Recent Trends of Artificial Intelligence and Machine Learning for Insomnia Research

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Recently, the research using artificial intelligence (AI) have been actively conducted in various fields. In the sleep medicine, the research using an AI such as machine learning and deep learning have begun to increase explosively to keep pace with this trend of the times. The field where the most research is being done is the automation of diagnosis of obstructive sleep apnea syndrome and scoring of polysomnography. Studies using AI on insomnia also have shown a remarkable increase in recent years. In this paper, we look at the recent trends of insomnia research using AI and provide a milestone to researchers.

Key Words: Sleep Initiation and maintenance disorders; Artificial intelligence; Machine learning; Deep learning; Systematic review

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INTRODUCTION

Artificial intelligence (AI) refers to machines or algorithms that do what human intelligence can do and machine learning (ML) is a technology and technique that aims to implement functions such as human learning ability in a computer [1]. Mainly, a supervised learning is used in ML and it is a method that let the algorithm learns a pattern from big data and performs classification for the pre-labeled outcome variable [1]. Deep learning (DL), which is in the spotlight these days, is one of ML, a nonlinear regression technique for learning data and pattern recognition using artificial neural networks (ANNs) [2]. According to a report by the U.S. Patent and Trademark Office in 2020, AI patent applications doubled in 2018 (60000/year) compared to 2002 (30000/year) and the proportion in all patent applications is also showing an explosive increase from 9% to 16% [3]. This is a proof that the use of AI has begun to take root in our daily lives.

In the medical research field, using AI is showing an explosive increase [2]. It is actively introduced in various fields such as neurology, radiology, ophthalmology, anesthesia, intensive care medicine and oncology [4-8]. Research using AI is also increasing in sleep medicine and the American Academy of Sleep Medicine published a position statement in 2020 [9]. The leading field in

sleep research using AI is the automated scoring of polysomnography (PSG) and the screening of obstructive sleep apnea syndrome (OSAS) [4,10]. PSG and continuous positive airway pressure data was used mainly and is expected to be used more in the future [4]. In the field of sleep medicine, insomnia is probably the next most studied disease after OSAS. Therefore, the author has conducted this study to examine the recent trends in the use of AI in the insomnia research, and to present a milestone to researchers planning future research.

METHODS

In PubMed (<https://pubmed.ncbi.nlm.nih.gov/>), the author searched for papers satisfying the MeSH term including “Sleep Initiation and Maintenance Disorders” and “Artificial Intelligence” regardless of the publication year. In addition, related papers identified in the reference and hand searching were also included in the analysis.

The inclusion criterion was a paper using AI for the research of the diagnosis, treatment, and pathophysiology of insomnia.

Exclusion criteria are as follows: 1) even if insomnia patients were the subjects of the study, the aim of study was only an automated scoring of PSG, 2) AI methods were not used for research

methods and interventions, 3) papers that did not go through peer-review, 4) meta-analysis, systematic review, and conference material.

This review was conducted partially using guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [11].

RESULTS

Applying the search strategy in PubMed, 17 results were initially found. In addition, handsearching of relevant studies yielded 9 studies. After checking duplicates, the title and abstract of 26 studies were screened and the full text of 21 studies were reviewed. Finally 17 studies satisfied the inclusion criteria (Figure 1).

The most common subject and method was diagnosis and screening of insomnia using classification. The most used algorithm was support vector machine (SVM), followed by decision tree and advanced tree (XGBoost, random forest) and ANN.

In addition, the most common modality was PSG. Particularly, there were many studies using signals of the electroencephalography (EEG) channel, and recently there was one study using the electrocardiography (ECG) channel. Next, there were many studies using MRI, followed by studies using questionnaire and using wearable devices.

Table 1 shows the details of the included studies.

DISCUSSION

As a result of the analysis, it was found that Insomnia's research

using AI has exploded in the last three years. Most of the studies were studies to make a predictive model of insomnia using features extracted from the EEG signal of PSG in the extension of automated scoring of PSG [12-16]. Recently there was an interesting study for the prediction of insomnia using ECG signal, and it seems to be in sync with the sleep stage and sleep respiratory event prediction studies using ECG signal of PSG [17].

There were also unsupervised learning studies that reflected recent trends in ML and DL. There was a phenotyping study using clustering of time series data extracted from wearable device, and a symptomatology study using natural language processing of electrical medical records (EMR) [18,19].

In addition, there was also research on intervention using smartphone application reflecting the recent COVID-19 confinement era [20].

There were still more studies derived from PSG and fMRI studies than insomnia's unique research.

In terms of methodology, there are still more ML studies than DL studies, and many studies using relatively small dataset at individual hospitals or institutions due to the absence of a large database used in OSAS or PSG studies. Due to this tendency, there was no external clinical validation using external data unseen in training, and the internal validation study using cross-validation holds a majority stake. There was no study even separating the training set from the test set. To overcome this, it is necessary to create a public big dataset that can be used for training and external validation.

ML does not aim to find a model that best describes a given data, but to find a model that gives more accurate predictions when

Figure 1. PRISMA 2009 flow diagram [11] of study review process and exclusion papers.

Table 1. Summary of included studies

Study	Task	Algorithm	Modality	Main feature source	Total data	Validation data	Best performance	Dataset
Spiegelhalter et al. [24]	Classification	SVM	MRI	Brain volume cortical thickness	66 (28 insomnia)	LOOCV	Balanced accuracy 55.95% (p=0.16)	Private
Mulaffer et al. [12]	Classification	SVM	PSG	Hypnogram, EEG	124 (54 insomnia)	5-fold CV	Accuracy 81%	Private
Shahin et al. [13]	Classification	ANN	PSG	EEG	83 (42 insomnia)	5-fold CV	Accuracy 92%	Private
Shahin et al. [14]	Classification	ANN (feature), LDA, CART, SVM	PSG	EEG	115 (54 insomnia)	LOOCV	F1 0.88, sensitivity 84%, specificity 91%	Private
Doan et al. [25]	NLP	Rule-based	Twitter	Message	24 million messages		Precision 88.1%	Private
Jansen et al. [15]	Classification	ANN, DT, RF, GBM	PSG	EEG, EMG, EOG, nasal airflow, breathing effort, ECG	118 (59 insomnia)	5-fold CV	Accuracy 93%	Private (insomnia) SIESTA database [22] (control)
Park et al. [18]	Clustering	ANN (feature), kMC, HC	Wearable device	Fitbit	42 insomnia		NC/AS/SSE 6/0.47/21.55 (kMC), 6/0.45/24.40 (HC)	Private
Rodriguez-Morilla et al. [26]	Classification	DT	Wearable device	Wrist temperature motor activity body position environmental light	261 (184 insomnia, 58 DSPD)	10-fold CV	AUROC 0.90, F1 0.92, accuracy 88%, sensitivity 89%, specificity 71%	Circadian Health Database
Li et al. [27]	Classification	SVM	MRI	Voxel-wise FCS, large-scale FC, ReHo	82 (38 insomnia)	5-fold CV	AUROC 0.83, accuracy 81.5%, sensitivity of 84.9%, specificity of 79.1%	Private
Schwartz et al. [28]	Classification	Elastic net	Questionnaire	DSQ	247 (60 insomnia)	5-fold CV 200 bootstrap	AUROC 0.83, sensitivity 80.3%, specificity 69.4%, accuracy 72.9% (threshold 0.3)	Private
Ma et al. [29]	Regression	RVR	MRI	Whole-Brain nodal rsFC, PSQI	73 insomnia	LOOCV 10-fold CV	r/MAE 0.65/2.18 (short-term/acute) 0.37/1.84 (chronic)	Private
Philip et al. [20]	Classification	DT	Smartphone	ISI, sleep diary	47 insomnia (773 entered)		SE -3.89% (p = 0.002), nocturnal awakening -0.42 (p<0.001)	Private
Hu et al. [19]	NLP, clustering	ANN (feature), kMC	EMR	Words	807 insomnia		Degree centrality 0.96 (difficulty falling a sleep)	Private
Ge et al. [30]	Classification	XGBoost	Questionnaire	ISI-7, GAD-7, CSMHSS	2009 (332 insomnia)	5-fold CV	AUROC 0.98, accuracy 96.2%, sensitivity 95.5%, specificity 100%	Private
Dai et al. [31]	Classification	SVM	MRI	VMHC	96 (48 insomnia)		AUROC 0.76, sensitivity 73%, sepcificity 71%	Private
Andrillon et al. [16]	Classification	RF	PSG	Hypnogram, EEG	436 (347 insomnia)	3-fold CV	Cohen's kappa 0.87 (insomnia vs. control)	Private
Sharma et al. [17]	Classification	KNN, SVM	PSG	ECG	13 (7 insomnia)	10-fold CV	AUROC 0.99, F1 0.97, accuracy 98% (SVM)	CAP sleep database [23]

ANN: artificial neural network, AS: average silhouettes, AUROC: area under receiver operating characteristic curve, CAP sleep database: Cyclic Alternating Pattern sleep database in Physionet, CART: classification and regression tree, Circadian Health Database: Circadian Health Database of the Chronobiology Laboratory at the University of Murcia (<https://kronowizard.um.es/>), CSMHSS: College Students Mental Health Screening Scale, DL: deep learning, DSPD: delayed sleep phase disorder, DSQ: Digital Sleep Questionnaire: DT: decision tree, ECG: electrocardiography, EEG: electroencephalography, EMG: electromyography, EMR: electronic medical record, EOG: electrooculography, FCS: functional connectivity strength, Fold CV: fold cross validation, GAD-7: General Anxiety Disorder-7, GBM: Gradient Boosting Model, HC: hierarchical clustering, ISI: Insomnia Severity Index, ISI-7: Insomnia Severity Index-7, kMC: k-means clustering, KNN: K-nearest neighbor, LDA: linear discrimination analysis, LOOCV: leave one out cross validation, MAE: mean absolute error, NC: number of clusters, NLP: natural language processing, PSG: polysomnography, PSQI: Pittsburgh Sleep Quality Index, r: Pearson's correlation, ReHo: regional homogeneity, RF: random forest, rsFC: resting-state functional connectivity, RVR: relevance vector machine, SIESTA: database with sleep recording as part of a European Commission funded research project, SSE: sum of squared errors, SVM: support vector machine, VMHC: voxel-mirrored homotopic connectivity, XGBoost: eXtreme gradient boosting

given new explanatory data [1]. In other words, the goal is to find an optimal model that consider the trade-off between model variance and bias [21]. The variance of the model is the degree to which the model changes when the training data is changed, and the bias is the difference between the hypothesized model and the unknown true model. To do this, it is necessary to solve the problem of overfitting, and for this, recent ML and DL studies tend to separate the training dataset used for model training and the test dataset used for evaluation [21]. So it is worthwhile to use dataset unseen during training to evaluate the performance of the final model [1]. For hyperparameter tuning to select the best model, it is also recommended to use the validation dataset separated from a training and a test dataset [21].

In classification analysis, which is mainly aimed at making predictive models of insomnia, ML algorithms such as SVM and advanced trees show strengths over DL, which is a phenomenon often seen in studies in other fields. The DL algorithm has no choice but to use a sigmoid or a softmax function in the output layer, and that functions are similar with logistic regression [1]. Therefore, DL does not show strength in the classification task, but shows strength in the feature extraction from primary data such as EEG, ECG, MRI, and EMR [2]. Researchers should keep this in mind, and depending on the task, it is recommended to plan tests on various algorithms besides DL.

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Conflicts of Interest

The author has no potential conflicts of interest to disclose.

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