Al-Khwarizmi Engineering Journal
ISSN (printed): 1818 – 1171, ISSN (online): 2312 – 0789
Vol. 20, No. 4, December (2024), pp. 1-12

Al-Khwarizmi Engineering Journal

Deep Learning Model for Prediction of Dementia Severity based on EEG Signals

Noor Kamal Al-Qazzaz [1]*, Sawal Hamid Bin Mohd Ali [2,3]
Siti Anom Ahmad [4,5]

[1] *Department of Biomedical Engineering, Al-Khwarizmi College of Engineering, University of Baghdad, Baghdad 47146, Iraq*
[2] *Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, UKM Bangi, Selangor 43600, Malaysia*
[3] *Centre of Advanced Electronic and Communication Engineering, Department of Electrical, Electronic and Systems Engineering, Universiti Kebangsaan Malaysia, Selangor, Malaysia, 43600*
[4] *Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia, UPM Serdang, Selangor 43400, Malaysia*
[5] *Malaysian Research Institute on Ageing (MyAgeing™), Universiti Putra Malaysia, Serdang, Selangor 43400, Malaysia*
*Corresponding Author' s Email: noorbme@kecbu.uobaghdad.edu.iq

(Received 27 March 2024; Revised 3 July 2024; Accepted 11 August 2024; Published 1 December 2024)
https://doi.org/10.22153/kej.2024.08.002

Abstract

This study aimed to determine variations in the electroencephalograms (EEGs) of 15 individuals who were diagnosed with mild cognitive impairment (MCI) following stroke, 5 individuals suffering from vascular dementia (VD) and 15 healthy normal control (NC) individuals who performed a working memory task. Conventional filters including notch and bandpass filters were utilised to remove noise from the EEG data. The proposed method comprises computing the estimates of the attention entropy (AttEn), bubble entropy (BubbEn) and symbolic dynamic entropy (SyDyEn) of univariate data sequence features. The long short-term memory (LSTM) deep learning neural network was used to automatically classify dementia severity through noninvasive EEG-based recordings. The LSTM classification result with AttEn exceeds an average of 88.9% than BubbEn and SyDyEn, with classification results of 69.2% and 77.7%, respectively. The analysis of the brain EEG-based dementia severity dataset suggests that AttEn could potentially serve as a biomarker for detecting dementia severity. AttEn can capture relevant patterns and features in the EEG data and may be indicative of the severity of dementia with LSTM RNN to differentiate patients with VD, patients with MCI and NC individuals.

Keywords: dementia; deep learning; transfer learning; long short-term memory; classification

1. Introduction

Cognitive impairment occurs due to vascular lesions that arise from a diverse range of medical conditions, including ischemic heart disease and stroke [1]. About 1% to 4% of the elderly population over the age of 65 years suffers from vascular dementia (VD), and this number will double every 5 to 10 years [2]. VD is the second most common form of dementia, after Alzheimer's disease (AD) [3]. Mild cognitive impairment (MCI) refers to a decrease in cognitive function that is more severe than one would expect given one's age and degree of education but does not significantly impact one's ability to carry out daily tasks [4, 5]. Patients diagnosed with MCI have a high risk of developing dementia within the third month of the onset of dementia symptoms [3, 6]. This clinical transitional stage occurs between early normal cognition and late severe dementia. Most people with MCI only experience memory loss, but their ability to do daily tasks is unaffected [7].

Electroencephalograms (EEGs) are used to detect dementia. Multiple studies have demonstrated the utility of EEGs to identify and assess the severity of dementia [3] as well as differentiate AD from VD and other types of dementia [8, 9,10].

Various machine learning classification algorithms have been used to classify EEGs of cognitively challenged participants [11]. Relative frequencies play a prominent role in each case [12, 13, 14]. However, traditional machine learning approaches are unsuitable for processing high-dimensional volumes of data because they are based on the explicit definition of features. Deep learning is a cutting-edge machine learning technology that can address those drawbacks and has an advantage over traditional machine learning techniques; deep neural networks (NNs) can process and learn latent discriminative features from raw data or end-to-end learning.

Deep learning-powered AD detection systems have emerged given that deep learning has been proven to have many real-world applications, such as in biomedicine [15, 16] and image detection [17, 18]. The majority of these systems rely on neuroimaging analysis (structural and functional magnetic resonance imaging or sMRI and fMRI, respectively), with data from the AD Neuroimaging Initiative (ADNI) database. Very few deep learning studies have focused on the differentiation of AD by using EEG recordings [19].

Given the nonlinearity and complexity of biological systems, scholars have suggested alternative entropy measures to characterise EEG signals [20, 21]. The approximate entropy (ApEn) algorithm derives a measure of entropy for noisy biomedical time series that is statistically valid. This measure represents the likelihood that time series patterns that are similar at first glance will retain their similarity even after the pattern lengths are increased. As such, this algorithm offers an inherent assessment of the regularity of time series [22]. Nevertheless, previous research demonstrated that ApEn is a highly sensitive estimator that is skewed by the number of data samples [23].

Sample entropy (SampEn), an adaptation of ApEn, excludes self-matches from the probability calculation [24]. A reduced value of SampEn signifies increased self-similarity within the time series. SampEn exhibits greater consistency in its behaviour and is more independent of data samples than ApEn [24]. However, SampEn possesses certain limitations, such as potential instability and unreliable results when applied to brief time series [25].

Fuzzy entropy (FuzEn) employs the notion of fuzzy sets to address limitations associated with sample entropy. FuzEn exhibits a more robust relative consistency and reduced reliance on data length than SampEn [25]. Additionally, continuity is ensured by the continuous and flexible boundaries of fuzzy functions. However, the degree of freedom associated with selecting internal parameters is greater than that of sample entropy because of the introduction of fuzzy power and membership function to delineate the boundary [26].

Determining internal parameters is a crucial aspect of obtaining entropy metrics. Manis et al. proposed bubble entropy (BubbEn), a new definition of entropy derived from permutation entropy (PerEn) that ranks vectors in the embedding space of the time series [27]. The effort from the number of exchanges is quantified for permutation, which is executed via the 'bubble sort' algorithm. Bubble entropy is virtually devoid of internal parameters; its definition completely omits the scaling factor r, and the significance of embedding dimension m is drastically diminished [27].

In general, symbolism can increase performance in characterisation and quantification of time series [28]. Time series representation depends on the method of delay time on the scheme introduced by Tekens for phase space reconstruction.

Methods for state space reconstruction rely on the detection of lags of some degree of independence (linear or nonlinear); signal strength has been used as a statistical tool to determine the presence of dependence in time series [29]. Symbolic dynamics entropy (SyDyEn) is a convenient tool for selecting the optimal state space reconstruction parameters for chaotic time series. Thus, having defined the symbolic properties of the problem, we then used the entropy measure associated with the symbolic space (symbolic entropy) for parameter selection [29].

The attention entropy (AttEn) approach has been innovated to isolate the most critical observations and measure their frequency of prevalence within the time series. The model may cognizance at the time steps that have maximum information but ignore those that are too noisy. This approach has improved typical performance and resistance to noisy inputs [30].

In the realm of deep learning, models such as 1D-convolutional neural networks (CNNs) [31] and CNNs [32, 33, 15] are common. CNNs provide many benefits, such as speed, accuracy and power when processing visual data, huge amounts of data, and complex pattern predictions. However, CNNs need labelled data and have high computational cost of training, and their predictions are difficult to confirm. Different types of NNs have been employed for signal classification, including RNNs [34, 35] and LSTMs [36, 37, 38] for EEG and other critical signal processing. RNNs and LSTM can handle data of varying lengths, catch patterns across time and integrate complex NN designs. Regular Neural Networks (RNNs) have a lot of drawbacks, such as a high computing cost, lengthy training durations and problems with bigger datasets. Every approach has its advantages and disadvantages, so selecting a suitable method depends on the type of problem and the level of precision needed.

This study could provide insights into dementia. Patients with dementia frequently exhibit diminished nonlinear cell dynamics and/or nonlinear coupling within the brain cortex as well as linear couplings. These factors can result in a decline in complexity and functional connections. To comprehend this phenomenon, scholars should investigate the nonlinear EEG dynamics of patients with dementia. In the early stages of dementia, EEGs may appear normal and have the same rhythm as healthy individuals of the same age. EEG recordings obtained from individuals with dementia should be analysed and interpreted using signal analysis techniques to assess the influence of dementia on the brain and understand the progression of the disease [5].

This study aimed to determine if individuals have VD, MCI, or normal control (NC) condition by using deep learning recurrent neural networks. The features of univariate EEG data sequences should be estimated using attention entropy (AttEn), bubble entropy (BubbEn) and symbolic dynamic entropy (SyDyEn). The long short-term memory (LSTM) deep learning neural network was used to discriminate dementia severity. This study aims to develop a paradigm that could be used in real-world clinical settings and classify patients as having VD, MCI, or NC based on noninvasive scalp EEG recordings.

2. Materials and Methods

The recorded EEGs would go through a series of signal processing stages designed to separate the symptoms of patients with dementia to diagnose post-stroke clinical manifestations. Fig. 1 shows the flowchart of the proposed method.

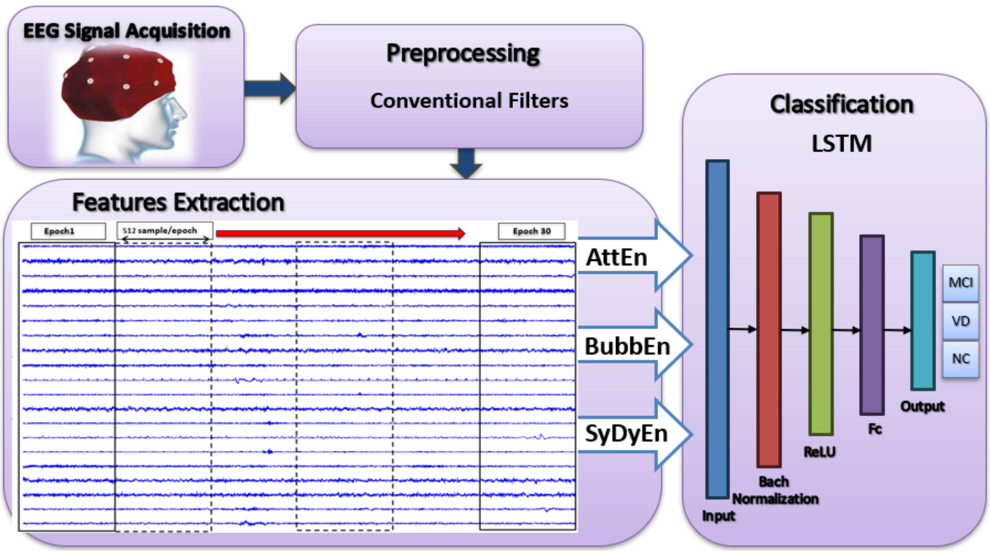

Fig. 1. Flowchart of the proposed method.

2.1 Subjects and EEG recording procedure

The EEG datasets of 15 NC individuals (aged 60.06±5.21) years), 15 patients (aged 60.26±7.77 years) with MCI due to stroke and 5 people with VD (aged 64.6±4.8 years). Healthy volunteers had no known history of mental disorders. Patients suffering from stroke were culled from the stroke ward at Pusat Perubatan Universiti Kebangsaan Malaysia Hospital. The groups were evaluated cognitively by using the Mini-Mental State Examination (MMSE) [39] and Montreal Cognitive Assessment (MoCA) [40]. The Hospital Human Ethics Committee gave their approval to all of the experiment protocols. All participants also signed an information consent (ICF) form.

NicoletOne (V32) systems were used to record EEG activities. In accordance with the 10-20 international system, 19 electrodes, including the ground and system reference electrodes, were placed (Fp1, Fp2, F7, F3, Fz, F4, F8, T3, T5, T4, T6, P3, Pz, P4, C3, Cz, C4, O1 and O2).

In this study, all participants engaged in an auditory working memory (WM) task session. As the subjects were instructed to relax completely, an auditory session began with a 0.5-second fixation cue. The participants were then given a brief WM test, during which they were asked to memorise five words for 10 seconds. The participants were then asked to try to recall the words while keeping their eyes closed, and EEG data were collected. They closed their eyes for 60 seconds, opened them and list as many words as they could remember [8].

2.2 Preprocessing Stage

In the first step of processing each channel of recorded EEG datasets, conventional filters were used; in particular, a notch filter at 50 Hz was used to remove interference noise, and a bandpass filter with a (0.5–64) Hz frequency range was used to limit the band of the recorded EEG signals [41, 42].

2.3 Feature Extraction Stage

The EEG signals for all channels were segmented into nonoverlapping windows of 2 s for feature extraction. Entropy features including attention entropy (AttEn) [38], bubble entropy (BubbEn) [43] and symbolic dynamic entropy (SyDyEn) [44, 45, 46] of univariate data sequence features were extracted. The dimension of each feature vector from each subject was equal to 30 windows × 19 EEG channels.

Patients with VD were a minority in this research. Synthetic oversampling technique (SMOTE) was utilised to rectify the data imbalance [47]. Empirical evidence is lacking to support the efficacy of BubbEn or DispEn in the characterisation of EEG signals. The present work aimed to assess the discriminatory capability of AttEn, BubbEn and SyDyEn in discerning the severity of dementia based on EEG signals

A. Symbolic Dynamic entropy (SyDyEn)

Symbolic dynamics evaluates dynamical systems based on the proper partitioning of the symbol sequences obtained for the state space. Symbolic dynamic entropy (SyDyEn) is based on an entropy unit. Simple methods can preserve some important properties of the dynamics, such as periodicity and dependence, despite the loss of a certain amount of detail. Symbolic dynamics (SDE) has been used to locate dynamics in nonlinear systems [48, 49, 50, 51].

To apply the SyDyEn approach, the time series must first be transformed into a symbolic series, $X = x_1, x_2, x_3, \ldots, x_n$, which represents a time series of length N. One way to transform time series into symbolic time series is by using maximum entropy partitioning, which offers adaptive segmentation [45]. In the equation, λ stands for the time delay and m for the embedding dimension in the symbolic time series. The next step is to determine the probability of state transitions [52]. Equation 1 defines the SDE in accordance with the theorem of Shannon entropy.

$$SDE(X, \mu, m, \lambda) = -\sum_{a=1}^{\mu^m} P\left(q_a^{\mu,m,\lambda}\right) lnP\left(q_a^{\mu,m,\lambda}\right) - \sum_{a=1}^{\mu}\sum_{a=1}^{\mu^m} P\left(q_a^{\mu,m,\lambda}\right) lnP\left(q_a^{\mu,m,\lambda}\right) P\left(\sigma_b | q_a^{\mu,m,\lambda}\right) \quad \ldots(1)$$

Lastly, the SDE is adjusted to ensure that it follows the normal distribution with 0 < SyDy < 1, as shown in Equation 2.

$$SyDyE(\bar{X}, \mu, m, \lambda) = SDE(\bar{X}, \mu, m, / \ln(\mu^{m+1}) \quad \ldots(2)$$

B. Bubble entropy (BubbEn)

Manis et al. [43] suggested the use of BubbEn to differentiate congestive heart failure from a healthy control group. The BubbEn formula is an adaptation of the permutation entropy that incorporates elements from the permutation entropy and the Renyi entropy as well as some additional terms from the ApEn [53]. The number of swaps needed to sort a vector x½i is counted in BubbEn, which uses the bubble sort algorithm. Its discriminatory power is independent of input parameters, thus it is almost a parameter-free entropy [43]. These are the steps involved in the calculation: first, for a certain system X, the entropy may be determined by Equations 3 and 4.

$$H_a^m(X) = \frac{1}{\alpha}\log(\sum_{i=1}^{n} P_i^a) \quad \ldots(3)$$

$$H_2^m(X) = -\log(\sum_{i=1}^{n} P_i^2) \quad \ldots(4)$$

The Renyi entropy, also known as the generalised entropy, is obtained as Shannon entropy when α → 1. In this paper, we take α = 2 to obtain Equation 4, so that the peaks and mutation points in the sequence can be well described and the effect of chance is not overly weakened. The following step makes m increases 1 and calculation like Equation 4 and gain H_2^{m+1}. BubbEn can be obtained from Equation 5.

$$BubbEn(X,m)) = \frac{H_2^{m+1} - H_2^m}{\log\frac{m+1}{m-1}} \quad ..(5)$$

Sequence rearrangement using the traditional sorting method solely takes the original sequence's size order into account and ignores the effect of amplitude differences. Symbolisation cannot assign unique alignment to subsequences containing components of the same size; for instance, the sequence (2,1,2) can be assigned to both (1,0,2) and (1,2,0). This assignment method will, to some extent, cause the important information to be ignored. When it comes to parameter selection, bubble entropy is optimised for reducing the model's dependence on input parameters (such as data length or embedding size) by calculating the number of sample exchanges needed to generate an ordered subsequence instead of counting the ordered pattern [43].

C. Attention entropy (AttEn)

Entropy methods are sensitive to parameter settings, but AttEn focuses only on observations of key features. Instead of counting all observation frequencies, it finds the frequency distribution interval between key observations in a time series.

The advantage of AttEn is that it does not need any parameters to tune, it is robust to long time series and requires only linear data when calculating AttEn. The calculation can be done in three basic steps [30]: to define the basic model, to calculate the distance between two adjacent principal patterns and to compute the Shannon entropy of the intervals. The difference between classical entropy methods and attention entropy methods involves classical frequency-based entropy methods, which cannot separate two chains because both models have the same frequency distribution. In AttEn, the distribution of distances between key patterns in the chain is different [30, 55].

Three primary procedures are used to determine attention entropy (AttEn). Key patterns are defined, intervals between adjacent key patterns are calculated and the Shannon entropy of intervals is computed. Classical frequency-based entropy algorithms are unable to distinguish between the Series 1 and 2 because of the identical pattern distribution. The interval distributions of the series' key patterns are different. AttEn can accomplish this. Primarily, we establish the key pattern Ω when we are given a finite series X. Secondly, for every sub-series ui, uk and uj of X that do not match in for any i_j, k_j we determine the intervals $I^{\Omega} - v|v - j - i$ by comparing u_i and u_j to the pattern **Ω**. Attention entropy, or Shannon entropy over IV, is computed [30].

Dementia Classification using LSTM model
The deep learning method represented by the LSTM network was used for EEG-based signal dementia classification. LSTM [56] is a type of recurrent neural network (RNN) used in many biomedical indications to detect unidirectional duration-dependent time steps between time series or continuous data [57, 58]. This study reports the first use of LSTM to classify EEG-based symptoms of dementia.

After implementing the LSTM model and validating it using selected EEG features, the model design adopted for this study consisted of a layer of 200 hidden in the layered architecture of the implemented LSTM model batch normalisation, improved linear unit (ReLU) layer, ending with a fully connected level (the number of nodes is equal to the number of severe dementia groups) and a SoftMax activation level for segmentation. Optimal moment calculation for training "adam" solver, gradient threshold 1, maximum number of 64 epochs and 8 small batch size.

Optimisation was performed in MATLAB R2023b. The dataset was divided into the training, validation and testing datasets at a ratio of 70:15:15. Splitting the dataset in this manner can provide sufficient data for model development; however, we made sure to have good validation and test datasets for model validation and hyperparameter selection.

2.4 Dementia Classification using LSTM model

The deep learning method represented by the LSTM network was used for EEG-based signal dementia classification. LSTM [56] is a type of recurrent neural network (RNN) used in many biomedical indications to detect unidirectional duration-dependent time steps between time series or continuous data [57, 58]. This study reports the first use of LSTM to classify EEG-based symptoms of dementia severity.

By implementing the LSTM model and validating it using selected EEG features, the model design adopted for this study consisted of a layer of 200 hidden in the layered architecture of the implemented LSTM model batch normalisation, improved linear unit (ReLU) layer, ending with a fully connected level (the number of nodes is equal to the number of severe dementia groups) and a

SoftMax activation level for segmentation. Optimal moment calculation for training ‘adam’ solver, gradient threshold 1, maximum number of 64 epochs and 8 small batch size.

Optimisation was performed in MATLAB R2023b. The dataset was divided into the training, validation, and testing datasets at the ratio of 70:15:15. Splitting the data in this manner can provide sufficient data for model development; however, we made sure to have good validation and test datasets for model validation and hyperparameter selection.

3. Results and Discussion

The results of the conventional filters on channel 'Fp1' are illustrated in Fig. 2. Compared with the original recorded EEG (dashed black colour), the artifactual components were effectively and sufficiently suppressed (blue colour).

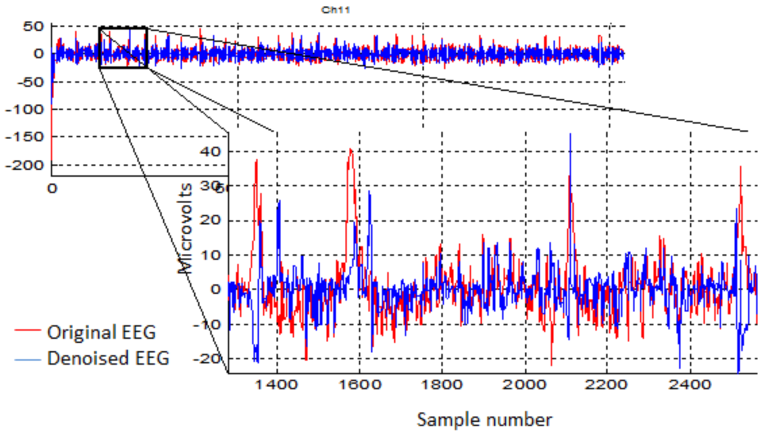

Fig. 2. Preprocessing results of EEG Ch1, which represents Fp1, following the application of conventional filters.

As demonstrated in Figs. 3, 4 and 5, a confusion matrix was used to assess the classifier’s effectiveness in categorising VD (class1), MCI (class 2) and NC (class3) occurrences. The projected classes are shown in the rows of the matrix, and the actual classes are shown in the columns. The number of examples that were successfully identified is represented by the diagonal elements, which show the classifier’s accuracy for each class.

Fig. 3 shows the confusion matrix of the classification results of the LSTM model obtained using SyDyEn, which successfully distinguished between VD and NC cases, as shown by the zero false positive and negative numbers for MCI, indicating a high accuracy of 100%. However, the classifier cannot correctly categorise NC (accuracy of 66.7%) and VD (accuracy of 75%). The confusion matrix shows that the LSTM model with SyDyEn achieves a total classification accuracy of 77.8%. The SyDyEn’s inability to close this performance difference raises concerns about its ability to distinguish between VD, MCI and NC classes, either because its features are too complicated or too comparable. Investigating the BubbEn feature might be essential to improve the classifier’s capacity to correctly categorise VD, MCI and NC groups.

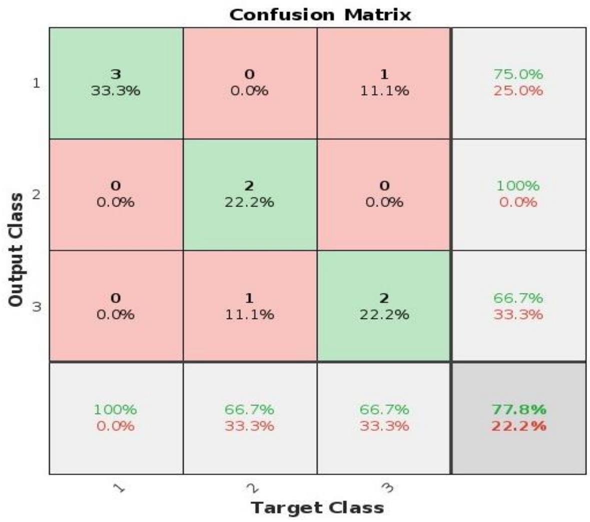

Fig. 3. Confusion matrix of the classification results for the LSTM model using SyDyEn.

The classification results for the LSTM model with BubbEn are shown in Fig. 4. We obtained 69.2% rate of correct classifications. Although 80% of VD cases are accurately identified as VD, 7.7%

are mistakenly labelled as NC. Meanwhile, 50% of NC cases were wrongly forecasted as MCI, and 100% of MCI cases were accurately categorised.

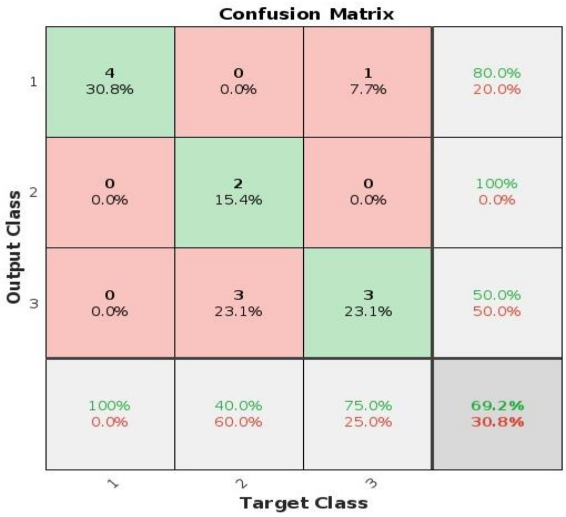

Fig. 4. Confusion matrix of the classification results for the LSTM model using BubbEn.

To address the discrimination based on dementia severity, further research was conducted using the AttEn feature in conjunction with LSTM. The results of using AttEn improved the classification accuracy to 88.9% (Fig. 5). After applying the AttEn feature, the three diagonal cells display the proportion of correct LSTM classification. For VD, the correct classification was 100%. All individuals with MCI due to stroke were appropriately categorised as such, 75% as non-concussional (NC) subjects and 25% as misclassified patients with MCI.

Fig. 5. Confusion matrix of the classification results for the LSTM model using AttEn.

In this study, new methods have been proposed to diagnose people with VD, MCI as a result of a stroke or NC by using EEG data and LSTM deep learning. The findings of this research can be summarised as follows. The LSTM deep learning model using the AttEn feature obtained the highest average classification accuracy of 88.9% and thus presented better results than SyDyEn and BubbEn. Table 1 shows that the results are consistent with other benchmark studies [31, 32, 33, 15, 34, 35] and that the LSTM feature that made use of the AttEn yielded good classification rates. To the best of our knowledge, our work is the first to propose a set of novel features based on entropy to differentiate between MCI, VD and NC based on EEG data. The superior performance in the AttEn feature can be attributed to the desirable characteristics of the temporal analysis of the EEG signals and the presence of attention-related features that are affected in conditions such as AD and dementia. The LSTM model's utilisation of such hinges on its overall performance in learning and modelling complex temporal patterns, contributing to high levels of classification.

This investigation has several limitations; for example, the study has a limited number of participants, especially in the VD category. For future work, researchers should replicate the findings with larger and more varied data to ensure the robustness of the method. Moreover, they should implement the proposed approach in clinical practice scenarios. The findings revealed in our study provide evidence that deep learning-based methods integrated with newly proposed EEG features can be effectively used to distinguish between MCI, VD and NC groups. The presented study adds to the current knowledge about identifying cognitive decline in memory and dementia by employing neurophysiological markers.

Table 1,
Comparison of our findings to relevant studies in the literature.

Study	Algorithm	Accuracy (%)
Klepl et al. [31]	Adaptive Gated Graph CNN	90.2
Shikalgar et al. [32]	Hybrid Deep Learning	93.3
Fouladi et al. [33]	Efficient Deep Neural Networks	92.5
Huggins et al. [15]	Deep Learning	84.2
Alessandrini et al. [34]	LSTM	91.2
Amini et al. [35]	CNN	94.1
Our study	AttEn with LSTM	88.9

4. Conclusion

Dementia stands out among many diseases that affect the lives of the elderly. Therefore, fighting dementia requires a precise assessment of its severity. EEG-based dementia data are filtered using notch and bandpass filters. To automatically categorise the severity of the multi-classification tasks of patients with dementia by using noninvasive EEG-based recordings, this study suggests using the LSTM deep learning neural network. This approach includes finding the AttEn, BubbEn and SyDyEn of features in a univariate data sequence. The LSTM classification results using AttEn entropy are 88.9% more accurate than those using BubbEn and SyDyEn (77.2% and 69% accuracy, respectively). These results point to the potential utility of AttEn as a biomarker extracted from the EEG data to assess the severity of dementia. Moreover, the proposed LSTM could be a potential RNN model that can identify key EEG patterns and characteristics and distinguish patients suffering from VD and MCI.

References

[1] J. Jeong, “EEG dynamics in patients with alzheimer’s disease,” Clinical neurophysiology, vol. 115, no. 7, pp. 1490–1505, 2004.

[2] C. McVeigh and P. Passmore, “Vascular dementia: prevention and treatment,” Clinical interventions in aging, vol. 1, no. 3, pp. 229–235, 2006.

[3] N. K. Al-Qazzaz, S. H. B. Ali, S. A. Ahmad, K. Chellappan, M. Islam, J. Escudero et al., “Role of EEG as biomarker in the early detection and classification of dementia,” The Scientific World Journal, vol. 2014, 2014.

[4] N. K. Al-Qazzaz, S. H. Ali, S. A. Ahmad, S. Islam, and K. Mohamad, “Cognitive impairment and memory dysfunction after a stroke diagnosis: a post-stroke memory assessment,” Neuropsychiatric disease and treatment, pp. 1677–1691, 2014.

[5] N. K. Al-Qazzaz, S. H. Ali, S. A. Ahmad, and S. Islam, “Cognitive assessments for the early diagnosis of dementia after stroke,” Neuropsychiatric disease and treatment, pp. 1743–1751, 2014.

[6] N. K. Al-Qazzaz, S. H. M. Ali, S. Islam, S. Ahmad, and J. Escudero, “EEG wavelet spectral analysis during a working memory tasks in stroke-related mild cognitive impairment patients,” in International Conference for Innovation in Biomedical Engineering and Life Sciences. Springer, 2015, pp. 82–85.

[7] N. K. Al-Qazzaz, S. Ali, M. S. Islam, S. A. Ahmad, and J. Escudero, “EEG markers for early detection and characterization of vascular dementia during working memory tasks,” in 2016 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES). IEEE, 2016, pp. 347–351.

[8] N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, M. S. Islam, and M. I. Ariff, “Selection of mother wavelets thresholding methods in denoising multichannel EEG signals during working memory task,” in 2014 IEEE conference on biomedical engineering and sciences (IECBES). IEEE, 2014, pp. 214–219.

[9] N. K. Al-Qazzaz, S. Hamid Bin Mohd Ali, S. A. Ahmad, M. S. Islam, and J. Escudero, “Selection of mother wavelet functions for multi-channel eeg signal analysis during a working memory task,” Sensors, vol. 15, no. 11, pp. 29015–29035, 2015.

[10] J. Escudero, R. Hornero, D. Ab´asolo, and A. Ferna´ndez, “Quantitative evaluation of artifact removal in real magnetoencephalogram signals with blind source separation,” Annals of biomedical engineering, vol. 39, no. 8, pp. 2274–2286, 2011.

[11] N. K. Al-Qazzaz, S. H. M. Ali, and S. A. Ahmad, "Entropy-based eeg markers for gender identification of vascular dementia patients," in 3rd International Conference for Innovation in Biomedical Engineering and Life Sciences: Proceedings of ICIBEL 2019, December 6-7, 2019, Kuala Lumpur, Malaysia. Springer, 2021, pp. 121–128.

[12] N. K. Al-Qazzaz, S. H. B. M. Ali, S. A. Ahmad, and J. Escudero, "Optimal EEG channel selection for vascular dementia identification using improved binary gravitation search algorithm," in International Conference for Innovation in Biomedical Engineering and Life Sciences. Springer, 2017, pp. 125–130.

[13] N. K. Al-Qazzaz, S. H. B. M. Ali, S. A. Ahmad, M. S. Islam, and J. Escudero, "Discrimination of stroke-related mild cognitive impairment and vascular dementia using eeg signal analysis," Medical & biological engineering & computing, vol. 56, pp. 137–157, 2018.

[14] N. K. Al-Qazzaz, S. H. M. Ali, and S. A. Ahmad, "Differential evolution based channel selection algorithm on EEG signal for early detection of vascular dementia among stroke survivors," in 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES). IEEE, 2018, pp. 239–244.

[15] C. J. Huggins, J. Escudero, M. A. Parra, B. Scally, R. Anghinah, A. V. L. De Arau´jo, L. F. Basile, and D. Abasolo, "Deep learning of resting-state electroencephalogram signals for three-class classification of alzheimer's disease, mild cognitive impairment and healthy ageing," Journal of Neural Engineering, vol. 18, no. 4, p. 046087, 2021.

[16] A. F. A. Rabea, S. A. Ahmad, A. C. Soh, A. J. Ishak, R. N. E. R. Adnan, N. K. Al-Qazzaz et al., "Driver's fatigue classification based on physiological signals using rnn-lstm technique," in 2022 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES). IEEE, 2022, pp. 280–285.

[17] N. Subramanian, O. Elharrouss, S. Al-Maadeed, and M. Chowdhury, "A review of deep learning-based detection methods for covid-19," Computers in Biology and Medicine, p. 105233, 2022.

[18] T. A. Soomro, L. Zheng, A. J. Afifi, A. Ali, S. Soomro, M. Yin, and J. Gao, "Image segmentation for mr brain tumor detection using machine learning: A review," IEEE Reviews in Biomedical Engineering, 2022.

[19] I. Marin, T. Marasovi´c, and S. Gotovac, "Siamese network for contentbased image retrieval: Detection of alzheimer's disease from neuroimaging data," in 2022 International Conference on Software, Telecommunications and Computer Networks (SoftCOM). IEEE, 2022, pp. 1–6.

[20] L. A. Bugnon, R. A. Calvo, and D. H. Milone, "Dimensional affect recognition from hrv: An approach based on supervised som and elm," IEEE Transactions on Affective Computing, vol. 11, no. 1, pp. 32–44, 2020.

[21] Y. Isler, A. Narin, M. Ozer, and M. Perc, "Multi-stage classification of congestive heart failure based on short-term heart rate variability," Chaos, Solitons & Fractals, vol. 118, pp. 145–151, 2019.

[22] H.-H. Chao, C.-W. Yeh, C.-F. Hsu, L.-W. Hsu, and S.-C. Chi, "Multiscale entropy analysis with low-dimensional exhaustive search for detecting heart failure," Appl. Sci., vol. 9, no. 17, p. 3496, 2019.

[23] M. Shi, C. Zhan et al., "Renyi distribution entropy analysis of shortterm heart rate variability signals and its application in coronary artery disease detection," Front. Physiol., vol. 10, 2019.

[24] M. Costa, A. L. Goldberger, and C.-K. Peng, "Multiscale entropy analysis of complex physiologic time series," Phys. Rev. Lett., vol. 89, no. 6, p. 68102, 2002.

[25] R. Clausius, The mechanical theory of heat: with its applications to the steam-engine and to the physical properties of bodies. J. van Voorst, 1867.

[26] L. Boltzmann, "Weitere studien u¨ber das w¨armegleichgewicht unter gasmoleku¨len," pp. 115–225, 1970.

[27] J. W. Gibbs, Elementary principles in statistical mechanics developed with especial reference to the rational foundation of thermodynamics/by J. Willard Gibbs. C. Scribner, 1902.

[28] M. Ferrario, M. G. Signorini, G. Magenes, and S. Cerutti, "Comparison of entropy-based regularity estimators: Application to the fetal heart rate signal for the identification of fetal distress," IEEE Trans. Biomed. Eng., vol. 53, pp. 119–125, 2006.

[29] M. Matilla-Garc´ıa, I. Morales, J. M. Rodr´ıguez, and M. Ruiz Mar´ın, "Selection of embedding dimension and delay time in phase space reconstruction via symbolic dynamics," Entropy, vol. 23, no. 2, p. 221, 2021.

[30] J. Yang, G. I. Choudhary, S. Rahardja, and P. Franti, "Classification of interbeat interval time-series using attention entropy," IEEE Transactions on Affective Computing, 2020.

[Online]. Available: https://doi.org/10.1109/TAFFC.2017.2784832

[31] D. Klepl, F. He, M. Wu, D. Blackburn, and P. Sarrigiannis, “Adaptive gated graph convolutional network for explainable diagnosis of alzheimer’s disease using eeg data,” arXiv preprint arXiv:2304.05874, Apr 2023, accessed: May 26, 2023. [Online]. Available: https://arxiv.org/abs/2304.05874v1.

[32] A. Shikalgar and S. Sonavane, “Hybrid deep learning approach for classifying alzheimer disease based on multimodal data,” in Advances in Intelligent Systems and Computing, vol. 1025, 2020, pp. 511–520.

[33] S. Fouladi, A. Safaei, N. Mammone, F. Ghaderi, and M. Ebadi, “Efficient deep neural networks for classification of alzheimer’s disease and mild cognitive impairment from scalp eeg recordings,” Cognitive Computation, vol. 14, no. 4, pp. 1247–1268, Jun 2022.

[34] M. Alessandrini, G. Biagetti, P. Crippa, L. Falaschetti, S. Luzzi, and C. Turchetti, “Eeg-based alzheimer’s disease recognition using robustpca and lstm recurrent neural network,” Sensors, vol. 22, no. 10, p. 3696, 2022.

[35] M. Amini, M. Pedram, A. Moradi, and M. Ouchani, “Diagnosis of alzheimer’s disease by time-dependent power spectrum descriptors and convolutional neural network using eeg signal,” Computational and Mathematical Methods in Medicine, vol. 2021, 2021.

[36] U. Senturk, I. Yucedag, and K. Polat, “Repetitive neural network (rnn) based blood pressure estimation using ppg and ecg signals,” in ISMSIT 2018 - 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies, Proceedings, Dec 2018.

[37] U. Senturk, K. Polat, and I. Yucedag, “A non-invasive continuous cuffless blood pressure estimation using dynamic recurrent neural networks,” Applied Acoustics, vol. 170, p. 107534, Dec 2020.

[38] G. Sharma, A. Parashar, and A. Joshi, “Dephnn: A novel hybrid neural network for electroencephalogram (eeg)-based screening of depression,” Biomedical Signal Processing and Control, vol. 66, p. 102393, Apr 2021.

[39] M. F. Folstein, S. E. Folstein, and P. R. McHugh, ““mini-mental state”: a practical method for grading the cognitive state of patients for the clinician,” Journal of psychiatric research, vol. 12, no. 3, pp. 189–198, 1975.

[40] T. Smith, N. Gildeh, and C. Holmes, “The montreal cognitive assessment: validity and utility in a memory clinic setting,” The Canadian Journal of Psychiatry, vol. 52, no. 5, pp. 329–332, 2007.

[41] N. K. Al-Qazzaz, M. K. Sabir, S. H. B. M. Ali, S. A. Ahmad, and K. Grammer, “Multichannel optimization with hybrid spectral-entropy markers for gender identification enhancement of emotional-based eegs,” IEEE Access, vol. 9, pp. 107059–107078, 2021.

[42] N. K. Al-Qazzaz, S. H. M. Ali, and S. A. Ahmad, “Comparison of the effectiveness of aica-wt technique in discriminating vascular dementia EEGs,” in 2018 2nd International Conference on BioSignal Analysis, Processing and Systems (ICBAPS). IEEE, 2018, pp. 109–112.

[43] G. Manis, M. Aktaruzzaman, and R. Sassi, “Bubble entropy: An entropy almost free of parameters,” IEEE Transactions on Biomedical Engineering, vol. 64, pp. 2711–2718, 2017. [Online]. Available: https://doi.org/10.1109/TBME.2017.2664105

[44] J. Wang, T. Li, R. Xie, X. M. Wang, and Y. Y. Cao, “Fault feature extraction for multiple electrical faults of aviation electro-mechanical actuator based on symbolic dynamics entropy,” in 2015 IEEE International Conference on Signal Processing, Communications and Computing (ICSPCC). IEEE, Sep 2015, pp. 1–6.

[45] V. Rajagopalan and A. Ray, “Symbolic time series analysis via waveletbased partitioning,” Signal processing, vol. 86, no. 11, pp. 3309–3320, 2006.

[46] Y. Li, Y. Yang, G. Li, M. Xu, and W. Huang, “A fault diagnosis scheme for planetary gearboxes using modified multi-scale symbolic dynamic entropy and mrmr feature selection,” Mechanical Systems and Signal Processing, vol. 91, pp. 295–312, 2017. [Online]. Available: https://doi.org/10.1016/j.ymssp.2016.12.040

[47] N. K. Al-Qazzaz, S. Ali, S. A. Ahmad, and J. Escudero, “Classification enhancement for post-stroke dementia using fuzzy neighborhood preserving analysis with qr-decomposition,” in 2017 39th annual international conference of the IEEE engineering in medicine and biology society (EMBC). IEEE, 2017, pp. 3174–3177.

[48] D. Schlembach, W. L. Maner, R. E. Garfield, and H. Maul, “Monitoring the progress of pregnancy and labor using electromyography,” Eur. J. Obstet. Gynecol. Reprod. Biol., vol. 144, pp. 2–8, 2009.

[49] J. Mas-Cabo, Y. Ye-Lin, J. Garcia-Casado, A. D´ıaz-Martinez, A. Perales-Marin, R. Monfort-Ortiz, A. Roca-Prats, A. Lo´pez-Corral,´ and G. Prats-Boluda, “Robust characterization of the uterine myoelectrical activity in different obstetric scenarios,” Entropy, vol. 22, p. 743, 2020.
[50] J. Mas-Cabo, G. Prats-Boluda, J. Garcia-Casado, J. Alberola-Rubio, R. Monfort-Ortiz, C. Martinez-Saez, A. Perales, and Y. Ye-Lin, “Electrohysterogram for ann-based prediction of imminent labor in women with threatened preterm labor undergoing tocolytic therapy,” Sensors, vol. 20, p. 2681, 2020.
[51] S. M. Pincus, “Approximate entropy as a measure of system complexity,” Proc. Natl. Acad. Sci. USA, vol. 88, pp. 2297–2301, 1991.
[52] H. Tan, S. Xie, H. Zhou, W. Ma, C. Yang, and J. Zhang, “Sensible multiscale symbol dynamic entropy for fault diagnosis of bearing,” International Journal of Mechanical Sciences, vol. 256, p. 108509, 2023.
[53] Y. Mi, A. Lin, D. Gu, X. Zhang, and X. Huang, “Bubble transfer spectral entropy and its application in epilepsy eeg analysis,” Communications in Nonlinear Science and Numerical Simulation, vol. 110, p. 106294, 2022.
[54] Author(s), “Detection of sudden cardiac death by a comparative study of heart rate variability in normal and abnormal heart conditions,” Journal Name, vol. Volume, no. Number, p. Page range, Year.
[55] M. W. Flood and B. Grimm, “Entropyhub: An open-source toolkit for entropic time series analysis,” PloS one, vol. 16, no. 11, p. e0259448, 2021.
[56] F. A. Gers, J. Schmidhuber, and F. Cummins, “Learning to forget: Continual prediction with lstm,” Neural computation, vol. 12, no. 10, pp. 2451–2471, 2000.
[57] K. Greff, R. K. Srivastava, J. Koutn´ık, B. R. Steunebrink, and J. Schmidhuber, “Lstm: A search space odyssey,” IEEE transactions on neural networks and learning systems, vol. 28, no. 10, pp. 2222–2232, 2016.
[58] Z. Cui, R. Ke, Z. Pu, and Y. Wang, “Deep bidirectional and unidirectional lstm recurrent neural network for network-wide traffic speed prediction,” arXiv preprint arXiv:1801.02143, 2018.

نموذج التعلم العميق للتنبؤ بشدة الخرف من إشارات تخطيط الدماغ

نور كمال القزاز[1]*، شوال حميد بن محمد علي[2،3]، سيتي أنوم أحمد [4،5]
[1]قسم الهندسة الطبية الحيوية، كلية الخوارزمي للهندسة، جامعة بغداد، بغداد ، العراق
[2] قسم الهندسة الكهربائية والإلكترونية والنظم، كلية الهندسة والبيئة المبنية، جامعة كيبانغسان ماليزيا، سيلانغور، ماليزيا
[3] مركز الهندسة الإلكترونية وهندسة الاتصالات المتقدمة، قسم الهندسة الكهربائية والإلكترونية وهندسة النظم، جامعة كيبانغسان، ماليزيا، سيلانغور، ماليزيا
[4] قسم الهندسة الكهربائية والإلكترونية، كلية الهندسة، جامعة بوترا ماليزيا، سيلانغور، ماليزيا
[5] المعهد الماليزي لبحوث الشيخوخة ، جامعة بوترا ماليزيا، سيردانغ، سيلانغور، ماليزيا
*البريد الالكتروني:noobme@kecbu.uobaghdad.edu.iq

الخلاصة

تهدف هذه الدراسة إلى تحديد الاختلافات في مخطط كهربية الدماغ (EEGs) لـ 15 فردًا تم تشخيص ضعفهم الإدراكي الخفيف (MCI) بعد السكتة الدماغية، و 5 أفراد كانوا يعانون من الخرف الوعائي (VD)، و 15 شخصًا يتمتعون بصحة جيدة. التحكم الطبيعي (NC) الذين كانوا يؤدون مهمة الذاكرة العاملة (WM). تم استخدام المرشحات التقليدية بما في ذلك مرشحات الشق والعصابة لإزالة الضوضاء من بيانات EEG. تشمل الطريقة المقترحة حساب تقديرات إنتروبيا الانتباه (AttEn)، وإنتروبيا الفقاعة (BubbEn) والانتروبيا الديناميكية الرمزية (SyDyEn) لميزات تسلسل البيانات الأحادية. تستخدم هذه الدراسة الشبكة العصبية للتعلم العميق للذاكرة طويلة المدى (LSTM) لتصنيف شدة مرضى الخرف تلقائيًا من خلال التسجيلات غير الغازية القائمة على تخطيط كهربية الدماغ. من حيث دقة التصنيف، تتجاوز نتائج تصنيف LSTM مع AttEn متوسط 88.9٪ من منتجات BubbEn و SyDyEn المستخدمة الأخرى بنتائج تصنيف 69.2٪ و 77.7٪ على التوالي. بناءً على تحليل مجموعة بيانات شدة الخرف القائمة على تخطيط دماغ الدماغ، تشير النتائج إلى أن AttEn يمكن أن يكون بمثابة علامة حيوية لاكتشاف شدة الخرف. لدى AttEn القدرة على التقاط الأنماط والميزات ذات الصلة في EEG وقد يكون مؤشرًا على شدة الخرف مع LSTM RNN للتمييز بشكل أفضل بين مرضى VD و MCI والمشاركين في CN، وقد يكون فعالًا في تحديد المرضى الذين يعانون من VD و MCI.