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DEMNET NeuroDeep: Alzheimer detection using electroencephalogram and deep learning

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ABSTRACT

Alzheimer's disease (AD) stands out as the most prevalent neurological brain disorder, and its diagnosis relies on various laboratory techniques. The electroencephalogram (EEG) emerges as a valuable tool for identifying AD, offering a quick, cost-effective, and readily accessible means of detecting early-stage dementia. Detecting AD in its early stages is crucial, as early intervention yields more successful outcomes and entails fewer risks than treating the disease at a later stage. The objective of this research is to create an advanced diagnosis system for AD using machine learning (ML) and EEG data. The proposed system utilizes a multilayer perceptron (MLP) and a deep neural network with bidirectional long short-term memory (BiLSTM) as the classifier. The feature extraction process involves incorporating Hjorth parameters, power spectral density (PSD), differential asymmetry (DASM), and differential entropy (DE). The BiLSTM classifier, particularly when combined with DE, exhibits outstanding performance with an accuracy of 97.27%. This amalgamation of DE and the deep neural network surpasses current state-of-the-art techniques, underscoring the substantial potential of this approach for precise and advanced diagnosis of AD.

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1. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurological disorder characterized by symptoms such as delusional beliefs, psychosis, and short-term memory loss, often misinterpreted as normal signs of aging or stress [1], [2]. Given its persistent nature, AD can last for years or the entire lifespan of an individual, making it crucial to administer medication at the right stage to prevent significant brain damage. Early identification of AD is a challenging and costly process, involving the collection of extensive data, the application of advanced prediction algorithms, and the expertise of medical professionals. The introduction of automated systems, which are less prone to human error, holds promise for integration into medical decision support systems.

In this study, the integration of brain waves and deep learning techniques aims to establish a robust classification system for the diagnosis of AD. Despite the absence of a definitive cure for AD, timely detection plays a pivotal role in potentially mitigating it is progression. Identifying the condition at an early stage offers the prospect of slowing down its advancement, underscoring the critical importance of early detection for effective patient care and successful treatment strategies. Researchers have utilized various modalities, including visuals such as MRI scans, biomarkers, and numerical data extracted from MRI scans, to examine and diagnose AD [3], [4]. The automation of Alzheimer's diagnosis offers the potential to not only expedite the diagnostic process but also reduce reliance on human interaction. Automation has the added benefits of lowering overall expenses and improving diagnostic precision. For instance, the examination of MRI images using prediction algorithms allows for the early identification of dementia, particularly in its early stages, contributing to enhanced accuracy. As the disease progresses, Alzheimer's symptoms become more pronounced, leading to persistent dementia that impairs individuals' abilities to communicate, adapt to their surroundings, and carry out daily tasks. In addressing this challenge, cutting-edge and computationally intensive methods, such as machine learning (ML), have become increasingly important. The application of ML techniques in disease prediction and representation is on the rise, offering more accurate and personalized approaches to medicine. This shift not only enhances the quality of life for patients but also aids medical professionals in making informed treatment choices and provides valuable data for health economists in their analyses [5], [6].

The review on AD detection, conducted by Shukla *et al.* [7], delves into the application of ML algorithms for predicting AD. The review covers a range of methodologies, including feature extraction and selection techniques, along with classification methods. Their summary provides a quick overview of the various techniques employed in the analysis of disease diagnosis. The discussion encompasses significant topics related to the application of these technologies for the detection and understanding of AD, shedding light on the advancements and challenges within the field. Ibrahim *et al.* [8] implemented a hybrid methodology incorporating the particle swarm optimization (PSO) algorithm to optimize the convolutional neural network (CNN) architecture parameters for the detection of MRI images, focusing on brain tumor and AD. The application of the PSO algorithm resulted in a reduction of the loss function value, leading to enhanced disease prediction accuracy and improved area under curve (AUC) results. Kavitha *et al.* [9] focused on determining optimal parameters for AD prediction using various classifiers. The study conducted AD prognostications specifically on the open access series of imaging studies (OASIS) dataset. The results indicated that the suggested approach achieved the best validation average accuracy of 83% on the test data for AD, showcasing superior outcomes in the context of AD detection.

AlSharabi *et al.* [10] employed the empirical mode decomposition (EMD) approach in their study. The EMD technique was utilized to construct feature vectors by amalgamating various signal features, leading to an enhancement in diagnostic performance. These results indicate that the suggested diagnostic support technique holds promise as a highly effective supplemental tool for identifying potential diagnostic biomarkers. This approach could significantly contribute to the early clinical diagnosis of AD. Mujahid *et al.* [11] introduced an innovative deep ensemble model incorporating transfer learning strategies to predict AD in patients from a multiclass dataset. They implemented adaptive synthetic oversampling (ADASYN) to rectify the class imbalances. The proposed model demonstrated an impressive accuracy of 97.35% in identifying instances of the disease. The study's outcomes imply that the deep learning approach effectively automated the identification of pertinent and crucial features from the samples. Moreover, the ensemble of deep learning models utilized successfully captured diverse elements within the provided data, offering a comprehensive analysis. This approach highlights the effectiveness of leveraging deep learning techniques, including transfer learning and ensemble methods, for accurate prediction and classification of AD from a multiclass dataset.

Hamdi *et al.* [12] developed and comprehensively evaluated a computer-aided diagnostic (CAD) device designed for differentiating AD from normal control (NC) patients. The CAD system utilized features extracted from 18FDG-PET images, and the design incorporated a CNN. The feature extraction process involved splitting the FDG-PET images into multiple 2D slices, followed by clustering the slices at specific intervals without overlaps. The proposed CAD machine was validated on the AD neuroimaging initiative (ADNI) dataset. Comparative analysis with existing approaches revealed that the suggested CAD system performed exceptionally well in distinguishing between AD and NC cases based on the simulation results. This underscores the potential effectiveness of the proposed CAD device in aiding the diagnostic process for AD using 18 FDG-PET images. Imani *et al.* [13] suggested that bidirectional long short-term memory (BiLSTM) networks are used for analysing temporal sequences, whilst CNN are utilised for exploring the relationship between electroencephalogram (EEG) signals recorded by different channels situated in different areas of the brain.

The research paper addresses critical research gaps identified in conventional AD detection systems and introduces novel methodologies to overcome these challenges. The key contributions and resolutions in the proposed system are outlined below:

– Utilization of image processing techniques: i) research gap, many existing computer-aided diagnosis systems heavily rely on image processing techniques, often limited to specific areas of interestand and ii) resolution, the proposed method takes a distinctive approach by analyzing entire brain EEG signals, avoiding the constraints of specific regions of interest. This innovative strategy aims to overcome limitations associated with feature selection and regional data focus observed in conventional methodologies.
– Optimization of deep learning architectures: i) research gap: conventional methods often use deep learning architectures for brain MRI image classification, with some designing their own architectures, resulting in high time consumption and ii) resolution: in the proposed approach, raw EEG data is not directly fed to the deep learning model. Instead, relevant features are extracted first, minimizing memory requirements, and reducing the time needed for feature extraction from the raw EEG signal. This optimization enhances the efficiency of the deep learning network.

Furthermore, this paper introduces a novel framework for EEG signal processing in AD diagnosis using deep learning techniques. It explores two perspectives on EEG signal analysis, focusing on temporal dynamics and functional connectivity patterns within different areas of the cerebral cortex. This dual approach aims to provide a comprehensive understanding of brain activities over time, contributing to the early detection of AD. In contrast to existing apps, the proposed system offers distinctive features: comprehensive EEG signal analysis covering the entire brain, optimization of deep learning architectures for efficient feature extraction, and dual approach to EEG signal analysis, enhancing understanding of brain activities. These unique features set the proposed system apart from existing applications, providing a more comprehensive and efficient approach to AD diagnosis and management.

2. METHODS AND MATERIALS

In this research, our objective is to explore the potential of EEG signals in detecting affective states through the implementation of a deep learning algorithm. In our proposed methodology, a deep learning approach is utilized to extract discriminative features, thereby enhancing the accuracy in AD classification. The adoption of deep learning aims to efficiently capture and learn intricate patterns within the data, ultimately contributing to improved performance in identifying AD.

The outlined methodology for emotion classification is represented in Figure 1. The approach is systematically divided into three distinctive phases, each playing a crucial role in the overall process. The initial phase concentrates on the collection and preprocessing of a comprehensive database relevant to EEG signals. This step ensures the availability of a diverse and representative set of data, laying the foundation for subsequent analysis. Rigorous preprocessing techniques are applied to enhance the quality of the dataset, minimizing noise, and optimizing signal integrity. Moving to the second phase, the emphasis shifts towards feature extraction. This stage involves the identification and extraction of relevant features from the preprocessed EEG data. The goal is to capture essential patterns and characteristics that contribute to the differentiation of affective states. Leveraging advanced techniques in signal processing, this phase is instrumental in transforming raw data into a more compact and informative representation. The final phase of the proposed method is dedicated to classification. A deep learning algorithm is employed to categorize the extracted features into distinct affective states. The model, trained on the preprocessed and feature-rich dataset, can make nuanced distinctions and discerning subtle patterns associated with various emotional states. By systematically integrating these three phases, our study aims to advance the understanding and application of EEG signals in the realm of affective state detection. The proposed method holds the potential to contribute valuable insights to fields such as psychology, neurology, and human-computer interaction.

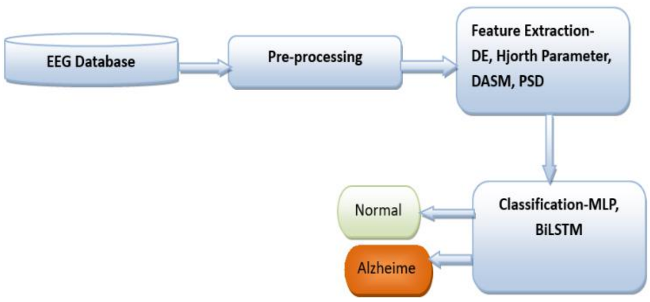

Figure 1. Workflow of proposed system

2.1. Database description
The dataset used in this study is publicly accessible [14] and was gathered using a 19-electrode recorder adhering to the international 10-20 standard for electrode placement. This dataset encompasses three distinct groups: mild cognitive impairment (MCI), AD, and normal cognitive function (NC), representing individuals with varying cognitive conditions. The dataset comprises 102 NC subjects, 59 AD patients, and 7 individuals with MCI. To ensure a logical and unbiased comparison, the study randomly selected only the initial 7-second recordings from 55 participants in both the AD and NC groups for further analysis. This meticulous approach guarantees a fair representation of the dataset in the comparative analysis. Preprocessing steps were employed to enhance the quality of the EEG data. A 50 Hz notch filter was applied to all EEG recordings to mitigate power line interference. Additionally, the independent component analysis (ICA) approach was utilized to effectively eliminate signals originating from blinking and muscle movements, ensuring the integrity of the EEG data used in the subsequent analysis. The EEG dataset used in this study is openly accessible at [15].

2.2. Feature extraction
EEG attributes play a crucial role in the development of human brain-computer interfaces. The existing literature, as referenced in [16], [17], highlights various features pertinent to EEG analysis. In this study, we focus on the evaluation of emotion identification performance, considering four key features:

2.2.1. Power spectral density
Power spectral density (PSD) stands out as a prominent metric in signal processing for characterizing time series data. This metric effectively illustrates changes in power (energy) concerning frequency. The computation of PSD can be achieved through either the autocorrelation function or the fast Fourier transform (FFT) [18]. The resulting PSD plot provides valuable insights into the distribution of signal power across different frequency components, enabling a comprehensive understanding of the frequency characteristics within the given time series data.

2.2.2. Hjorth parameters
Hjorth parameters, introduced by B. Hjorth in 1970, are statistical properties employed for time domain analysis in signal processing. These parameters, namely activity, mobility, and complexity, serve as feature descriptors commonly applied in the analysis of EEG signals [19], [20]. Activity reflects the signal's energy, mobility characterizes its frequency content, and complexity provides insights into the intricacy of the signal waveform. In EEG signal analysis, Hjorth parameters offer valuable information for understanding and interpreting the temporal dynamics and characteristics of the recorded signals.

– Activity:

$$Activity = var\big(s(t)\big) \tag{1}$$

where *s(t)* is a signal.

– Mobility:

$$Mobility = \sqrt{\frac{var(D)}{var(s)}} \tag{2}$$

where D is the first derivative of the signal with respect to time.

– Complexity:

$$\text{Complexity} = \frac{var(D)}{var(DD)} \tag{3}$$

where DD is the second derivative of the signal with respect to time.

2.2.3. Differential entropy
Differential entropy (DE) is a metric employed to quantify the entropy of a continuous random variable [21]. When dealing with a normal distribution, the DE is illustrated as (4):

$$\text{DE} = \text{h(j)} = \frac{1}{2}\ln\,(2\pi e\sigma^2\,) \tag{4}$$

where σ^2 is variance. This equivalence suggests that the measure of uncertainty or disorder associated with a continuous random variable, as captured by DE, aligns with the logarithmic spectral energy in the context of EEG signals within a defined frequency band.

2.2.4. Differential asymmetry

Differential asymmetry (DASM) is given by (5):

$$DASM = h(j_k^{left}) - h(j_k^{right}) \tag{5}$$

where h (j) is illustrated in (4) and k is the pair number [22].

These features are selected based on their significance in capturing relevant patterns and characteristics related to emotional states, aiming to enhance the accuracy and effectiveness of emotion identification within the context of EEG analysis.

2.3. Classification methods

In the classification process, the classifier is provided with the extracted features from the EEG signal. The role of the classifier is to discern the category to which the new observation belongs. Specifically, to differentiate AD patients from healthy participants, two distinct neural network architectures, namely the multilayer perception (MLP) and the BiLSTM network, are employed. These neural networks are adept at capturing implicit changes in the brain patterns, facilitating the accurate classification of individuals into their respective categories. The utilization of advanced neural network models enhances the system’s capability to discern subtle and intricate patterns within EEG signals, contributing to the effectiveness of AD detection.

2.3.1. Multilayer perceptron

The MLP, as highlighted in reference [23], stands as a widely acclaimed and dominant architecture within artificial neural networks (ANNs), particularly favored for its effectiveness in pattern classification. The classification process involves two main stages: training and testing. MLP training employs the well-established Levenberg-Marquardt backpropagation technique. This training methodology refines the network’s internal parameters, adjusting them to minimize the difference between predicted and actual outcomes. The training process continues until an acceptable level of training error is achieved, signifying that the network has learned the underlying patterns within the provided dataset. Once the MLP is trained, it is subjected to testing using new data. During this phase, the network’s performance is evaluated on data it has not encountered before. The aim is to assess the model’s ability to generalize and accurately classify instances beyond the training set. The combination of MLP architecture and the Levenberg-Marquardt backpropagation technique contributes to the proficiency of the network in handling complex pattern recognition tasks. This approach enhances the MLP's capability to accurately classify new observations, making it a robust choice for various applications in pattern classification.

2.3.2. Long short-term memory

To achieve a heightened level of accuracy, the proposed deep learning network incorporates multiple layers, supported by the BiLSTM layer [24], designed to emulate the memory processes of the brain. The deep learning architecture is divided into two main parts: the classification and computational components. The computational part encompasses four layers, namely the input layer, fully connected layer, BiLSTM layer, and softmax layer. These layers work collaboratively to extract higher-level features from the input data. The input layer captures the input sequence, followed by the BiLSTM layer, which analyzes and interprets the data bidirectionally, simulating the input file. The processed information is then forwarded to the fully connected layer, acting as a feed-forward network to convey the sequence of crucial information to the subsequent layer. In the softmax layer, the information is transformed into a probability distribution reflecting the likelihood of each class. The classification layer is responsible for categorizing the organized data based on the maximum probability of classification percentage. Figure 2 represents the overall algorithmic process, providing a clear illustration of the interplay between different layers and their respective roles in enhancing the accuracy of the classification system.

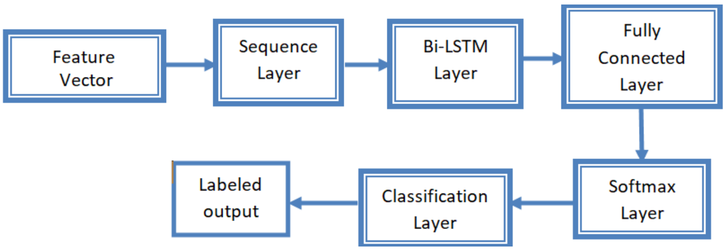

Figure 2. The block of a deep learning model

3. RESULTS AND DISCUSSION

In this research, we effectively extracted features using the Hjorth parameter, DE, DASM, and PSD. Ultimately, MLP and BiLSTM were the two categorization techniques we used. To evaluate the classifiers' accuracies, to guarantee that the results were accurate, the experiment used the five-fold cross-validation approach. Parameter tuning was done for the two classifiers. The optimal parameters were selected for these classifiers after tuning. The learning rate for the MLP classifier was 0.001, the optimizer was the Adam method, and the activation function was rectified linear unit (ReLU) and single hidden layers, respectively. The BiLSTM classifier utilised the Adam method as it is optimizer, ReLU as its activation function, two hidden layers, and 0.0001 learning rate. The three most popular criteria used to measure classification performance are accuracy (acc), precision (preci), sensitivity (senv), and specificity (spec), which are determined using (6) to (9).

$$Acc = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (6)$$

$$Preci = \frac{(TP)}{(TP+FP)} \quad (7)$$

$$Senv = \frac{(TP)}{(TP+FN)} \quad (8)$$

$$Spec = \frac{TN}{(FP+TN)} \quad (9)$$

In the context of this study, where true positive (TP), false positive (FP), true negative (TN), and false negative (FN) represent key evaluation metrics. Table 1 presents the accuracy results for various classifiers and feature extraction methodologies. Upon comparing the accuracy of different features and classifiers, it is evident that the DE with BiLSTM mode attains the highest accuracy at 97.27% in effectively distinguishing between healthy individuals and those diagnosed with AD.

Table 1. The results of different classifiers and feature extractor for AD detection

Feature extractor	Classifier	Accuracy %	Precision	Specificity	Sensitivity
DE	BiLSTM	97.27	0.9643	0.9636	0.9818
	MLP	95.45	0.9310	0.9273	0.9818
Hjorth parameters	BiLSTM	93.64	0.9444	0.9455	0.9273
	MLP	84.55	0.8276	0.8182	0.8727
PSD	BiLSTM	84.55	0.8276	0.8182	0.8727
	MLP	78.18	0.7925	0.8000	0.7636
DASM	BiLSTM	72.73	0.7451	0.7636	0.6909
	MLP	65.45	0.6491	0.6364	0.6727

The identification of nonlinear changes in brain signals, particularly in Alzheimer's patients, is a crucial aspect of understanding the disease. These changes are effectively extracted through the utilization of feature extraction methods such as the Hjorth parameter, DE, PSD, and detrended fluctuation analysis (DASM), followed by classification using ML classifiers.

AD manifests abnormal symptoms that impact the EEG signal, including decreased rhythms (slow signal) and reduced interdependence between different areas of the brain. The EEG signal proves to be a valuable tool for several reasons. Abnormal states in AD, as reflected in the brain signal, directly indicate functional and anatomical defects within the damaged cerebral cortex. Therefore, the dynamic analysis of EEG signals proves to be effective and yields better results compared to state-of-the-art methods.

By leveraging the intricate details captured by these feature extraction methods and utilizing ML classifiers, the proposed approach enhances the understanding of AD through the analysis of EEG signal dynamics. This not only aids in the detection of abnormal states but also contributes to a more comprehensive and effective diagnosis compared to existing methodologies. Table 2 provides a comparative analysis, demonstrating that the proposed strategy surpasses previous research efforts in the realm of Alzheimer's disease detection. Notably, the incorporation of DE as a feature in AD detection yields a significant improvement in accuracy when contrasted with traditional features. The primary focus of this study revolves around achieving enhanced performance in the identification of AD through the utilization of the BiLSTM classifier.

Table 2. Comparison of the results with state of art

Ref.	Features type	Classifier	Accuracy (%)
Kulkarni [25]	Complexity features	K-Nearest Neighbors (KNN)	96
Tzimourta *et al.* [26]	Statistical and spectral features	Shannon entropy and approximate entropy	96.78
Bairagi [27]	Spectral properties	SVM	94
Cai *et al.* [28]	Functional brain networks (FBN)	SVM	92.50
Wu *et al.* [29]	-	Spatial-temporal autoencoder	96.30
Yu *et al.* [30]	-	Takagi-Sugeno-Kang	97.12
Proposed	DE	BiLSTM	97.27

4. CONCLUSION

Advancements in healthcare have significantly improved global well-being, emphasizing the importance of early disease detection. This study highlights the effectiveness of combining DE and BiLSTM techniques for early AD detection. Utilizing four features and two classification algorithms, our approach achieves commendable accuracy, particularly with EEG data, reaching a maximum accuracy of 97.27%. Despite limited clinical trials on computational techniques for Alzheimer’s diagnosis, our findings underscore their potential to revolutionize disease management and positively impact society and the economy. Future efforts will focus on leveraging pre-trained models, staged performance verification, advanced data augmentation, and developing user-friendly interfaces for remote clinical assessments. These initiatives aim to enhance AD classification and management, ultimately improving patient care and treatment strategies.

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