HYBRID HONEY BATCHER OPTIMIZATION BASED EEG SIGNAL PROCESSING FOR ALZHIEMER DETECTION

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Abstract

Accurate identification of Alzheimer's disease (AD) with electroencephalograph (EEG) is crucial in clinical diagnosis of neurological disorders. However, the effectiveness and accuracy of manually labeling EEG signals is barely satisfactory, due to lacking effective biomarkers. In this work, we propose a deep learning network-based method for AD identification, which employs the FFT based feature extraction. With the construction of functional network of AD subjects, the topological features of weighted and unweighted networks are extracted. Taken the network parameters as independent inputs, Deep Echo State Networks (DeepESN) -based model is established and further trained to identify AD EEG signals. The metaheuristic algorithm for honey badger optimization is used for parameter tuning to get a higher accuracy. Experimental results of MATLAB demonstrate the effectiveness of the proposed scheme in AD identification and ability of ESN system. This work provides a potential tool for identifying neurological disorders from the perspective of functional networks with EEG signal, especially contributing to the diagnosis and identification of AD.

Introduction

Alzheimer's disease is a progressive disorder that causes brain cells to waste away (degenerate) and dies. Alzheimer's disease is the most common cause of dementia — a continuous decline in thinking, behavioral and social skills that disrupts a person's ability to function independently. The early signs of the disease may be forgetting recent events or conversations. As the disease progresses, a person with Alzheimer's disease will develop severe memory impairment and lose the ability to carry out everyday tasks. Current Alzheimer's disease medications may temporarily improve symptoms or slow the rate of decline. These treatments can sometimes help people with Alzheimer's disease maximize function and maintain independence for a time. Different programs and services can help support people with Alzheimer's disease and their caregivers. There is no treatment that cures Alzheimer's disease or alters the disease process in the brain. In advanced stages of the disease, complications from severe loss of brain function — such as dehydration, malnutrition or infection — result in death.

Symptoms

Memory loss is the key symptom of Alzheimer's disease. An early sign of the disease is usually difficulty remembering recent events or conversations. As the disease progresses, memory impairments worsen and other symptoms develop. At first, a person with Alzheimer's disease may be aware of having difficulty with remembering things and organizing thoughts. A family member or friend may be more likely to notice how the symptoms worsen. Brain changes associated with Alzheimer's disease led to growing trouble with:

Memory

Everyone has occasional memory lapses. It's normal to lose track of where you put your keys or forget the name of an acquaintance. But the memory loss associated with Alzheimer's disease persists and worsens, affecting the ability to function at work or at home.

People with Alzheimer's may:

- Repeat statements and questions over and over
- Forget conversations, appointments or events, and not remember them later
- Routinely misplace possessions, often putting them in illogical locations
- Get lost in familiar places
- Eventually forget the names of family members and everyday objects
- Have trouble finding the right words to identify objects, express thoughts or take part in conversations

The studies on EEG could be used to understand the mechanism underlying brain activity, human cognitive process, and diagnosis of brain disease, as well as the field of the Brain Computer Interface (BCI), which has attracted much attention in recent years. Compared to Computed Tomography (CT) and Functional Magnetic Resonance Imaging (FMRI), EEG has a higher time resolution, a lower maintenance cost, and a simpler operation method. Thus, as an objective physiological method to obtain data, EEG was proposed as a nonintrusive approach to study cognitive behaviour and other illness symptoms, such as insomnia, epilepsy, and sleep disorder. EEG has also been used in the diagnosis of mental disorders, such as anxiety, psychosis, and depression. In addition, depression as a mental disorder with clinical manifestations such as significant depression and slow thinking is always accompanied by abnormal brain activity and obvious emotional alternation. Therefore, as a method tracking the brain functions, EEG can detect these abnormal activities.

Literature Review

Fiscon et al [2018] proposed an integrated approach based on EEG signals processing combined with supervised methods to classify Alzheimer’s disease patients. It encompasses the following steps: (1) data collection; (2) data preprocessing of EEG-signals data; (3) features extraction by applying time-frequency transforms on EEG-signals (Fourier and Wavelet analysis); and (3) a supervised learning approach to classify samples in patients suffering from AD, patients affected by MCI, and healthy control (HC) subjects. Dominik Klepl **et al [2020]** use eight FC measures to estimate FC brain graphs from sensor-level EEG signals. GNN models are trained in order to compare the performance of the selected FC measures. Additionally, three baseline models based on literature are trained for comparison. We show that GNN models perform significantly better than the other baseline models. The best GNN reaches 0.984 area under sensitivity-specificity curve (AUC) and 92% accuracy, whereas the best baseline model, a convolutional neural network, has

0.924 AUC and 84.7% accuracy. Ozlem Karabiber Cura et al [2022] studieda time-frequency representation and deep feature extraction based model is introduced to distinguish EEG segments of control subjects and AD patients. TF representations of EEG segments are obtained using high-resolution Synchro Squeezing Transform (SST), and conventional short-time Fourier transform (STFT) methods. The magnitudes of SST and STFT are used for deep feature extraction. Various classifiers are used to classify the extracted features to distinguish the EEG segments of control subjects and AD patients. STFT based deep feature extraction approach yielded better classification results than that of the SST method. Haitao et al [2021] propose a novel machine learning method network-based Takagi-Sugeno-Kang (N-TSK) for AD identification which employs the complex network theory and TSK fuzzy system. With the construction of functional network of AD subjects, the topological features of weighted and unweighted networks are extracted. The highest accuracy can achieve 97.3% for patients with closed eyes and 94.78% with open eyes.

Cassani et al [2019] propose a new type of features derived from the 2-dimensional modulation spectral domain representation of the rsEEG signal in order to characterize the neuromodulator deficit emergent with AD. The proposed features are computed as the power in specific "patches" or regions of interest in the power modulation spectrogram, which are shown to be highly discriminant of AD severity levels. The proposed features were compared with traditional features used in the rsEEG AD monitoring literature. Results showed the proposed features not only achieving improved performance at discriminating between healthy normal elderly controls (Nold) and AD patients with varying severity levels, but also at monitoring severity levels.

Ashik Mostafa Alvi et al [2022**]** provide a deep learning-based framework using the Long Short-term Memory (LSTM) model for effective identification of MCI individuals from healthy volunteers (HV). The suggested framework consists of four phases: denoising, segmentation, down sampling, uncovering deep hidden features using the LSTM model, and identifying MCI patients with the sigmoid classifier. This study has designed 20 different LSTM models and investigated them to a publicly available MCI database to find out the best one. After performing 5-fold cross validation, the best model achieved 96.41% of accuracy, 96.55% of sensitivity and 95.95% of specificity.

Existing Work

Depression is the world’s major health concern and economic burden worldwide. However, due to the limitations of current methods for depression diagnosis, a pervasive and objective approach is essential. In the present study, a psycho physiological database, containing 213 (92 depressed patients and 121 normal controls) subjects, was constructed. The Electro Encephalo Gram (EEG) signals of all participants under resting state and sound stimulation were collected using a pervasive prefrontal lobe three electrode EEG system at Fp1, Fp2, and Fpz electrode sites. After denoising using the Finite Impulse Response filter combining the Kalman derivation formula, Discrete Wavelet Transformation, and an Adaptive Predictor Filter, a total of 270 linear and nonlinear features were extracted. Then, the minimal redundancy maximal relevance feature selection technique reduced the dimensionality of the feature space. Four classification methods (Support

Vector Machine, K-Nearest Neighbor, Classification Trees, and Artificial Neural Network) distinguished the depressed participants from normal controls. The classifiers' performances were evaluated using 10-fold cross validation.

Proposed Work

Deep learning is an artificial intelligence function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in Artificial Intelligence (AI) that has networks capable of learning unsupervised from data that is unstructured or unlabeled. Also known as deep neural learning or deep neural network.

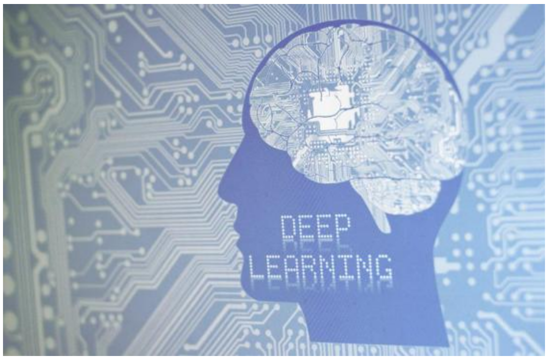

Figure 1 Deep Learning

One of the most common AI techniques used for processing big data is machine learning, a self-adaptive algorithm that gets increasingly better analysis and patterns with experience or with newly added data. Deep learning, a subset of machine learning, utilizes a hierarchical level of artificial neural networks to carry out the process of machine learning. The artificial neural networks are built like the human brain, with neuron nodes connected together like a web. While traditional programs build analysis with data in a linear way, the hierarchical function of deep learning systems enables machines to process data with a nonlinear approach. A type of advanced machine learning algorithm, known as artificial neural networks, underpins most deep learning models. As a result, deep learning may sometimes be referred to as deep neural learning or deep neural networking. Neural networks come in several different forms, including recurrent neural networks, convolutional neural networks, artificial neural networks and feed forward neural networks and each has benefits for specific use cases. However, they all function in somewhat similar ways, by feeding data in and letting the model figure out for itself whether it has made the right interpretation or decision about a given data element.

In this project, a optimization based CNN network design is proposed that is trained to classify multi-channel human EEG signal data into alzimer stages, and that improves upon the classification performance of prior CNN work for the same task. Fig shows that an overview of proposed work.

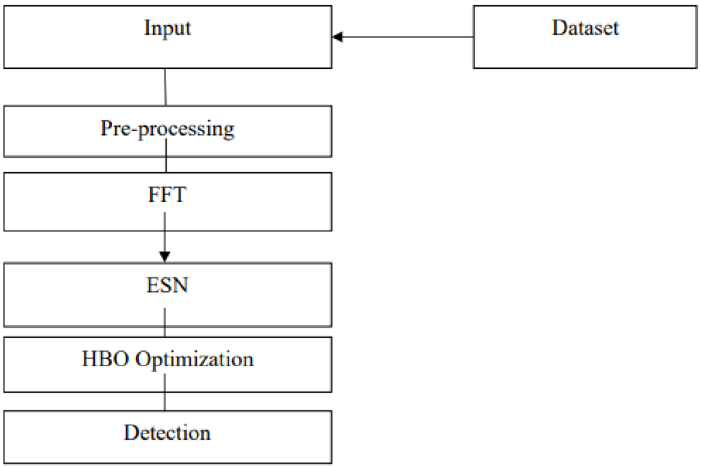

Figure 2 Overview of Proposed Work

ESN Architecture

Deep Echo State Networks (DeepESN) represent a powerful advancement in the field of recurrent neural networks (RNNs) and machine learning. They are a type of reservoir computing model that has gained attention for their ability to efficiently handle complex temporal data while mitigating some of the challenges associated with training traditional deep RNNs. DeepESN is an extension of the original Echo State Network (ESN) concept, incorporating multiple hidden layers to enable the learning of hierarchical features from sequential data.

Honey Badger Optimization Algorithm

In this work, a Honey Badger optimization (HBO) algorithm with levy flight is presented which is based on Swarm based algorithm. The HBO is motivated from a honey badger's excellent foraging behaviour. This HBO method is presented mathematically to solve an optimization issue using a searching strategy. It carries two strategies of honey badger with digging and honey searching strategy to provide an effective solution. This HBO provided an ample population diversity process to achieve a best solution in a larger landscape area. The Honey Badger Optimization is based on the foraging behaviour of Honey Badger. Thus the pseudo code of HBO method is given in the Algorithm 1.

Algorithm 1: pseudo code of HBO method

Input: t_{max}, N, β, C.

Output: Optimal location
Initialize random position based on population
Determine objective function of every honey badge
Allot fi, i ∈ [1, 2, ..., N].

Store X_{prey} best position

Allot fitness f_{prey}

While $t \leq t_{max}$ do

Update α using equation (10)
For i = 1 to N do
Evaluate intensity I_l using Equation (9)

If $rand < 0.5$ then

Update X_{new} using Equation (11)

else
Update X_{new} using Equation (13).

end if
Estimate new position
Assign f_{new}

if $f_{new} \leq f_l$ then

Set $f_l = X_{new}$ and $f_l = f_{new}$

end if
if $f_{new} \leq f_{prey}$ then

Set $x_{prey} = x_{new}$ and $f_{prey} = f_{new}$.

end if
end for
end while Stop condition satisfied.
Return x_{prey}

Result and Conclusion

In the proposed network was trained and tested to detect alzimer. Then, an overall performance is computed by averaging the results from all 5000 iterations.

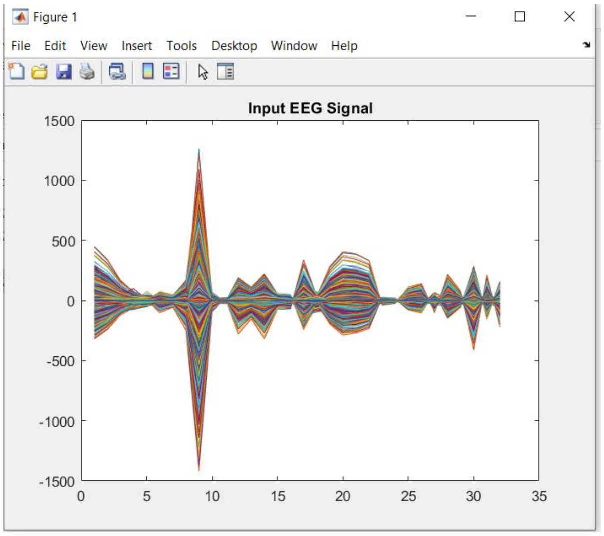

Figure 3 Shows that the Representation of BETA Band After Feature Extraction Process

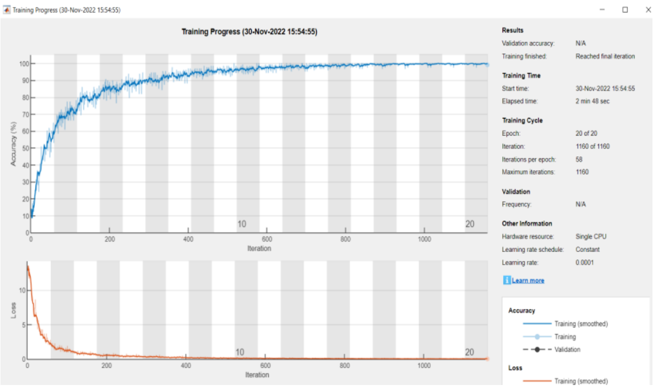

Figure 4 Training Process

Fig. represents the training process of proposed network. After completing the training process, the network is tested and validated using the test dataset.

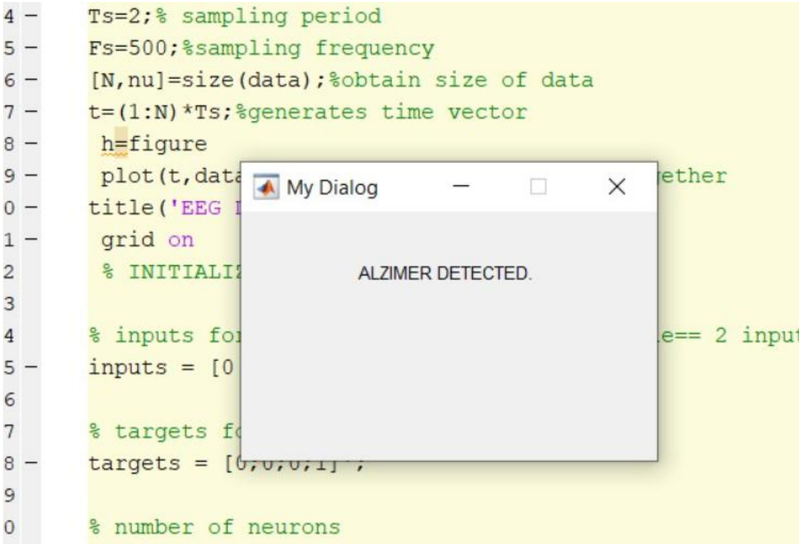

Figure 5 Trained Output

Fig 1.5 shows that the mental status (Normal/abnormal) of a test input data which is shown by the dialog box format. Here, the subject is depressed.

Diagnosis of AD is an important clinical problem. Since EEG is a non-invasive, imple, relatively inexpensive, and potentially mobile brain imaging technology with high temporal resolution, it seems to be a natural candidate as diagnostic tool for AD. Numerous studies indeed confirm the great potential of EEG for diagnosing AD; moreover, some studies show promising results for MCI ("predementia"), which is the stage before AD. However, many crucial issues will need to be addressed before EEG can enter clinical practice for diagnosing AD. The present work explores a novel method of alzimer detection using ESN optimization . These findings suggest that our approach provides new ideas for automatically identify neurological diseases from the perspective of functional networks using MATLAB.

Future, the hybrid model is proposed, A hybrid model for signal classification combines two or more different models to improve the accuracy and robustness of signal classification. The hybrid model takes advantage of the strengths of each individual model to overcome their weaknesses.

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