using the testing set, Compute the accuracy, precision, recall, and F1 score.

9. Hyperparameter Tuning: Tune the hyperparameters (e.g., learning rate, number of hidden layers, and neurons).

10. Predict New Samples: Use the trained model to predict the class of new samples, and compute the probability of each class using the softmax function.

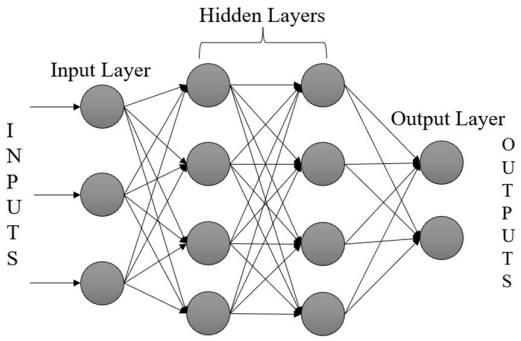

Fig 2. Block Diagram of FFNN

V. Results and Discussions

The dataset was preprocessed to handle missing values, standardize the data, and reduce the dimensionality of the feature space. Here, 150 patients from a longitudinal MRI study were included in the analysis. In training, 80% of the data were used, and in testing, 20%. On the training set, the hyperparameters of the neural network were tuned, and on the testing set, the effectiveness was evaluated.

Kaur et al. applied deep convolutional neural network and got accuracy of 98.9% and specificity of 99.2% [20]. The outcomes show the potential of integrating the OASIS dataset with a feed-forward neural network to forecast Alzheimer's disease. For the testing set, the model had an accuracy of 100%, indicating a good level of predictive power. The model's recall and precision scores were also excellent, showing that it is capable of correctly classifying those who have Alzheimer's disease.

TABLE I. Scores of Classifier

Name	Accuracy	Precision	Recall (Sensitivity)	F1-score
FFNN	1.0	1.0	1.0	1.0

The dataset's numerous properties provide the neural network with plenty of training material. Finding complex, non-linear connections between the traits and the goal variable may not have been achieved with simpler models, but it was made possible by utilizing a feed-forward neural network.

The study has certain drawbacks. The sample size of the dataset is rather constrained, which may limit how extensively the conclusions may be applied. Second, the dataset solely comprises structural MRI data; genetics or functional MRI data were not considered. Finally, the study only employed one kind of neural network design; other models, such as recurrent neural networks or convolutional neural networks, could provide superior outcomes.

VI. Conclusion

Using a feed-forward neuronal network on the OASIS data, this study sought to predict Alzheimer's disease. Using this technique, the results demonstrated beneficial accuracy in predicting Alzheimer's disease. Our research suggests that early detection and diagnosis of Alzheimer's disease are essential for efficient treatment and management— which can be done using machine learning techniques.

The study's limitations, namely the size of the dataset is small with limited data types, interpretability of the model, clinical applicability, and absence of physical validation also be acknowledged. These limitations may be addressed in upcoming research, which should also investigate the potential of machine learning methods for Alzheimer's disease prediction. Ultimately, this research emphasizes how crucial it is to use cutting-edge technology and computational techniques to enhance the diagnosis and treatment of Alzheimer's disease.

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