Time Frequency Distribution and Deep Neural Network for Automated Identification of Insomnia Using Single Channel EEG-signals

Kamlesh Kumar, Prince Kumar, Ruchit K. Patel, Manish Sharma, Varun Bajaj, *Senior Member, IEEE*, and U. Rajendra Acharya, *Senior Member, IEEE*

***Abstract*—It is essential to have enough sleep for a healthy life; otherwise, it may lead to sleep disorders such as apnea, narcolepsy, insomnia, and periodic leg movements. A polysomnogram (PSG) is typically used to analyze sleep and identify different sleep disorders. This work proposes a novel convolutional neural network (CNN)-based technique for insomnia detection using single-channel electroencephalogram (EEG) signals instead of complex PSG. Morlet wavelet-based continuous wavelet transforms and smoothed pseudo-Wigner-Ville distribution (SPWVD) are explored in the proposed method to obtain scalograms of EEG signals of duration 1s along with convolutional layers for features extraction and image classification. The Morlet transform is found to be a better time-frequency distribution. We have developed Morlet wavelet-based CNN (MWTCNNet) for the classification of healthy and insomniac patients using cyclic alternating pattern (CAP) and sleep disorder research centre (SDRC) databases with C4-A1 single-channel EEG derivation. We have used multiple cohorts/settings of the CAP and SDRC databases to analyse the performance of proposed model. The proposed MWTCNNet achieved an accuracy, sensitivity, and specificity of 98.9%, 99.03%, and 98.66%, respectively, using the CAP database, and 99.03%, 99.20%, and 98.87%, respectively, with the SDRC database. Our proposed model performs better than existing state-of-the-art models and can be tested on a vast, diverse database before being installed for clinical application.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/8382

***Index Terms*—Insomnia Diagnosis, Sleep Disorder Classification, Signal Processing, EEG Analysis, Sleep Disturbance, Image Classification.**

I. Introduction

Sleep is a physiological process carried out by the brain to maintain our physical and mental well-being. During sleep, the human body repairs and rebuilds itself, eliminating metabolic waste that accumulates during awakeness [1], [2]. In addition, reorganization and promotion of long-term memory is also done by good sleep. Due to the numerous advantages of sleep in our daily lives, it is essential that an individual receive an adequate amount of sleep. Furthermore, several sleep problems, including nocturnal frontal lobe epilepsy, periodic limb movement disorder, rapid eye movement behavioral disorder- bruxism, apnea, and insomnia seriously affected human lives. Recent studies on the rapid identification and treatment of sleep problems have captured the interest of several scientists [3].

Insomnia is a most common sleep disorder along with a paramount public health concern. According to AASM (American Academy of Sleep Medicine), insomnia is characterized by not able to initiate, maintain sleep or get enough sleep [4]. Insomnia can last for a short time (acute) or a long time (chronic), or it can also be occasional. Some signs of insomnia are feeling sleepy during the day, tired, grumpy, difficulty in concentrating or remembering things, and in falling asleep [5]. The research on various sample data compiled from various nations revealed that approximately 30% of individuals with insomnia symptoms are recognized [6]. This disorder may cause conditions such as stroke, asthma attacks, impaired immune system, seizures, depression, diabetes mellitus, cardiovascular disease, anxiety, obesity, and hypertension. Mazzotti et al. [7] also showed a crucial relation between the mortality rates and insomnia, in five Latin American countries.

Generally, the cure for insomnia is difficult for medical practitioners. They typically diagnose insomnia based on patients' sleep patterns. Sometimes doctors advocate study on sleep stages. For the study of sleep, a patient is taken to a sleep laboratory for a night-long PSG screening containing multi-channel and multi-modal data such as EEG, electromyogram (EMG), electrooculogram (EOG), and electrocardiogram (ECG) [8] are explored. Recordings of PSG are used when the initial inquiry is insufficient because of the existence of behavioral or pharmacological disturbances of sleep [8]. The study of EEG signals performed by doctors during sleep is hectic, time-consuming, and error-prone. Monitoring a single-channel EEG signal is the most promising method for identifying sleep disorders, given that the gold standard for understanding sleep stages is EEG [9]–[13]. Therefore, it becomes crucial to score sleep automatically with artificial intelligence methods.

Recently, researchers have been developing models to detect insomnia automatically. Aydin et al. [14] used artificial neural

K. Kumar is with department of Electrical and Electronics Engineering at San Jose State University, San Jose California-95192, United States (e-mail: kamlesh.kumar@sjsu.edu).

P. Kumar, R. K. Patel, and M. Sharma are with the Department of EECS, Institute of Infrastructure Technology Research And Management, Ahmedabad, 380026, India (e-mails: prince.kumar, ruchitkumar.patel.19e@iitram.ac.in and manishsharma@iitram.ac.in).

V. Bajaj is with the Department of ECE, PDPM Indian Institute of Information Technology Design and Manufacturing Jabalpur, 482005, India (e-mail: varunb@iiitdmj.ac.in).

U. Rajendra Acharya is with the School of Mathematics, Physics and Computing, University of Southern Queensland, Australia (e-mail: rajendra.acharya@unisq.edu.au).

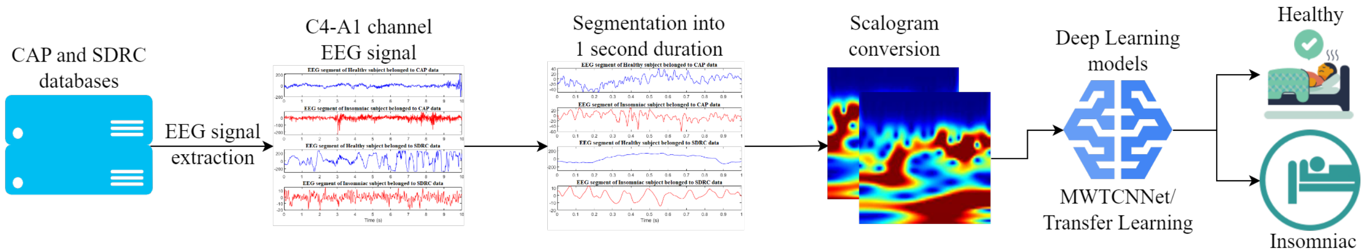


Fig. 1. Proposed MWTCNNet model for automated detection of insomnia using 1-sec single-channel EEG signal.

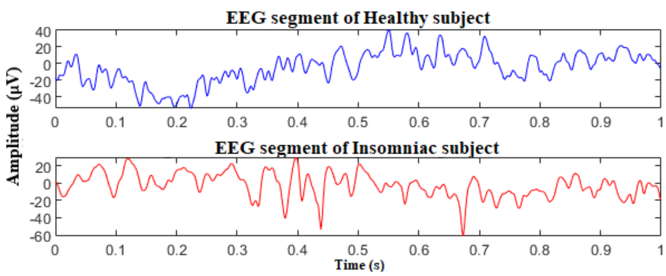


Fig. 2. Typical normal and insomnia 1-second EEG (C4-A1) signals of CAP database where amplitude is in micro-volt and time is in second.

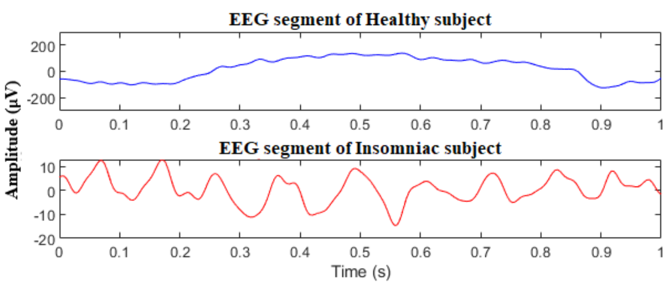


Fig. 3. Typical normal and insomnia 1-second EEG (C4-A1) signals of SDRC database where amplitude is in micro-volt and time is in second.

networks to detect insomnia with a 14.5% error rate. Abdullah et al. [15], [16] employed multi-model PSG signals, achieving an 18.7% error rate by combining characteristics from sleep-related EEG and ECG signals. Hamida et al. [17] used Hjorth parameters and a k=means classifier to classify normal and insomniac subjects, achieving a sensitivity of 91.6% and a kappa value of 0.83, but on a small dataset. Sharma et al. [5] developed a model using an antisymmetric biorthogonal wavelet filter bank and L-1 norm, achieving 97.87% classification accuracy with ECG signals during REM sleep. Malik et al. [18] achieved 94.03% accuracy using RR-time series and EEG signals with a deep neural network. Shahin et al. [19] compared a deep learning-based classifier's accuracy for identifying insomnia in two scenarios, obtaining 92% for recordings with only insomniac patients and 86% for those with insomnia and at least one other sleep disorder.

It is advisable to train and test deep learning models using two or more databases or a single large-volume database [20], for a classification task. The standard practice has been increasing and generalizing the ability of models by including more variation in the training and testing datasets. However, there has been no study on the automatic detection of insomnia using multiple databases. The proposed MWTCNNet is a novel model developed for identifying insomnia using wavelet transform and CNN using two diverse databases for cross-examination. The main objective of this paper is to study the performance of wavelet transform such as Morlet and SPWVD with deep neural network in automated identification of insomnia. Also, we wanted to explore that single channel EEG can identify insomnia accurately. Our CNN based deep neural network has outperformed state-of-the-art architectures.

II. Methodology

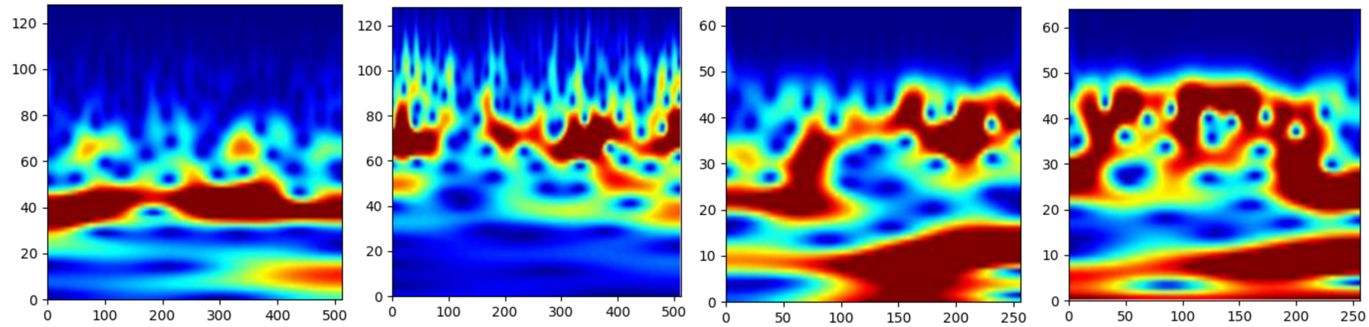
This work presents a unique technique to detect insomnia via EEG signals. The method involves collecting the available open source datasets, selecting an appropriate channel to acquire the data, pre-processing the data, decomposing wavelets, and classifying insomnia using deep learning techniques (as shown in Fig. 1).

A. Data Description

In this paper, two publicly available databases: (i) CAP-sleep [21] and (ii) SDRC [22], have been used for the experimentation.

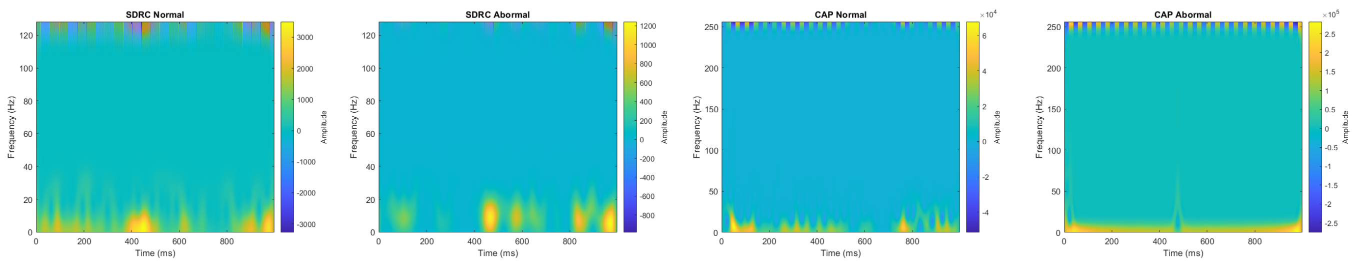
1) CAP Database: It was developed at the Ospedale Maggiore sleep disorder facility in Parma, Italy, which has 108 PSG recordings, nine insomniac, and 16 normal subjects. These PSG recordings include multimodal signals such as EEG with at least three channels, EOG with two, ECG, and respiratory signals (SpO_2, abdominal and thoracic effort, and airflow) solely during sleep recorded from handheld mobile devices with activities <=3. This study uses only the C4-A1 channel of EEG signal from this database, which has been recorded at 256Hz and 512Hz sampling frequencies. This study utilizes a total of 13 database recordings of the database. SThere are six normal and seven insomniac EEG recordings are sampled at 512 Hz with an average subject age of 46.6 years andwith a 10.53 standard deviation. The average duration of the EEG recordings is 33710.8 seconds.

2) SDRC Database: It consists of PSG recordings of 60 people referred to the Sleep Disorders Research Center, Kermanshah, Iran. The study included 11 healthy volunteers and 11 psychophysiological insomniac patients. The aim of this study is to emphasize insomnia detection, so we have utilized only 22 individuals. The data was sampled at 256 Hz and



(a) (b) (c) (d)

Fig. 4. Scalograms using Morlet wavelet of 1-sec EEG signals from two databases: (a)Normal (b)Insomniac (CAP, fs*=512Hz), and (c)Normal (d)Insomniac (SDRC, fs*=256Hz). * fs=sampling frequency. Here (x,y) axis of the above plots refers to the width and height of the scalogram images.



(a) (b) (c) (d)

Fig. 5. SPWVD wavelet, of 1-sec EEG signals from two databases: (a)Normal (b)Insomniac (SDRC, fs*=256Hz), and (c)Normal (d)Insomniac (CAP, fs*=512Hz). **SPWVD=smoothed pseudo wigner-wille distribution,*fs=sampling frequency.

contains 8 EEG, 6 EOG, and 3 EMG channels recorded from handheld mobile devices. Among these 22 recordings, with an average age of 43 years and a standard deviation of 15.38 years. The average duration of of EEGthese recordings is 28870.72 seconds.

B. Data Pre-processing and Segmentation

The databases recordcontains recording of various signals through polysomnography (PSG), including respiratory, EOG, EEG, and ECG signals. In our experiment, we focused on extracting EEG signals specifically from the $C4-A1$ channel in the PSG recordings. To reduce the processing time and increase the accuracy of detection, we have segmented the whole signal into 1 sec. duration [23] and converted these sub-signals into RGB images using continuous wavelet transform with Morlet mother wavelet functions and SPWVD. The EEG-$C4-A1$ signals, extracted from CAP and SDRC database and sample C4-A1 channel recording, are shown in Figs. 2 and 3, respectively with one-second duration. Dividing the signals into such small divisions helps the CNN to analyze the features of EEG signal features quickly, and accurately.

C. Scalogram Generation

The scalogram of the signal is extracted using Morlet CWT (Continuous wavelet transform). The deep convolutional neural network component of the proposed methodology uses CWT coefficients as features. This work evaluates the performance of the proposed method on Morlet wavelet functions and Smoothed pseudo wigner-wille distribution based scalograms. Calculating the coefficients scales is done on the 1sec segment of each signal. Then scalograms are retrieved and scaled using bi-cubic interpolation following the specifications. Figs. 4 and 5 show illustrations of a scalogram images created using the Morlet wavelet transforms and SPWVD, respectively. These images are then fed into deep CNN to develop the model.

1) Continuous Wavelet Transform: EEG signals are challenging to evaluate due to their highly oscillating variable frequency components and amplitudes [24]. To have complete understanding of the signals, it is necessary to explore them in different domains. Transformation methods enable simultaneous capture of time-domain signal data in the frequency domain as well. The time-frequency representation measures the temporal and spectral variation of a signal. This research is carried out on the continuous wavelet transform (CWT) with the Morlet and SPWVD wavelet functions to transform the signal representation into the time-frequency format [24].

The wavelet is a finite-energy, zero-average-function oscillating bandpass filter. CWT of a signal s(t) is represented as [25]-

$$W_{\varphi,\phi}[s(t)] = \int_{-\infty}^{\infty} s(t)\psi^*\left(\frac{t-\phi}{\varphi}\right)dt \qquad (1)$$

where φ controls the scaling of the function $\psi((t-\phi)/\varphi)$ with time-shift ϕ. Continuous Wavelet Transform has the advantage as its ability to alter the size of the window. The flexibility of window size is the main benefit of CWT. A wide window is useful for analyzing low-frequency components, whereas a narrow window is useful for analyzing high-frequency ones. The typical scalogram images obtained for normal and insomniac EEG signals (1sec duration) belonging to the two databases are shown in Figs. 4 and 5.

D. Transfer Learning

Large annotated dataset, time, and high computing resources are required for training a CNN from scratch than using a CNN that has been pre-trained on a huge database [26]. There are two primary transfer learning scenarios: freezing and fine-tuning the layers of CNN architecture. In fine-tuning, the weights and biases of a CNN that has already been trained are used instead of random initialization, followed by a normal training procedure on the unseen dataset. However, in another scenario, the pre-trained CNN layers are considered to be fixed feature extractors. In this case, the fully connected layers are tweaked across the target dataset and number of defined classes whereas the biases and weights of our ideal convolutional layers remain fixed. The frozen layers are not restricted to convolutional layers alone. Frozen layers may be fully connected layers or any subset of convolutional; nevertheless, it is usual practice to freeze the more superficial convolutional layers. In our study, we have used the freezing method by freezing all the CNN layers and re-trained the last three fully-connected layers with number of output classes as two for last layer of AlexNet [27], GoogLeNet [28], VGG16 [29], ResNet50 [30], and MobileNetV2 [31], using the same training pipeline used for the proposed method and compared the performance of these models with our proposed MWTCNNet model for classification between normal and insomniac scalogram.

E. Convolutional Neural Network

Traditional approaches to categorization and feature extraction need quantitative and qualitative analysis to make decisions. Due to the ability of CNN to automatically extract and classify deep features, CNN has become a popular DL approach. CNN employs convolutional operations instead of matrix multiplication and finds distinct characteristics that distinguish one class from another [32]. A total of 12 layers of feature maps are used to organize the convolution layers [33]. As shown in the Fig. 6, the last layer of the fully linked network is the SoftMax layer; the output is an N-dimensional vector, where N is the desired number of classes. The first layer is created by convolving the input layer, i.e., layer-1, with a kernel size of three. Then each feature map is fed into a second convolutional layer of the same kernel size and given into a max-pooling size 1. The max-pooling process results in extracting the feature map from the previous layer. The layer 4 feature map is created by convolving the layer 3 feature map with a kernel size 3. Each feature map is again subjected to a max-pooling of kernel size 2, which reduces the feature map by 2. And the output is further fed into the next convolutional neural layers, and a similar set of multiple units forms the complete architecture. Then, after the max-pooling dropout layer is followed, which reduces the number of neurons for this work, we have to reduce 20% of neurons. Finally, The Dense layer connects all the neurons completely, two output neurons are connected between the last layer and the bottom layer. Further, layer-by-layer analysis is presented in Table I.

TABLE I
DESCRIPTION OF EACH CONVOLUTIONAL LAYER USED IN THIS WORK

Layer (type)	Output Shape	Param
Conv2D	(None, 510, 510, 32)	896
Conv2D	(None, 508, 508, 32)	9248
MaxPooling2D	(None, 254, 254, 32)	0
Conv2D	(None, 252, 252, 64)	18496
Conv2D	(None, 250, 250, 64)	36928
Conv2D	(None, 248, 248, 64)	36928
MaxPooling2D	(None, 124, 124, 64)	0
Conv2D	(None, 122, 122, 128)	73856
Conv2D	(None, 120, 120, 128)	147584
Conv2D	(None, 118, 118, 128)	147584
MaxPooling 2D	(None, 59, 59, 128)	0
Conv2D	(None, 57, 57, 256)	295168
Conv2D	(None, 55, 55, 256)	590080
Conv2D	(None, 53, 53, 256)	590080
MaxPooling2D	(None, 26, 26, 256)	0
Conv2D	(None, 24, 24, 512)	1180160
Conv2D	(None, 22, 22, 512)	2359808
Conv2D	(None, 20, 20, 512)	2359808
Conv2D)	(None, 18, 18, 512)	2359808
MaxPooling2D	(None, 9, 9, 512)	0
Conv2D	(None, 7, 7, 1024)	4719616
Conv2D	(None, 5, 5, 1024)	9438208
Conv2D	(None, 3, 3, 1024)	9438208
Dropout	(None, 3, 3, 1024)	0
Flatten	(None, 9216)	0
Dense	(None, 1024)	9438208
Dense	(None, 1024)	1049600
Dense	(None, 1024)	1049600
Softmax	(None, 2)	2050

F. Training and Testing pipelines

In this work, a typical backpropagation with a batch size of 24 is carried out. The learning rate is chosen to be 0.001. To achieve the best performance, this parameter is tuned appropriately. The NVIDIA-RTX A4000 was employed as the graphics processing unit (GPU) in this study for training purposes. It has 64 gigabytes of total random access memory and 24 gigabytes of dedicated memory, and it executed each epoch on average in 5 minutes. Based on the model's performance throughout these iterations, we trained it for 100 epochs and measured the performance based on the following metrics-

$$\mathrm{Specificity}(\mathrm{S_{PC}}) = \frac{\mathrm{T_N}}{\mathrm{T_P} + \mathrm{F_P}} \tag{2}$$

$$\mathrm{Sensitivity}(\mathrm{S_{EN}}) = \frac{\mathrm{T_P}}{\mathrm{T_P} + \mathrm{F_N}} \tag{3}$$

$$\mathrm{Accuracy}(\mathrm{A_{CC}}) = \frac{\mathrm{T_P} + \mathrm{T_N}}{\mathrm{T_P} + \mathrm{T_N} + \mathrm{F_P} + \mathrm{F_N}} \tag{4}$$

TABLE II
PERFORMANCE OBTAINED FOR PROPOSED MWTCNNET MODEL FOR AUTOMATED INSOMNIA DETECTION USING CAP AND SDRC DATABASES USING MORLET WAVELET FUNCTIONS AND SPWVD WITH DIFFERENT DATA SPLITTING STRATEGIES

	Training		Validation		Testing		Performance with Morlet			Performance with SPWVD		
Database	**CAP**	**SDRC**	**CAP**	**SDRC**	**CAP**	**SDRC**	**Accuracy**	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**
Data Splitting	80%	0%	20%	0%	0%	100%	97.39%	97.46%	97.32%	95.43%	96.31%	96.78%
	70%	0%	15%	0%	15%	0%	98.90%	99.03%	99.27%	96.85%	96.11%	97.33%
	0%	70%	0%	15%	0%	15%	99.03%	99.20%	98.87%	97.80%	97.55%	96.32%
	0%	80%	0%	20%	100%	0%	97.40%	97.67%	97.22%	95.12%	96.47%	95.46%

TABLE III
SUMMARY OF RESULTS OBTAINED FOR AUTOMATED INSOMNIA DETECTION USING MORLET WAVELET-BASED SCALOGRAMS AND OTHER CNN ARCHITECTURES WITH CAP AND SDRC DATABASES

Model	**Accuracy**	**Sensitivity**	**Specificity**
CAP database			
AlexNet	96.60%	95.13%	96.13%
GoogLeNet	95.76%	94.55%	92.10%
VGG16	93.99%	93.05%	93.06%
ResNet50	91.55%	91%	92%
MobileNetV2	91.30%	91%	92.21%
MWTCNNet	**98.9%**	**99.03%**	**99.27%**
SDRC database			
AlexNet	94.55%	93.44%	94.24%
GoogLeNet	93.64%	93.15%	92.88%
VGG16	91.10%	91.55%	90.76%
ResNet50	90.45%	90.32%	91.25%
MobileNetV2	89.30%	89.45%	90.13%
MWTCNNet	**99.03%**	**99.20%**	**98.87%**

where T_N, T_P, F_N, and F_P represent True Negatives, True Positives, False Negatives, and False Positives, respectively.

Table II shows that four combinations of the CAP and SDRC datasets were used for training, validation, and testing purposes. We chose variable ratios for dividing the whole datasets to train the CNN model and its later assessment or testing. Internal bifurcation of each class, normal and abnormal for each subset, was carried out using the *Tensorflow* in-build attribute *shuffle*, randomly selecting the proportion of all the available classes. This attribute ensures that the MWTCNNet is not biased towards any of the defined classes and equally focuses on the features of all types. Training and validation curves of MWTCNNet is shown in Fig. 7 for all four database settings.

III. RESULTS

We performed the experiments and verified the performances using the confusion matrix, overall accuracy (Accuracy), sensitivity, and specificity parameters.

The confusion matrix drawn from the prediction of healthy (or normal, label "0") and abnormal (or insomniac, label "1") detection are shown in Fig. 8. This depicts the testing results obtained using CAP and SDRC databases. The following conclusions can be drawn based on Fig. 8-

- Fig. 8a: When the proposed model was trained on CAP database (80%-training, 20%-validation) and tested on SDRC dataset (100%-testing), as shown in column-1 of Table II, MWTCNNet miss-classified only 0.0261% of the images which shows the reliability of the model for training on one dataset and testing on another dataset.
- Fig. 8b: For the cohort described in column-2 of Table II, the model showed 0.01104% error rate, which supports the robustness of the model for training and testing on the same dataset.
- Fig. 8c: MWTCNNet showed 99.04% accuracy and 0.00963% error rate for column-3 of Table II implying that the proposed model performs better on SDRC dataset compared to CAP when trained and tested on the equal sampled unseen dataset.
- Fig. 8d: When the model is trained on the SDRC dataset and tested on CAP dataset, the proposed model shows significantly higher False Positives (near to double the False Positive), i.e., the model is classifying a higher number of 'normal' samples as 'insomniac' samples. This might be because of training on low frequency (SDRC dataset), and the model might not have adapted the features of higher frequency insomniac samples (CAP dataset).

The above analysis shows that the model performs better when trained on CAP (higher frequency samples) and used for generalization on unseen datasets (train on 512 Hz and test on 256 Hz). However, the SDRC dataset or low- frequency samples are good for testing on the equivalent sampled datasets, training on 256 Hz, and testing on unseen 256 Hz samples, for -example.

Further, the confusion matrices (Eqs. 2, 3, 4) were computed for this study next. Table III provides an overview of the performance rate obtained using CAP and SDRC databases. Using CNN with a scalogram-based technique, it is possible to reach average accuracy, sensitivity, and specificity values of 98.9%, 99.03%, and 98.66%, respectively. Additionally, for the SDRC database, the maximum average accuracy of 97.39%, sensitivity of 97.46%, and the specificity of 97.32% are obtained.

IV. DISCUSSION

Previous efforts in the state of the art have shown performance advances with their proposed methods, however, such studies have worked on a specific signal captured from polysomnography of a single database, and none of them worked on the further processing of these signals for their possible conversions such as scalograms and spectrograms [38] (as shown in Table IV). Our method employed the conversion of a signal into an image for identifying hidden features by

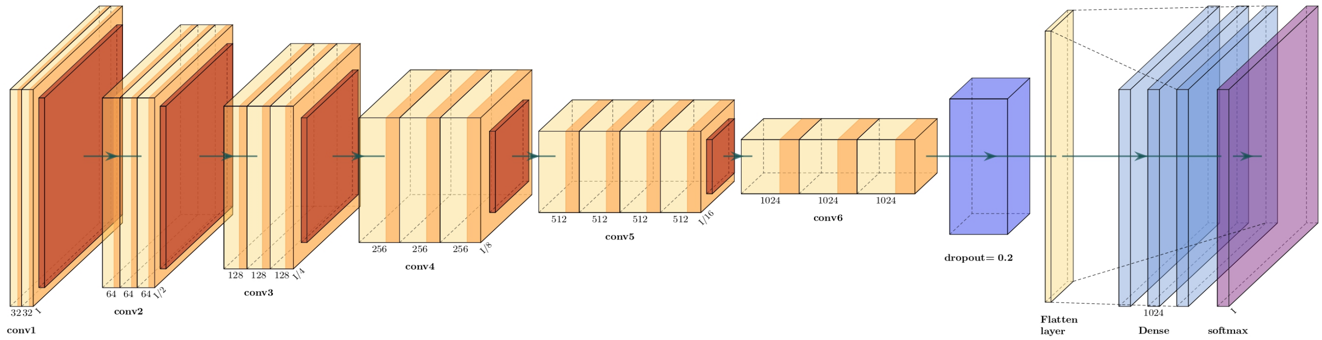
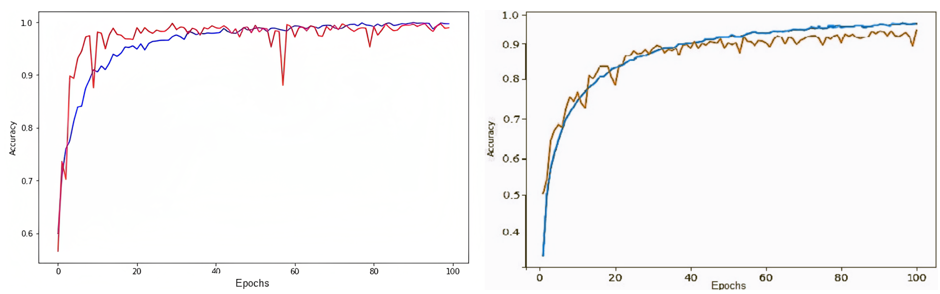


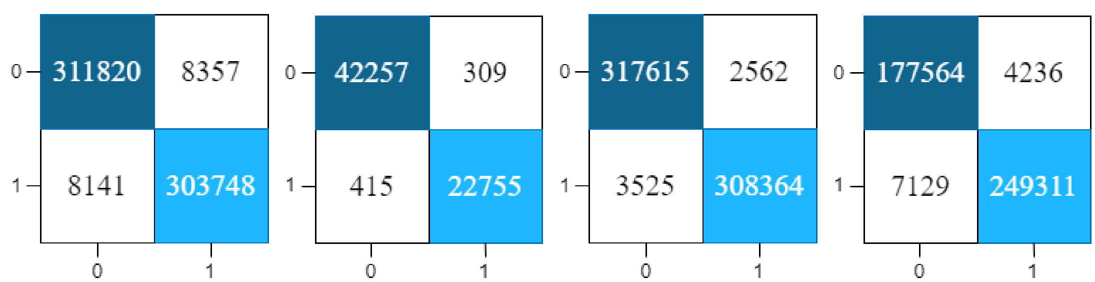
Fig. 6. Proposed CNN architecture for automated insomnia detection.



(a) Training on CAP.

(b) Training on SDRC.

Fig. 7. Training (blue) and Validation (red) accuracy in each epochs of MWTCNNet on CAP and SDRC database. Where x-axis represent number of epochs and y-axis represent the accuracy



(a) (b) (c) (d)

Fig. 8. Testing confusion matrices obtained for automated insomnia detection using Morlet wavelet-based scalograms with MWTCNNet model: (a)Trained with CAP and Tested with SDRC, (b)Trained and Tested with CAP, (c)Trained and Tested with SDRC, (d)Trained with SDRC and Tested with CAP.

using the CNNs. As shown in Table IV, the proposed method obtained the highest accuracy on both the databases.

Our developed method is compared with the pretrained deep neural networks such as AlexNet, GoogLeNet, VGG16, ResNet50, and MobileNetV2, because the designed architecture is able to capture the subtle changes from the scalograms converted from C4-A1 EEG signal. Moreover, using less number of features in the last dense layers of the architecture to consider the important features and the dropout layer further drops the less important features based on the calculated weights.

These results imply that the proposed MWTCNNet is efficient in identifying sleeplessness by scoring the highest accuracy over the well-established methods. The major outcomes of this work are as follows:

- The method used to convert a two-dimensional signal into an RGB image is completely independent of the type of signal, PSG channel, and the data length, which makes it universally applicable for the use of any physiological signal for insomnia detection.
- Comprehensive analysis helps to understand the working of this deep learning model easily.
- The proposed model yielded the best performance on both databases as compared to the transfer learning methods.
- As shown in Table V, the proposed method is faster and easy to -understand, implement, and integrate with other

TABLE IV
COMPARISON OF OUR SUGGESTED MODEL WITH OTHER CUTTING-EDGE TECHNIQUES FOR AUTOMATED INSOMNIA DIAGNOSIS BUILT UTILISING THE CAP AND SDRC DATABASES

Studies	Signal(s)	Method	Segment size (sec.)	Accuracy (%)
		CAP database		
Sharma et al. [5]	ECG (ECG1-ECG2)	Norm features; Classifier- kNN, SVM	30	97.87%
Widasari et al. [34]	ECG (ECG1-ECG2)	sleep quality parameters and Spectral features; Classifier- Ensemble Bagged trees	30	86.27%
Sharma et al. [35]	EEG (F4-C4 and C4-A1)	Hjorth parameter; Classifier- Ensemble Bagged trees	30	96.5%
Hamida et al. [36]	EEG (C3)	Principal Component Analysis	30	91%
Proposed	**EEG (C4-A1)**	Classifier- **MWTCNNet**	**1**	**98.9%**
		SDRC database		
Wei et al. [37]	EEG (C4-A1)	Classifier- LSTM	30	90.9%
Proposed	**EEG (C4-A1)**	Classifier- **MWTCNNet**	**1**	**99.03%**

TABLE V
COMPARISON OF TUNING PARAMETERS USED FOR VARIOUS CNN ARCHITECTURES FOR AUTOMATED INSOMNIA DETECTION USING CAP AND SDRC DATABASES

Parameters	MWTCNNet	AlexNet	ResNet50	VGG16	MobileNetV2	GoogLeNet
Convolutional Layers	**18**	5	50	16	27	51
Dense Layers	**3**	3	1	2	1	2
Filter size	**3**	11,5,3	7,3,1	3	3,1	7,5,3,1
Strides	**1**	1,4	2,1	1	2,1	2,1
Trainable Parameters (in Million)	**45.342**	61	25.5	198	3.47	6.8

systems because it is built with open-source frameworks that are readily available to collaborate with a wide range of other frameworks and devices.

Additionally, the limitations of the proposed method are listed below-

- Large number of intermediate layers (21) increases the total number of trainable parameters which makes this model bulky.
- The performance of the proposed method varies for different sampling frequencies (256Hz, and 512Hz).
- MWTCNNet is a typical CNN, considering only images as input obtained by including an additional step of converting EEG signal into its scalogram.

In the future, we may develop the CNN or some other deep learning techniques with only EEG signals as the input signal instead of scalogram plots. Our future work also focus on real-time detection of insomnia. The current method utilizes only one EEG channel, we would like to look for the possibility of heart rate variability (HRV) or electrocardiogram (ECG) signals as it uses less bandwidth as compared to the EEG signals [39], [40]. We also plan to develop a portable home-based smart device for real-time monitoring of an insomniac patient to prevent hazardous consequences and aid the caretakers in managing the patients.

V. CONCLUSION

In this paper, we introduced the MWTCNNet, a pioneering approach for the detection of insomnia utilizing single-channel C4-A1 EEG signals. Notably, our work stands as the first to leverage EEG signals from both the CAP and SDRC databases to identify insomnia, solely relying on a single-channel one-second EEG recording. Demonstrating the effectiveness of our model, we achieved remarkable accuracy rates of 98.9% and 99.03% with the CAP and SDRC databases, respectively.

However, it is crucial to acknowledge a notable limitation in our methodology. The conversion of EEG epochs into corresponding images, followed by their utilization in the CNN model, introduces computational intensity and time-consuming processes. Moving forward, to address this limitation and enhance efficiency, we propose future research directions that involve developing a deep learning model specifically tailored for automatic insomnia detection, utilizing single-channel EEG signals. This strategic refinement aims to optimize both computational resources and overall model performance, paving the way for more streamlined and effective diagnostic tools in the field of insomnia detection.

REFERENCES

[1] E. Mignot, "Why we sleep: the temporal organization of recovery," *PLoS biology*, vol. 6, no. 4, p. e106, 2008.

[2] M. Sharma, K. Kumar, P. Kumar, R.-S. Tan, and U. R. Acharya, "Pulse oximetry SpO_2 signal for automated identification of sleep apnea: a review and future trends," *Physiological Measurement*, vol. 43, p. 11TR01, Nov. 2022.

[3] V. M. Crabtree, A. Ivanenko, L. M. O'Brien, and D. Gozal, "Periodic limb movement disorder of sleep in children," *Journal of Sleep Research*, vol. 12, no. 1, pp. 73–81, 2003.

[4] S. C. Bos and A. F. Macedo, "Literature review on insomnia (2010–2016)," *Biological rhythm research*, vol. 50, no. 1, pp. 94–163, 2019.

[5] M. Sharma, J. Tiwari, and U. R. Acharya, "Automatic sleep-stage scoring in healthy and sleep disorder patients using optimal wavelet filter bank technique with eeg signals," *International Journal of Environmental Research and Public Health*, vol. 18, no. 6, p. 3087, 2021.

[6] T. Roth, "Insomnia: definition, prevalence, etiology, and consequences," *Journal of clinical sleep medicine*, vol. 3, no. 5 suppl, pp. S7–S10, 2007.

[7] D. Mazzotti, S. Garbuio, M. Ferri, S. Tufik, and C. Ferri, "Insomnia and mortality among older people in five latin american countries: a population based cohort study," *Sleep Medicine*, vol. 14, pp. e203–e204, Dec. 2013.

[8] M. Sharma, V. Patel, and U. R. Acharya, "Automated identification of insomnia using optimal bi-orthogonal wavelet transform technique with single-channel eeg signals," *Knowledge-Based Systems*, vol. 224, p. 107078, 2021.

[9] M. Shahbakhti, M. Beiramvand, T. Eigirdas, J. Sole-Casals, M. Wierzchon, A. Broniec-Wojcik, P. Augustyniak, and V. Marozas, "Discrimination of wakefulness from sleep stage i using nonlinear features of a single frontal EEG channel," *IEEE Sensors Journal*, vol. 22, pp. 6975–6984, Apr. 2022.

[10] U. Budak, V. Bajaj, Y. Akbulut, O. Atila, and A. Sengur, "An effective hybrid model for EEG-based drowsiness detection," *IEEE Sensors Journal*, vol. 19, pp. 7624–7631, Sept. 2019.

[11] C.-J. Lin, C. Wu, and W. A. Chaovalitwongse, "Integrating human behavior modeling and data mining techniques to predict human errors in numerical typing," *IEEE Transactions on Human-Machine Systems*, vol. 45, pp. 39–50, Feb. 2015.

[12] J. Du, Y. Tai, F. Li, Z. Chen, X. Ren, and C. Li, "Using beta rhythm from eeg to assess physicians' operative skills in virtual surgical training," *IEEE Transactions on Human-Machine Systems*, pp. 1–9, 2023.

[13] Y. Liu, Y. Yu, Z. Ye, M. Li, Y. Zhang, Z. Zhou, D. Hu, and L.-L. Zeng, "Fusion of spatial, temporal, and spectral eeg signatures improves multilevel cognitive load prediction," *IEEE Transactions on Human-Machine Systems*, vol. 53, no. 2, pp. 357–366, 2023.

[14] S. Aydın, H. M. Saraoğlu, and S. Kara, "Singular spectrum analysis of sleep eeg in insomnia," *Journal of medical systems*, vol. 35, no. 4, pp. 457–461, 2011.

[15] H. Abdullah, T. Penzel, and D. Cvetkovic, "Detection of insomnia from eeg and ecg," in *The 15th International Conference on Biomedical Engineering*, pp. 687–690, Springer, 2014.

[16] H. Abdullah, C. R. Patti, C. Dissanyaka, T. Penzel, and D. Cvetkovic, "Support vector machine classification of eeg nonlinear features for primary insomnia," in *International Conference for Innovation in Biomedical Engineering and Life Sciences*, pp. 161–164, Springer, 2017.

[17] S. T.-B. Hamida, B. Ahmed, and T. Penzel, "A novel insomnia identification method based on hjorth parameters," in *2015 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT)*, pp. 548–552, IEEE, 2015.

[18] A. Malik, S. Z. H. Naqvi, S. Aziz, M. U. Khan, T. Hussain, and F. Hasan, "Detection of insomnia using electrocardiography and electromyography," in *2021 International Conference on Artificial Intelligence (ICAI)*, pp. 234–239, IEEE, 2021.

[19] M. Shahin, B. Ahmed, S. T.-B. Hamida, F. L. Mulaffer, M. Glos, and T. Penzel, "Deep learning and insomnia: assisting clinicians with their diagnosis," *IEEE journal of biomedical and health informatics*, vol. 21, no. 6, pp. 1546–1553, 2017.

[20] S. Biswal, H. Sun, B. Goparaju, M. B. Westover, J. Sun, and M. T. Bianchi, "Expert-level sleep scoring with deep neural networks," *Journal of the American Medical Informatics Association*, vol. 25, pp. 1643–1650, Nov. 2018.

[21] M. G. Terzano, L. Parrino, A. Sherieri, R. Chervin, S. Chokroverty, C. Guilleminault, M. Hirshkowitz, M. Mahowald, H. Moldofsky, A. Rosa, R. Thomas, and A. Walters, "Atlas, rules, and recording techniques for the scoring of cyclic alternating pattern (CAP) in human sleep," *Sleep Medicine*, vol. 2, pp. 537–553, Nov. 2001.

[22] M. Rezaei, "Eeg/eog/emg data from a cross sectional study on psychophysiological insomnia and normal sleep subjects," 2017.

[23] A. N. Olesen, P. J. Jennum, E. Mignot, and H. B. D. Sorensen, "Automatic sleep stage classification with deep residual networks in a mixed-cohort setting," *Sleep*, vol. 44, Aug. 2020.

[24] S. K. Khare, V. Bajaj, and U. R. Acharya, "Spwvd-cnn for automated detection of schizophrenia patients using eeg signals," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–9, 2021.

[25] A. Grossmann, R. Kronland-Martinet, and J. Morlet, "Reading and understanding continuous wavelet transforms," in *Wavelets*, pp. 2–20, Springer, 1990.

[26] F. Zhuang, Z. Qi, K. Duan, D. Xi, Y. Zhu, H. Zhu, H. Xiong, and Q. He, "A comprehensive survey on transfer learning," 2019.

[27] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, pp. 84–90, May 2017.

[28] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," 2014.

[29] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2014.

[30] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2015.

[31] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "Mobilenetv2: Inverted residuals and linear bottlenecks," 2018.

[32] M. Z. Alom, T. M. Taha, C. Yakopcic, S. Westberg, P. Sidike, M. S. Nasrin, B. C. Van Esesn, A. A. S. Awwal, and V. K. Asari, "The history began from alexnet: A comprehensive survey on deep learning approaches," *arXiv preprint arXiv:1803.01164*, 2018.

[33] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015.

[34] E. R. Widasari, K. Tanno, and H. Tamura, "Automatic sleep disorders classification using ensemble of bagged tree based on sleep quality features," *Electronics*, vol. 9, p. 512, Mar. 2020.

[35] M. Sharma, J. Tiwari, V. Patel, and U. R. Acharya, "Automated identification of sleep disorder types using triplet half-band filter and ensemble machine learning techniques with EEG signals," *Electronics*, vol. 10, p. 1531, June 2021.

[36] S. T.-B. Hamida, M. Glos, T. Penzel, and B. Ahmed, "How many sleep stages do we need for an efficient automatic insomnia diagnosis?," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, IEEE, Aug. 2016.

[37] W. Qu, C.-H. Kao, H. Hong, Z. Chi, R. Grunstein, C. Gordon, and Z. Wang, "Single-channel eeg based insomnia detection with domain adaptation," *Computers in Biology and Medicine*, vol. 139, p. 104989, 2021.

[38] S. M. I. Niroshana, X. Zhu, K. Nakamura, and W. Chen, "A fused-image-based approach to detect obstructive sleep apnea using a single-lead ECG and a 2d convolutional neural network," *PLOS ONE*, vol. 16, p. e0250618, Apr. 2021.

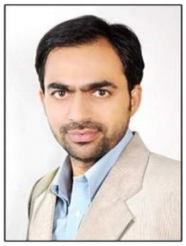
[39] J. Koh, C. P. Ooi, N. S. Lim-Ashworth, J. Vicnesh, H. T. Tor, O. S. Lih, R.-S. Tan, U. Acharya, and D. S. S. Fung, "Automated classification of attention deficit hyperactivity disorder and conduct disorder using entropy features with ECG signals," *Computers in Biology and Medicine*, vol. 140, p. 105120, Jan. 2022.

[40] P. Tripathi, M. A. Ansari, T. K. Gandhi, R. Mehrotra, M. B. B. Heyat, F. Akhtar, C. C. Ukwuoma, A. Y. Muaad, Y. M. Kadah, M. A. Al-Antari, and J. P. Li, "Ensemble computational intelligent for insomnia sleep stage detection via the sleep ecg signal," *IEEE Access*, vol. 10, pp. 108710–108721, 2022.

Kamlesh K. was born in Rajasthan, India in 2000. He received his B.Tech. degree in Electrical Engineering from IITRAM, India in 2023. Currently, he is pursuing his masters degree at San Jose State University, California, USA. He is the inventor of two Indian patents and author of multiple research and review papers. His research interests include image and signal processing, medical imaging, computer vision, artificial intelligence, human-computer interaction, etc.

Prince K. was born in Bihar, India in 1999. He received his B.Tech. degree in Electrical Engineering from IITRAM, India in 2023. He is the inventor of two Indian patents and author of multiple research and review papers. His research interests include image and signal processing, medical imaging, computer vision, artificial intelligence, human-computer interaction, etc.

Ruchit K. P. was born in Gujarat, India in 2001. He completed his B. Tech. in Electrical Engineering from IITRAM, Ahmedabad, India in 2023. His research interest include, image and signal processing, machine learning, modern control systems and aerial robotics.



Dr. Manish S. did Ph.D. from IIT, Bombay, in Electrical Engineering. He received the "Excellence in the Ph.D. Research Work" (Best Ph.D. thesis) award for his outstanding research contributions at IIT, Bombay 2015. He has been listed in the world's top 2% of scientists in a study by Stanford University, USA, for four consecutive years (2019-2022). He has been working as a faculty member in the Department of Electrical and Computer Science Engineering at IITRAM, Ahmedabad, India. He has over 80 publications in reputed journals and conferences, of which 37 are h-indexed and 57 are i-10 indexed (per Google Scholar, July 2023). His research includes Machine Learning, Healthcare data analytics, Signal processing, and their applications.

Dr. Varun B. (Senior Member, IEEE) received the Ph.D. degree from the IIT, Indore, India, in 2014.,He has been working as an Associate Professor at the IIITDMJ, Jabalpur, India. He has guided nine Ph.D. and eight M.Tech. scholars. He has authored or coauthored more than 150 publications. He has been listed as the World's Top 2% Researchers/Scientists by Stanford University, Stanford, CA, USA. His research interests include biomedical signal processing, AI in healthcare, brain–computer interface, and pattern recognition.

Dr. U. R. Acharya , Ph.D., DEng, DSc, is a Professor in School of Mathematics, Physics and Computing, at the University of Southern Queensland, Australia; Distinguished Professor (Artificial Intelligence in Healthcare) at the International Research Organization for Advanced Science and Technology, Kumamoto University, Japan; Adjunct Professor at the University of Malaya, Malaysia; Adjunct Professor at the Asia University, Taiwan. His research interests include biomedical imaging and signal processing, data mining, and visualization, as well as applications of biophysics for better healthcare design and delivery. His funded research has accrued cumulative grants exceeding six million Singapore dollars. He has authored over 500 publications, including 345 in refereed international journals, 42 in international conference proceedings, and 17 books. He has received over 70,000 citations on Google Scholar, with an h-index of 132. According to the Essential Science Indicators by Thomson, he consistently ranked among the top 1% of Highly Cited Researchers in Computer Science for the last seven years (2016 through 2022). He currently sits on the Editorial Boards of multiple journals and has served as Guest Editor on several AI-related issues.