# Optimized Echo State Networks with Leaky Integrator Neurons for EEG-Based Microsleep Detection

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***Abstract*—The performance of a microsleep detection system was calculated in terms of its ability to detect the behavioural microsleep state (1-s epochs) from spectral features derived from 16-channel EEG sampled at 256 Hz. Best performance from a single classifier model was achieved using leaky integrator neurons on an echo state network (ESN) classifier with a mean phi correlation (φ) of 0.38 and accuracy of 67.3%. A single classifier model of ESN with sigmoidal inputs achieved φ of 0.20 and accuracy of 48.5% and a single classifier model of linear discriminant analysis (LDA) achieved φ of 0.31 and accuracy of 53.6%. However, combining the output of several single classifier models (ensemble learning) via stacked generalization of the ESN with leaky integrator neurons approach led to a substantial increase in detection performance of φ of 0.51 and accuracy of 81.2%. This is a substantial improvement of our previous best result of φ = 0.39 on this data with LDA and stacked generalization.**

## I. Introduction

Tiredness and fatigue can often lead to brief instances of people falling asleep while engaged in some active task such as driving a motor vehicle. A study on fatigue by the General Association of German Insurance Industries, identified microsleep as the principal cause of 24% of fatal motorway accidents [1]. Lapses range from brief pauses to *behavioural microsleeps* (BM), which are brief, involuntary events of lapses in attention or responsiveness associated with events such as prolonged eye closure, blank stare, etc. [2], and which last 0.5–30 s [3]. Microsleeps are involuntary and, hence, other than awareness of feeling drowsy, don't come with a prior warning. They are also frequently fatal. For example, if a person has a 4-s microsleep when driving at 100 km/h, the vehicle will travel 111 m with the driver being completely non-responsive.

The aim of this study was to identify reliable physiological cues indicative of microsleeps from the EEG, which could in turn be used to develop a real-time microsleep detection (or, better still, prediction) system.

* Research supported by the Canterbury Medical Research Foundation and the University of Canterbury.

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EEG from scalp recordings has traditionally been used in numerous sleep related studies [4–7]. Previously, a lapse detection system was developed based on spectral power features from EEG, aimed at detecting lapses with second-scale resolution [2]. Another study used long short-term memory (LSTM) recurrent neural network (RNN) implementation to detect lapses [8].

Echo state networks (ESN) provide an architecture and supervised learning principle for recurrent neural networks (RNNs). The main idea is (i) to drive a random, large, fixed recurrent neural network with the input signal, thereby inducing in each neuron within this 'reservoir' network a nonlinear response signal, and (ii) combine a desired output signal by a trainable linear combination of all of these response signals [9].

RNNs are mostly used for modelling dynamical systems because of their inherent memory states. In general, ESNs have sigmoidal activation functions but an alterantive to this is the leaky integrator model in which the temporal characteristics of a learning task can be exploited by using the individual state dynamics of the system [11, 12]. This leaky-neuron approach can be used to study and exploit the long-time dependencies in the transient signals and attain higher memory spans. ESNs with leaky neuron configurations contain additional 'global control parameters' [11, 13] like the spectral radius of the reservoir weight matrix and a leaking rate (leakage factor) that can be optimized particularly for low frequency input signals.

We have reported using an ESN-based classifier optimized with leaky integrator neurons on EEG data, superimposed with bursts of 2-s sinusoids with varying signal-to-noise ratios (SNRs) [10]. The aim of this simulation was to determine the classification performance of several detection systems/configurations on a gold-standard dataset for which the events were precisely known.

The current study aimed to develop a microsleep detector using the echo state network (ESN) with leaky integrator neurons and compare its detection performance to that achieved in our earlier research with other methods [2, 8, 10, 14].

In addition to using different classifier modules, such as linear discriminant analysis (LDA), ESNs with sigmoidal units, and ESNs optimized with leaky integrator neurons, several signal processing and statistical methods were used to generate the features/ meta-features for the classification.

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## II. METHODS

### A. Data

Fifteen healthy male subjects aged 18–36 years (mean = 26.5) were recruited. All subjects had visual acuities of 6/9 (= 20/30) or better in each eye. In addition, all 15 subjects considered that they slept normally the previous night (mean = 7.8 h, SD = 1.2 h, min = 5.1 h) and, hence, were considered non-sleep-deprived [2].

EEG was recorded from electrodes at 16 scalp locations, band-pass filtered (0.5–100 Hz), and digitized at 256 Hz with a 16 bit A-D converter while the subjects performed a 1-D continuous visuomotor tracking task for 1 hour, in two separate sessions which were conducted a week apart from one another [1]. Bipolar derivations used to calculate power spectra were: Fp1–F3, Fp1–F7, Fp2–F4, Fp2–F8, F3–C3, F4–C4, F7–T3, F8–T4, T3–T5, C3–P3, P3–O1, T5-O1, C4–P4, T4–T6, P4–O2, and T6–O2 [2]. Bipolar derivations were preferred over the referential ones because they could reject the common mode noise better.

Facial video was also recorded during the tracking sessions and video-based microsleeps identified by prolonged eye-lid closure, sometimes accompanied by rolling upward or sideways movements of the eyes, head nodding, and often terminated by waking head jerks. Transitions in the video recording had a time resolution of 1.0 s.

### B. EEG analysis

A 50 Hz notch filter was applied to the EEG to remove power interference. Independent component analysis (ICA) was then applied to remove eye blink artefacts [2]. Each derivation was normalized into z-scores, using the mean and standard deviation of the first 2-min of each 1-hour-long record. Log-power spectral features were then calculated for each EEG. Thirty four spectral features for each channel were calculated using a 2-s sliding window function, stepping at 1-s intervals.

### C. Gold standard

Tracking task performance and video rating were the two independent measures used to identify when subjects were in the microsleep state. Performance lapses in the tracking task were recorded when the tracking response was non-coherent with the target and when the response cursor stopped moving for an extended period while the target was still in motion. Video recordings, synchronized to both EEG and tracking, provided a level of alertness in each subject. EEG data in the subjects who had at least a single lapse over the two sessions in both the video and the tracking response were selected for the microsleep detection system (N = 8).

### D. Feature selection and reduction

The resulting 544 power spectral features (34 spectral features from the frequency bands delta ($\delta$), theta ($\theta$), alpha ($\alpha$), alpha1 ($\alpha_1$), alpha2 ($\alpha_2$), beta ($\beta$), beta1 ($\beta_1$), beta2 ($\beta_2$), gamma ($\gamma$), gamma1 ($\gamma_1$), gamma ($\gamma_2$) & higher frequencies across all the 16 channels) were reduced using PCA. PCA is often used to reduce the redundancy within the original features and transform feature vectors into orthogonal components to aid in the formation of classification models. Therefore, it is possible to reduce the dimensionality of the data without any significant loss in the information. A total of 25 - 200 meta-features from the PCA were then used to form a classification system suitable for the microsleep detection.

### E. Performance evaluation

Performance of the microsleep detection system was calculated in terms of ability to detect the microsleep state in consecutive 1-s epochs. Classification performance was determined by leave-one-out cross-validation corresponding to the 8 subjects (leaving one subject aside for training and test on the rest). Performance metrics were mean accuracy, sensitivity, specificity, selectivity, and Pearson two-binary-variable correlation coefficient (Phi).

The proposed prototype microsleep detection system is depicted in Figure.2.

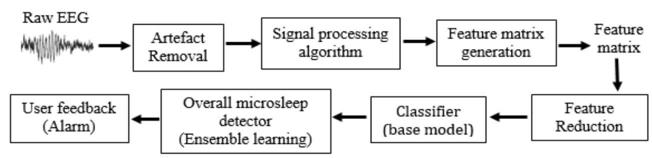


Figure 2. Proposed prototype microsleep detection system.

## III. CLASSIFICATION

To find the optimal model for microsleep detection, classifier models using LDA, ESN with sigmoidal inputs, and ESNs with optimized leaky integrator neurons, were compared. As a part of this study, the effectiveness of both linear and non-linear models in microsleep detection were also investigated.

### A. Linear discriminant analysis

LDA traditionally maximizes the ratio of between-class variance to within-class variance in data thereby, achieving maximal linear separability. Because of the simplicity of this approach and its usage in one of our earlier works [2], LDA was set as the baseline for comparison with other classifier models.

### B. Echo state networks

A traditional reservoir computing architecture consists of an input layer, a dynamical reservoir with numerous sparsely inter connected neurons and an output layer [8], as illustrated in Fig. 2. This standard architecture includes sigmoidal activation functions on some of the simplest additive units.

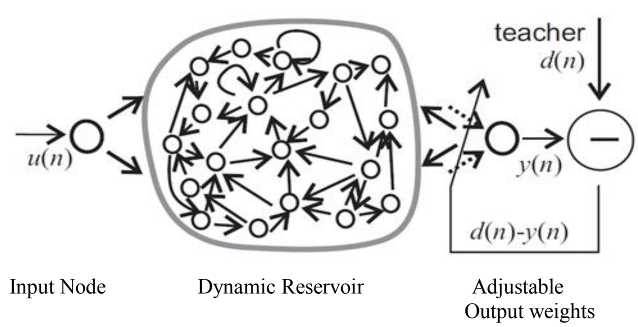


Figure 2. Echo state network (Image of reservoir layer adapted from [11])

*C. Optimized leaky integrator neuron approach*

ESNs are an innovative approach to the supervised training of a recurrent neural network (RNN) [3]. RNNs are mostly used for modelling dynamical systems because of their intrinsic memory states. ESNs usually incorporate sigmoidal activation functions as opposed to the leaky integrator model in which the temporal characteristics of a learning task can be exploited by using the individual state dynamics of the system [5]. This leaky neuron approach can be used to study and exploit long-time dependencies in transient signals and attain higher memory spans. ESNs with leaky neuron configurations contain additional 'global control parameters' [6], such as the spectral radius of the reservoir weight matrix and a leaking rate (leakage factor) that can be optimized particularly for low-frequency temporal dependencies. The main advantage associated with this type of architecture is that better classification can be achieved by varying the various parameters of each of these leaky integrator units, which in turn have their own individual state dynamics [7]. In the current study, we compare the sigmoidal ESN and cascaded ESN based classifier with leaky integrator models to other traditional approaches, such as LDA, in detection of microsleeps in EEG data.

We have reported high classification performance of the leaky integrator ESN approach on EEG with simulated sinusoidal events [10]. The motivation behind this was to estimate event detection performance on a gold-standard dataset for which the events were precisely known, unlike the actual microsleep events.

*D. Ensemble learning*

Several studies [2, 15, 16] have demonstrated increased classification accuracy by combining the output of several models to increase predictive performance over that from a single model. Bagging, boosting, and stacking (stacked generalization) are the three extensively used methods in machine learning literature to combine the output of multiple models.

In this study, the output of the multiple individual microsleep detectors was combined using stacked generalization. Stacking overcomes a substantial problem with the voting procedures in bagging and boosting which do not clarify which base models (output of the individual microsleep detectors) to trust [2]. Stacking maximizes ensemble learning by using a meta-learner process.

*E. Stacked generalization algorithm*

The stacking framework (Fig. 3) consists of level-0 and level-1 generalizers. The level-0 models are formed by base classifiers which are trained using the input data and the target output. The level-0 outputs are then presented as in input to the level-1 generalizer (meta-learner) which is also trainable.

For the classification phase of the stacking system, new cases were generated for the level-0 models, each producing a classification value at their output. Then, the resulting base model predictions were fed into the level-1 model and combined linearly. The linear combination scales the output of each model according to its weight, adds the new scaled model outputs, and applies a threshold to the added model output to obtain an overall prediction.

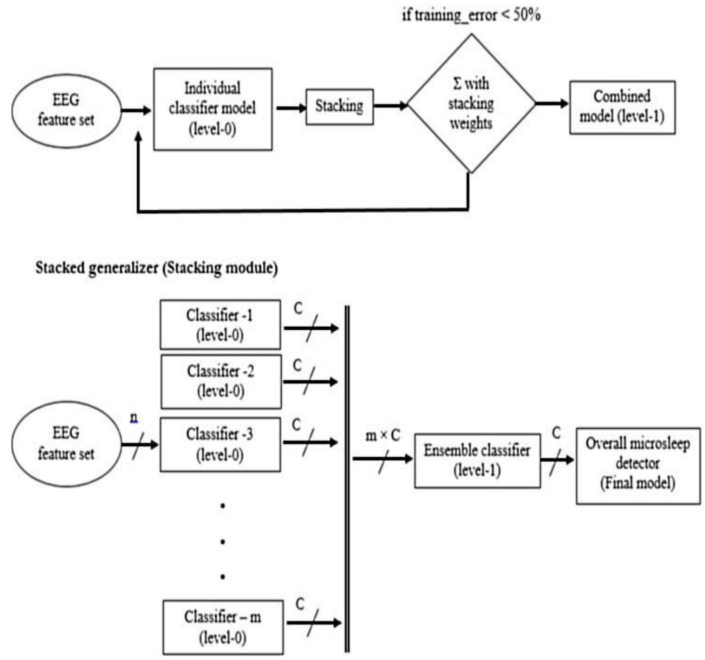


Figure 3. Stacking framework for microsleep detection

## IV. RESULTS

Multiple tests were performed on each of the feature selections/reductions, classifier modules, and methods used in prior research [2, 8, 10]. The first results were from leave-one-out cross validation using single classifier modules for LDA, sigmoidal ESN, and leaky-neuron ESN, and were compared to results from stacking ensembles of the classifiers (Table 1).

The microsleep detection system was trained and tested on both LDA and ESN based classifiers using a range of meta-features (25 to 400). LDA required 200 meta-features to attain the optimal performance depicted in table 1. However, ESN classifiers (standard and leaky) required only 40 meta-features to attain the optimal performance for the microsleep detection.

TABLE I. MICROSLEEP DETECTOR PERORMANCE

| % | **Single classifier modules** | | |
|---|---|---|---|
| | ***LDA*** | ***Sigmoidal ESN*** | ***Leaky ESN*** |
| Sensitivity | 64.2 | 66.3 | 76.6 |
| Specificity | 92.0 | 96.8 | 95.2 |
| Selectivity | 29.3 | 20.7 | 45.1 |
| Phi (φ) | 0.31 | 0.20 | 0.38 |
| **%** | **Stacked generalization (ensemble modules)** | | |
| | ***LDA*** | ***Sigmoidal ESN*** | ***Leaky ESN*** |
| Sensitivity | 73.5 | 61.9 | 85.8 |
| Specificity | 92.0 | 96.4 | 94.0 |
| Selectivity | 31.3 | 28.5 | 53.6 |
| Phi (φ) | 0.39 | 0.27 | 0.51 |

## V. Discussion

In this study, both linear and non-linear classifiers were analysed and our results show that the performance of our prototype ESN-based microsleep detection system was modest. An ESN with standard sigmoidal inputs provided the least performance on both single classifier and stacking ensemble. The best performance recorded on the single classifier modules was from the leaky integrator ESNs with a phi of 0.38.

LDA approach was the second best classifier module with a phi of 0.31 and phi of 0.40 for single classifier and ensemble models respectively. Use of ensemble learning has demonstrated a substantial increase in phi correlation across all classifier approaches indicating that combining outputs from multiple models can increase detection performance over a single model.

A classifier built on an ESN with leaky integrators and a stacking ensemble achieved the highest microsleep state detection performance seen to date on the current data set, with a phi of 0.51 trumping our previous best of 0.40 with LDA [2]. This also supports our hypothesis from our work with simulated events [10] that a leaky-integrator ESN would demonstrate superior performance on the real microsleep detection problem.

Furthermore, using the long short-term memory recurrent neural network [8] on the same subjects, a phi correlation of $\varphi = 0.38$ was reported. Interestingly, however, the performance recorded on the LSTM was surprisingly high, given the single classifier configuration, and that the EEG data being unprocessed and contaminated with eye blink artefacts.

Comparison between the linear and non-linear models (LDA vs. leaky- integrator ESN and LSTMs) clearly illustrates that the neural networks with non-linear models can perform better on the EEG-spectral-power-based microsleep detection system.

However, despite detecting most microstate states (sensitivity of 86%), the leaky-integrator ESN approach still reported too many false detections (selectivity of 45%). The number of false detections can be substantially reduced by increasing the output threshold of the overall detector but at a cost of missing more microsleeps.

## VI. Conclusion

ESNs with leaky integrator neurons proved to be the most consistent approach yielding encouraging results and suggesting that the memory effect can indeed be exploited using this model.

Future work on this project will include investigating supervised feature selection/reduction methods in addition to the other types of traditionally used non-linear classifier models such as the support vector machines (SVM). Research will also be focused on implementing more biologically-inspired models of reservoir computing structures such as the liquid state machines (LSM) [17] and exploring advantages they may confer to the microsleep detection problem. Additionally, performance metrics derived from receiver operator characteristic (ROC) and precision recall (PR) curves will be evaluated as alternatives to phi correlation on the current EEG-based microsleep detection system.

Overall, whilst the performance of the current prototype microsleep detection system is encouraging, we consider the detection accuracy to be insufficiently reliable for implementation into real-world environments. However, the benefits of achieving such in terms of preventing loss of lives, especially in transport sectors, are so immense as to well justify further efforts and explorations of innovative approaches to achieving high-accuracy microsleep detection and prediction systems.

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