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An IoT and Machine Learning-based Neonatal Sleep Stage Classification

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Abstract

Sleep, in neonates, is used to access the quality of brain and physical development. It is an important hallmark to access the deficiencies in the development of brain. Typically, neonatal sleep has been divided into three stages: active sleep (AS), quiet sleep (QS) and intermediate sleep (IS). Traditionally, neurologists are hired to classify neonatal and adult sleep. Polysomnography (PSG) is considered as a gold standard to classify sleep. However, PSG consumes tons of time and money. To address this issue, over the past two decades, researchers proposed multiple algorithms for automatic sleep stage classification. These algorithms work achieved outstanding results for some cases i.e. quiet sleep detection still, lacks in many aspects. One major drawback of the existing research is the amalgamation of awake and active sleep into low voltage irregular (LVI) state. This amalgamation corrupts 40% of the overall EEG signal. For this reason, we proposed an algorithm for neonatal sleep-wake classification using machine learning. The proposed research is divided into three steps. Firstly, EEG signal was pre-processed using finite impulse response filter to remove the noise and artifacts. Clean EEG signal is then divided into 4560 30-sec segments. Then, twenty prominent EEG features were extracted from time, frequency and spatial domain. After feature extraction, support vector machine was used for sleep stage classification. The propounded study outperformed all the existing algorithms for sleep-wake classification with a mean accuracy of 83.7%. Four-fold cross validation was used to validate the overall dataset. Multiple other performance metrices i.e. sensitivity, specificity, Kappa were calculated to prove the efficacy of the proposed study. Statistical results show that the proposed study can be used as a real-time neonatal sleep and Awake classification algorithms, as this did not use prior post-processing technique.

Keywords — Neonatal Sleep, Classification, Electroencephalography, Polysomnography, Machine Learning

1. Introduction

Sleep is categorized as an arrangement of modifications occurring in our body inside our brain, and muscles, working its way through our eyes (occipital lobe), and respiratory along with cardiac activity. Both mental and physical health are somehow dependent on the dynamic and defined course of sleep activity. The major function of sleep is to protect the metabolized energy which is a cause of nurturing neural acquaintances and associating learning with memory. In neonates, it is responsible for mental and physical development. To monitor neonatal sleep for the purpose of attaining a complete understanding of normal neurological productivity, intensive monitoring of the neonates is accompanied by bedside neuro-monitoring. For this reason, Polysomnography (PSG) is used as a gold standard. In PSG, multiple bio-physiological signals are extracted using electrodes and then professional neurologists are hired for overnight sleep classification (manual).

Hence, PSG despite possessing good results, is expensive, time consuming and requires professional neurologists for manual classification. In the preceding ten years, multiple research endeavours have elaborated the viability of automated sleep staging algorithms with PSG signals, among which EEG stood out as the most reliable signal in the case of both adults [1-3] and infants [4-6]. Hans Berger logged the first EEG of humans in 1924 [7]. The electrical activity of the brain takes place through electrical impulses and can be ascertained from the scalp. Neurologists have developed the EEG patterns in sleep wake cycling from 30 weeks postmenstrual age [8]. In 1937, Loomis et al. put forth the first study of human sleep patterns using EEG [9]. Subsequently, a number of algorithms have been suggested for adult sleep staging using machine [10-13] and deep learning [14-18].

Neonates and adults possess different sleep states. Neonatal sleep stages are classified into three types i.e. rapid eye movement (REM) sleep (Active sleep), non-rapid eye movement (NREM) sleep (Quiet sleep) and intermediate sleep. Whereas adults sleep stages are two-pronged; REM and NREM. NREM is then further classified into NREM1, NREM2, NREM3 and NREM4. Recently, NREM3 and NREM4 are combined to form NREM3 stage. The primary differentiation is the sleep time: neonates spend 17- 18 hours (70%) sleeping in a resting state whereas adults spend 7-9 hours (16-29%) in a sleeping state. Neonates do not exhibit circadian rhythms whereas adult's EEG contains circadian rhythms which help them sleep during night. Secondary contrast is the sleep spindles, pertinent for memory consolidation, yet they are not apparent in neonates. Sleep spindles develop after 42 weeks GA [19, 20]. Another difference is the sleep cycle time: neonate sleep cycle completes in 50-60 minutes whereas adult sleep cycle averages 80-110 minutes. Neonates spend 80% of their sleeping time in REM which reduces with the increase in GA. The REM sleep time reduces to 60% for full term neonate. Whereas for adults the distribution further concentrates to 20-25% in REM state.

In this study, we proposed an efficient and computationally inexpensive support vector machine for neonatal sleep-wake classification. The proposed network is composed of two parts: Feature extraction and classification.

Twenty features are extracted from 9-bipolar neonatal EEG recordings. The main contribution of this paper is given below:

- To the best of our knowledge, till date, there is no public dataset available online for neonatal sleep classification. Therefore, extraction of neonatal EEG from Fudan children hospital Shanghai, China, involving multiple experienced neurologists for the annotation.
- Pre-processing of neonatal EEG using latest signal processing tools and comparison with the already established schemes.
- Designing of a novel dedicated neural network to detect neonatal sleep-wake classes.

2. Related Work

In 1937, Loomis et al. [21] put forth the preliminary EEG-based application of human sleep patterns. After the introduction of high-performance super computers, machine/deep learning algorithms grow exponentially in the field of biomedical, classification, prediction and signal processing. In 2001, [22] Turnbull et al. developed an automatic sleep state detection algorithm using discrete wavelet transform (DWT). Trace alternant detection (TA) using DWT was carried out with six healthy neonates, within 3 days after birth. All 20 segments of TA were successfully detected using the proposed scheme. The DWT-based algorithm detects TA effectively however QS also constitutes TD and HVS signals. The proposed algorithm performs well for TA detection however cannot be used for entire QS detection over a wider range of neonates. For this reason, Gerla et al. [23] propounded an automatic sleep stage classification algorithm using 12 polysomnographic signals i.e., EEG, ECG, EOG, EMG and PNG. Features were extracted from these signals and then hybrid evolutionary algorithm combined with ant-colony approach was used for sleep stage classification. For all classes, the hybrid configuration can reach an accuracy of 68.83%.Some maturational changes can only be seen during QS. For this reason, multiple algorithms were proposed for QS detection. For this reason, Koolen et al. [24] suggested an algorithm based on greedy algorithm. 57 EEG features were extracted from 8- channels EEG using 10-minutes epochs. However, increased set of features can cause over-fitting, therefore a greedy algorithm was used to reduce the set of features. Finally, SVM was used for classification. The results demonstrated that the proposed network works well with greedy algorithm, reaching an accuracy of 85%. In 2017, Fraiwan et al. proposed an automatic sleep stage classification algorithm using deep auto encoders. Time-Frequency analysis was used for handcrafted feature extraction from 30-sec EEG segments. The proposed algorithm achieved an accuracy of 84 percent with mean kappa 0.65. This study works well for sleep classification however, the accuracy for awake stage is limited to only 17% [25]. this reason, Fraiwan et al proposed an automatic sleep stage classification algorithm using multiscale entropy. Neural Networks Random Forest analysis was used for handcrafted feature extraction from 30-sec EEG segments.The proposed algorithm achieved an accuracy of 81.3 with mean kappa of 0.65. [26]. Koolean et al. proposed a quiet sleep and active sleep classification algorithm using 57 features time, frequency, and spatial. Support Vector Machine analysis was used for handcrafted feature extraction from 600-sec EEG segments. The proposed algorithm achieved an accuracy of 85% with mean kappa of 0.65 [27]. To further improve the accuracy, [28] recently proposed an algorithm for neonatal QS detection using CNN. The proposed algorithm achieved mean kappa of 0.74.

Fraiwan et al. proposed an automatic sleep stage classification algorithm using 7 temporal and spectral features. Deep Auto encoders were used for handcrafted feature extraction from 60-sec EEG segments. The proposed algorithm achieved an accuracy of 80.4% with mean kappa of 0.65 [29]. K Pillay et al. proposed a 2 and 4-stage classification algorithm using 112 features time, frequency, and spatial. HMM, and GMM analysis was used for handcrafted feature extraction from 30-sec EEG segments. The proposed algorithm achieved an accuracy of 95% with mean kappa of 0.89 and with 4-stage classification algorithm achieved an accuracy of 86 percent with mean kappa of 0.62 [30]. In 2020 [31], Saadullah et al. proposed a sleep-wake classification algorithm using multilayer perceptron (MLP) neural network. The proposed network used 12- time and frequency domain features for classification. 5-layered MLP network achieved an accuracy of 82.53% with mean kappa 0.62. To further improve the accuracy of neonatal sleep-wake classification, an ensemble algorithm has been proposed in 2022 [32]. Multi-channel EEG extraction is a hectic process. For this reason, a single-channel EEG based algorithm has been proposed by Awais et al. [33]. The proposed algorithm achieved an accuracy of 77.5% with mean kappa 0.55.

3. Material and Methods

This section will explain the dataset, feature extraction and classification algorithm in detail.

3.1 Dataset and Feature Extraction

EEG sleep data recorded from 19 neonates of 32–42 weeks' postmenstrual age at the neonatal intensive care unit (NICU) at Children's hospital affiliated to Fudan University, Shanghai, China. The data collection of data was approved by the ethics committee of the Children's Hospital affiliated to Fudan University approved the study (Approval No. (2017) 89) [34-37]. In total, nineteen EEG sleep recordings with an average data length of 120 min were collected from neonates selected based on a 'normal' developmental outcome. The EEG data were recorded by using nine bi-polar EEG channels (Fp1, Fp2, T3, C3, Cz, C4, T4, O1 and O2) with a sampling frequency of 500 Hz according to the 10-20 international system with different placement of electrode. For data extraction an IoT based setup had been using Nicolet One EEG device.

During recording and transmission, EEG recordings got contaminated with noise and artifacts. These unwanted signals need to be removed before classification. For this reason, FIR filter was used with cut-off frequencies of 0.3-35Hz. After noise/artifact removal, 30-sec epochs were separated, and each epoch was labelled with their respective state using visual labelling by professional neurologists. "AS" and "awake" epochs were combined to form non-QS epochs.

Feature extraction is about dimensionality reduction, which transforms large raw data variables into the numerical features. Several features were extracted for the proposed study but based on the high performance, 20 most prominent ones were selected. In the proposed study, features are divided into two categories: time domain and frequency domain. Time domain features are further categorized into skewness, mean, median, standard deviation, kurtosis, minima, maxima, energy, power, number of peaks, zero crossings and rate, entropy, mobility and variance whereas, frequency domain features are: power spectral density, alpha band, delta band, theta band and beta band. Figure 1. Shows the block diagram of the proposed network.

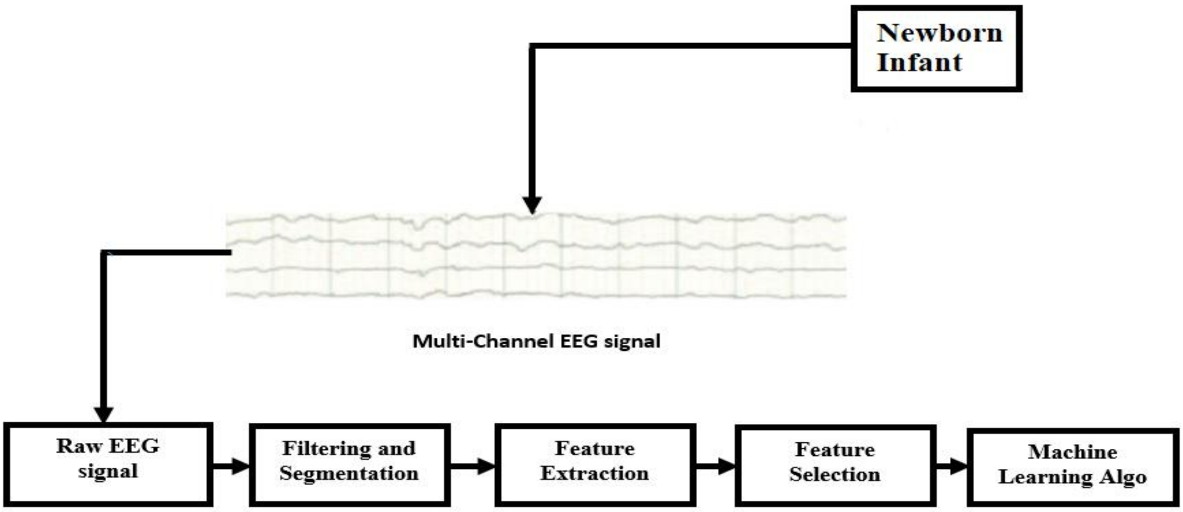

Fig. 1. Block diagram of the proposed algorithm

4. Methodology

The Support Vector Machine (SVM), originally introduced by Vapnik [38], is a versatile machine learning algorithm with unique capabilities that make it particularly well-suited for impact detection tasks. In this section, we delve into the functionality of the SVM classifier and our rationale for its selection in our research.

Physiological data is noisy [39]. The SVM classifier operates by constructing a decision boundary (hyperplane) that optimally separates data points belonging to different classes. This hyperplane is positioned to maximize the margin, which is the distance between the hyperplane and the nearest data points from each class. These closest data points are termed "support vectors" as they play a pivotal role in defining the decision boundary.

Figure 2 provides an illustration of the SVM classifier. In this figure, you can observe the following components:

The solid black line represents the classification boundary. It is strategically positioned to maximize the margin between the training samples.

- The circled data points on dashed lines are the support vectors. These points are closest to the decision boundary and have the lowest margin. They are crucial in defining the decision boundary.

- An orange solid line separates the data, but it results in a narrower margin, making it less desirable for generalization.

The concept of a "maximum margin separator" is demonstrated, highlighting the importance of support vectors in determining the classification boundary.

Let we consider the set of data points in the form

$$(x_1, y_1), (x_{2,} y_2), (x_3, y_3), \dots \dots \dots . (x_n, y_n) \qquad (1)$$

Where, yn = 1 or -1

n= number of total samples.

Xn is p dimensional real vector

The set of points for which the separator is defined

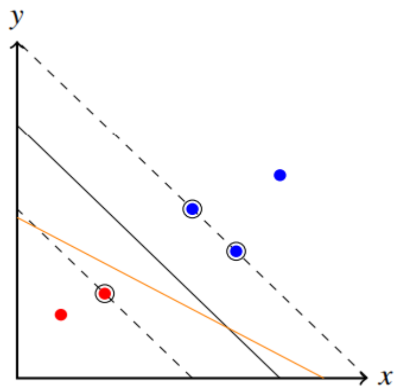

Fig. 2. Illustraion of Support Vector Machine

$$w.x + b = 0 \qquad (2)$$

Where ‘b’ is scalar and ‘w’ is p dimensional vector. If we have to increase the margin it’s only done by adding the offset parameter ‘b’. If the ‘b’ factor is not present, the hyperplane forcefully passes through the origin and restricts the solution.

The equations (3 and 4) that described the parallel hyperplanes are

$$w.x + b = 1 \qquad (3)$$

$$w.x + b = -1 \qquad (4)$$

Different test performance parameters were calculated using the confusion matrix shown in Fig 3. We calculated the error rate (ERR), accuracy (ACC), sensitivity, and specificity by putting values in the below-mentioned formulas.

Error rate:

$$\mathrm{ERR} = \frac{(\mathrm{FP} + \mathrm{FN})}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FN} + \mathrm{FP})}$$

Accuracy:

$$ACC = \frac{(TP + TN)}{(TP + TN + FN + Fp)}$$

Sensitivity:

$$SN = \frac{(TP)}{(TP + FN)}$$

Specificity:

$$SP = \frac{(TN)}{(TN + FP)}$$

Cohen's Kappa:

$$K = \frac{(P_{AGREE} - P_{CHANCE})}{(1 - P_{CHANCE})}$$

5. Results

The formation of the confusion matrix is from four outcomes. These four outcomes represent true positive (TP) which is the correct positive prediction, True negative (TN) which is the correct negative prediction, False positive (FP) which is the incorrect positive prediction, and False negative (FN) which is the incorrect negative prediction of test data set.

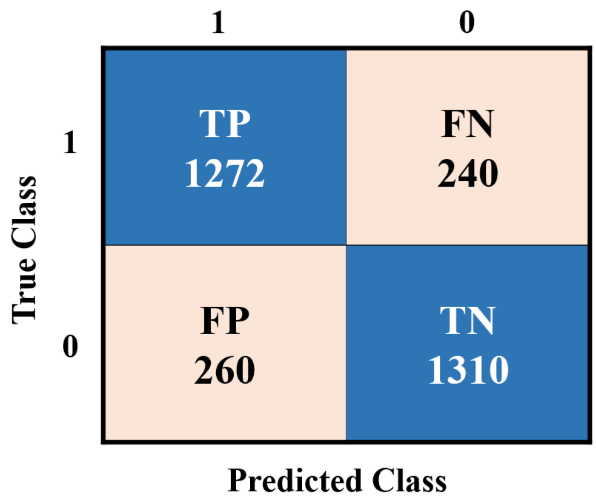

Fig. 3. Confusion Matrix of the proposed scheme

The performance matrices, calculated using the confusion matrix, are shown in Table 1. Usually, machine learning algorithms perform better for handcrafted features. For this, the proposed algorithm has been compared with other machine learning algorithms and the comparison is shown in Table 2.

TABLE I. *PERFORMANCE METRICES OF THE PROPOSED ALGORITHM.*

	Error Rate	Accuracy	Sensitivity	Specificity	Kappa

Proposed SVM	0.16	83.7%	84.1%	83.4%	0.68

TABLE II. *COMPARISON WITH MACHINE/DEEP LEARNING ALGORITHMS*

Sleep-Awake classification Results	**Accuracy (%) of Sleep Awake Classification SVM**
SVM (Quadratic Kernel)	**83.7**
MLP neural network	82.53
CNN (Convolutional neural network)	75.6
RNN (Random neural network)	71
Logistic Regression	65.1
K-Nearest Neighbours	63.1
Decision Tree	60.85

For a safe and smooth sleep, it is important that there is less number of electrodes implanted in the human body. This will increase the quality of sleep. For this reason, we have compared the results of the proposed scheme with a different number of electrodes (Table 2). From table 2, it is evident that the accuracy of the proposed network decreases significantly with reducing the number of EEG Channels. This is because of fact that each EEG channel has some important information about human sleep.

6. Conclusion

Sleep is categorized as an arrangement of modifications occurring in our body inside our brain, and muscles, working its way through our eyes (occipital lobe), and respiratory along with the cardiac activity. It makes the human body fresh and ready for the next day. In neonates, it is essential for brain and physical development. Polysomnography is the gold standard for determining and classification of sleep stages. However, it is expensive and requires human intervention. Therefore, over the past two decades, researchers proposed multiple algorithms for automatic neonatal sleep stage classification. In this study, an automatic sleep-wake classification algorithm has been proposed using SVM. Twenty prominent EEG features are extracted from the time, spatial and frequency domains. Then, a support vector machine has been deployed for classification. The proposed algorithm achieved an accuracy of 83.7% for sleep-wake classification. Statistical results show that the proposed algorithm can be used for neonatal sleep classification. To conclude, we can say that the proposed algorithm can be used as a real-time application for sleep-wake cycling in a NICU.

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