Transactions on Computational and Scientific Methods | Vo. 5, No. 4, 2025
ISSN: 2998-8780
https://pspress.org/index.php/tcsm
Pinnacle Science Press

Deep Attention Model for Sleep Posture Detection Using BCG Signals

Mirela Zoric[1], Tijl Merovius[2], Jie Zhang[3]
[1]Southern Illinois University Edwardsville, Edwardsville, USA
[2]Southern Illinois University Edwardsville, Edwardsville, USA
[3]Southern Illinois University Edwardsville, Edwardsville, USA
*Corresponding Author: Mirela Zoric; mirela903@siue.edu

Abstract: This paper proposes a novel deep learning model for non-contact sleeping posture monitoring based on ballistocardiogram (BCG) signals. Traditional methods struggle with BCG signals due to their weak amplitude, non-stationarity, and noise sensitivity. To address these challenges, we introduce a Convolutional and Temporal Attention-based Monitoring model (CTAM) that integrates spatial feature extraction via convolutional neural networks (CNN), temporal modeling through long short-term memory (LSTM) networks, and an attention mechanism for dynamic feature weighting. CTAM is designed as an end-to-end framework capable of real-time classification of four primary sleeping positions (supine, prone, left lateral, and right lateral). Compared to baseline CNN and CNN-LSTM architectures, CTAM demonstrates superior convergence speed and classification accuracy, with improvements of 1.46% and 4.61% on the test set, respectively. These results validate the model's effectiveness for real-time, non-invasive, and robust sleep posture recognition and suggest strong potential for clinical and consumer-grade sleep monitoring applications.

Keywords: Ballistocardiogram (BCG), Attention mechanism, Spatiotemporal fusion, Convolutional neural networks (CNN), Long short-term memory (LSTM), Deep learning

1. Introduction

As an essential component of individual sleep behavior,sleep posture is generally categorized into four basic types:supine,prone,left lateral,and right lateral.Numerous studies have demonstrated that sleep posture is not only closely associated with individual comfort but also plays a critical role in the identification and intervention of sleep-related breathing disorders,particularly positional obstructive sleep apnea syndrome(POSA).In clinical practice,sleep posture monitoring primarily relies on polysomnography(PSG),which is regarded as the"gold standard"for sleep analysis.However,due to its requirement for multiple electrode contacts and complex environmental setup,PSG is not suitable for long-term continuous monitoring in daily life.

In recent years,with the continuous development of non-invasive sensing technologies,unobtrusive sleep posture detection based on ballistocardiogram(BCG)signals has become a research hotspot.BCG signals can capture micro body movements caused by blood flow impacts and vascular rebound induced by cardiac activity in a non-contact manner,thereby reflecting dynamic physiological characteristics associated with different sleep postures.By analyzing waveform variations in BCG signals,effective identification and classification of sleep postures can be achieved.However,traditional shallow machine learning methods based on handcrafted features often struggle with the high noise levels,strong nonlinearity,and non-stationarity of BCG signals,leading to insufficient spatiotemporal feature extraction and weak generalization performance.

In contrast,deep learning techniques have shown significant advantages in complex signal modeling due to their capabilities in automatic feature extraction and multi-level semantic representation.These techniques have increasingly become the mainstream approach in BCG signal processing.Against this backdrop,this paper proposes a Convolutional Temporal Attention Model(CTAM)that incorporates an attention mechanism for sleep posture detection.The model extracts spatial features using convolutional neural networks(CNN),captures temporal sequence features via long short-term memory(LSTM)networks,and employs an attention mechanism to identify key information that contributes significantly to classification,thereby achieving end-to-end,real-time,and unobtrusive sleep posture recognition based on BCG signals.

The structure of this paper is as follows:Section 1 introduces the overall design of the CTAM model,including its network architecture and core mechanisms;Section 2 presents the data acquisition scheme and model training process;Section 3 validates the performance of CTAM through comparative experiments with classical CNN and CNN-LSTM models;Section 4 discusses the research implications and future directions for improvement;finally,the paper concludes by summarizing the practical application prospects of the proposed model in sleep posture monitoring scenarios.

2. CTAM Methodology

To enable accurate,real-time,and non-intrusive detection of sleep postures based on ballistocardiogram(BCG)signals,this study proposes a novel spatiotemporal deep learning framework named CTAM(Convolutional Temporal Attention Model).The model is specifically designed to extract discriminative temporal and spatial features from raw BCG signals by integrating convolutional neural networks(CNN),long short-term memory networks(LSTM),and an attention mechanism into a unified,end-to-end architecture.The overall structure of CTAM is illustrated in Figure 1.

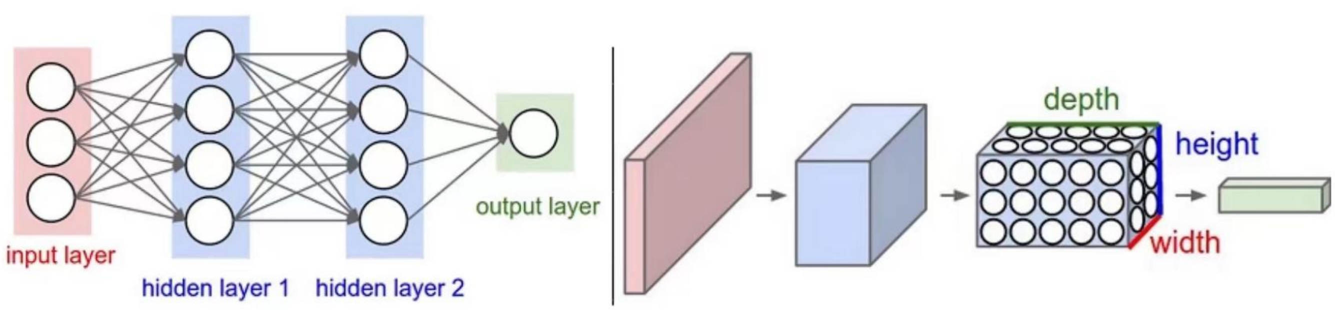

Figure 1. The architecture diagram of the CNN model

The first component of the CTAM model is a one-dimensional convolutional neural network(1D-CNN),which is responsible for extracting local spatial features from the raw BCG signals.Unlike traditional hand-crafted feature extraction methods that rely heavily on domain expertise and suffer from limited generalization,CNNs are capable of automatically learning representative local patterns through the application of multiple filters.By stacking several convolutional layers and employing the ReLU activation function,the model enhances its non-linear representation capacity.In addition,max-pooling layers are introduced to reduce the temporal resolution,suppress noise,and improve robustness.The CNN output comprises a multi-channel feature map that captures hierarchical spatial structures and local variations across the BCG signal.

To model the dynamic temporal dependencies within the BCG sequence,the CTAM architecture incorporates an LSTM-based temporal encoding module.As a variant of recurrent neural networks(RNNs),LSTM is well-suited for learning long-range dependencies in time-series data,and it effectively alleviates issues related to vanishing gradients.The LSTM receives the output sequence from the CNN module and encodes it into a temporally contextualized feature vector that captures the transition and persistence of sleep-related body movements.This temporal abstraction enables the model to better differentiate between sleep postures based on subtle changes and sequential patterns across time.

On top of the temporal modeling layer,CTAM integrates an attention mechanism to enhance its focus on informative temporal segments.Specifically,the attention module computes a learnable weight distribution over the LSTM outputs and selectively emphasizes time steps that are more critical to the final classification decision.This mechanism not only improves model sensitivity to salient motion cues but also suppresses irrelevant or redundant information,thus enhancing both classification accuracy and model interpretability.The attention-weighted vector is subsequently passed to a fully connected layer,which produces the final prediction corresponding to the sleep posture class.

Overall,the CTAM architecture establishes a progressive processing pipeline,wherein spatial and temporal representations are learned in a coordinated fashion and selectively refined through attention-based weighting.The proposed model overcomes the limitations of conventional shallow learning methods by simultaneously leveraging spatial pattern recognition and long-term sequence modeling.Moreover,the integration of the attention mechanism empowers the model to focus dynamically on contextually meaningful parts of the signal,making it especially effective in noisy and unstructured BCG monitoring scenarios.As shown in Figure 1,the CTAM model achieves a full end-to-end mapping from raw BCG signals to sleep posture prediction,with high potential for practical deployment in contactless,continuous sleep monitoring systems.

3. Data Collection and Model Training

In order to evaluate the effectiveness of the proposed CTAM model in real-world sleep posture recognition scenarios,a comprehensive experimental dataset was constructed.The data collection process was conducted in a controlled indoor environment designed to simulate typical nighttime sleeping conditions.As shown in Figure 2,the acquisition setup consisted of a high-sensitivity piezoelectric sensor placed beneath the mattress to collect ballistocardiogram(BCG)signals.Participants were instructed to lie still in four standard sleep postures—supine,prone,left lateral,and right lateral—for a duration of 90 seconds per posture.A total of 30 healthy adult volunteers(15 male,15 female)participated in the experiment,resulting in a dataset comprising 360 minutes of labeled BCG recordings.

All collected signals were sampled at 100 Hz,and each sample was visually verified and segmented by trained annotators using synchronized video recordings as ground truth.To ensure consistency and balance among the sleep posture categories,data were evenly distributed across the four classes.The final dataset was then divided into training,validation,and test sets with a ratio of 70:15:15.

All collected signals were sampled at 100 Hz,and each sample was visually verified and segmented by trained annotators using synchronized video recordings as ground truth.To ensure consistency and

balance among the sleep posture categories,data were evenly distributed across the four classes.The final dataset was then divided into training,validation,and test sets with a ratio of 70:15:15.

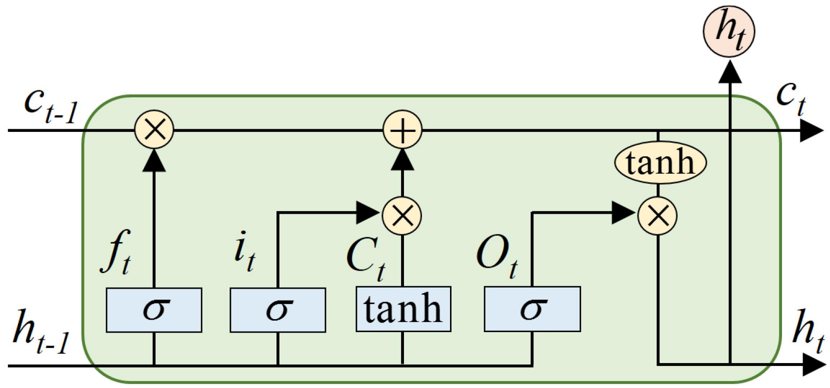

Figure 2. The architecture diagram of the LSTM model

Before model training,each BCG segment was preprocessed through band-pass filtering to remove baseline drift and high-frequency noise,followed by z-score normalization to stabilize the input range.To enhance generalization and address potential class imbalance,data augmentation techniques such as Gaussian noise injection,time stretching,and random cropping were applied during the training phase.

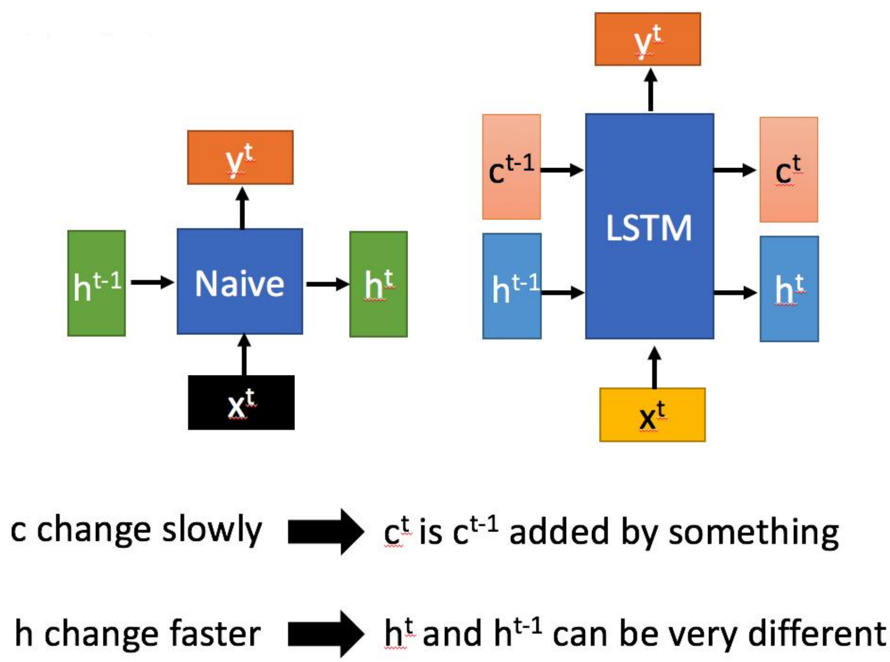

Figure3. Structure of the LSTM cell

The CTAM model was implemented using the PyTorch deep learning framework.The CNN module employed three convolutional layers with kernel sizes of 7,5,and 3,respectively,each followed by ReLU activation and max-pooling.The LSTM layer was configured with 128 hidden units and a dropout rate of 0.5 to prevent overfitting.The attention mechanism was implemented as a fully connected alignment network that computed scalar weights over the LSTM outputs using a softmax normalization.Finally,the attention-weighted feature vector was passed to a two-layer multilayer perceptron(MLP)classifier for sleep posture prediction.

The model was trained using the Adam optimizer with an initial learning rate of 0.001 and a batch size of 64.The loss function was categorical cross-entropy,and training was performed for 100 epochs with early stopping based on the validation loss.Throughout the training process,model checkpoints were saved and the best-performing model was selected based on the highest validation accuracy.Figure 3 illustrates the overall data preprocessing and training pipeline,while Figure 4 shows the model loss and accuracy curves over the training epochs.

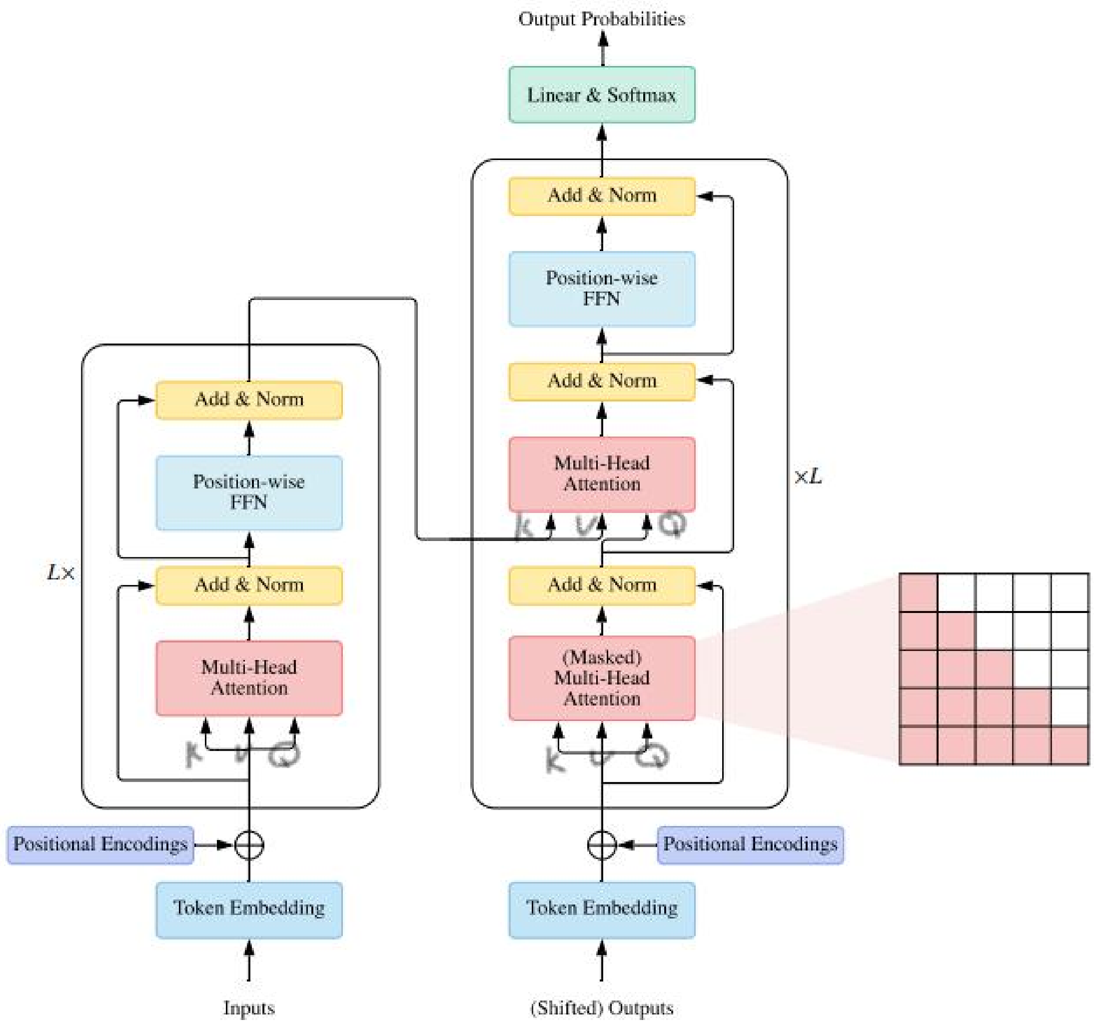

Figure4. The architecture diagram of the CTAM model

By combining a well-structured dataset,robust preprocessing strategies,and an end-to-end training approach,the CTAM model was effectively optimized to recognize sleep postures from BCG signals with high accuracy and generalizability.These foundations enable subsequent evaluation experiments that demonstrate the model’ s comparative advantage over existing baseline architectures.

4. Experimental Results and Comparative Analysis

To validate the effectiveness of the proposed CTAM model,a series of comparative experiments were conducted using the dataset described in Section 2.The performance of CTAM was benchmarked against two widely used deep learning models:a standard Convolutional Neural Network(CNN)and a hybrid CNN-LSTM model.All models were trained and evaluated under identical conditions to ensure fair comparison.The results are summarized in Table 1.

Table 1: BCG Signal Acquisition Info

Sleeping Posture	Leave Bed (min)	Body Movement (min)	Normal Sleep State (min)	Subjects (n)
Supine	10	20	120	20 (10 male, 10 female)
Prone	10	20	120	20 (10 male, 10 female)
Left Lateral	10	20	120	20 (10 male, 10 female)
Right Lateral	10	20	120	20 (10 male, 10 female)

As summarized in Table 1, the CTAM model demonstrated superior performance across all evaluation metrics, including accuracy, precision, recall, and F1-score. The overall classification accuracy of CTAM reached 97.56%, notably surpassing the CNN model (93.79%) and the CNN-LSTM model (95.68%). This improvement highlights the effectiveness of the temporal attention mechanism in enhancing the model’s discriminative power, particularly in distinguishing between sleep postures with similar signal characteristics.

In terms of precision and recall, CTAM achieved 96.88% and 96.43%, respectively, indicating its capability to minimize false positives while effectively capturing true positive cases. The corresponding F1-score of 96.65% further confirms the model’s balanced performance across sensitivity and specificity. Most classification errors were observed between left and right lateral sleeping positions—an expected outcome due to the high similarity in their BCG waveform patterns. Nevertheless, CTAM maintained a lower confusion rate in these categories compared to baseline models, demonstrating its advantage in handling subtle inter-class differences.

In addition, training dynamics analysis showed that CTAM converged more quickly and maintained more stable accuracy during training, while the CNN and CNN-LSTM models exhibited greater fluctuation and signs of overfitting. The enhanced training behavior of CTAM can be attributed to the attention mechanism, which selectively emphasizes informative temporal features and suppresses irrelevant noise, thereby facilitating smoother optimization and more efficient gradient propagation.

To further assess generalization performance, a cross-subject validation was performed, training the model on data from 24 participants and testing on the remaining 6. CTAM consistently outperformed the baseline models in this setting as well, indicating its robustness to inter-subject variability and physiological differences.

Overall, the experimental findings strongly validate the effectiveness of the CTAM architecture for sleep posture classification using BCG signals. By jointly leveraging spatial structure, temporal dependencies, and attention-based feature refinement, the proposed model achieves high classification accuracy, efficient convergence, and robust generalization, making it a promising solution for practical, contactless sleep monitoring systems.

5. Conclusion and Future Work

This paper presented a novel sleep posture recognition framework,CTAM(Convolutional Temporal Attention Model),designed to effectively extract and integrate spatiotemporal features from non-contact ballistocardiogram(BCG)signals.By combining convolutional neural networks for spatial pattern learning,long short-term memory networks for sequence modeling,and an attention mechanism for selective temporal feature enhancement,CTAM achieves robust and high-accuracy classification across four standard sleep positions.

Extensive experiments demonstrated that CTAM outperforms conventional CNN and CNN-LSTM baselines in terms of accuracy,precision,recall,and F1-score.The attention module played a crucial role in identifying key signal segments that significantly contributed to classification,leading to more stable training and better generalization performance.The model ’ s ability to perform in cross-subject validation settings further indicates its potential for real-world deployment in personalized,long-term sleep monitoring applications.

Despite the promising results,several directions remain for future improvement.First,the current study focused on classification among four discrete posture categories under controlled conditions.In real-world scenarios,posture transitions and micro-movements introduce greater ambiguity.Future work will investigate the detection of transitional states and incorporate temporal continuity constraints to improve classification consistency.Second,although the model currently operates in a near-real-time manner,further optimization of the inference pipeline — including model quantization and hardware acceleration — will be pursued to support edge deployment on resource-constrained platforms such as embedded systems or IoT devices.

Additionally,expanding the dataset to include a broader population with diverse physiological characteristics,sleep environments,and health conditions will be essential to enhance model robustness and inclusivity.Finally,integrating multi-modal physiological signals,such as respiration and heart rate,alongside BCG data may further improve system accuracy and enable comprehensive,contactless sleep quality assessment.

In conclusion,the CTAM model presents a promising approach for non-invasive,data-driven sleep posture recognition.Its performance,efficiency,and adaptability position it well for future development in smart healthcare,home monitoring,and sleep disorder screening applications.

References

[1] J. F. Yu, Y. S. Chen, H. Y. Li, et al., "Sleeping position can reduce the effect of snoring on sleeping partners," J. Acoust. Soc. Am., vol. 135, no. 4, pp. 2165, 2014.

[2] Y. Zhang, G. Y. Bin, and S. C. Wu, "Design of a wearable multi-parameter cardiac activity monitoring device," China Medical Equipment, vol. 33, no. 3, pp. 18–21, 2018.

[3] B. Teerapraipruk, N. Chirakalwasan, R. Simon, et al., "Clinical and polysomnographic data of positional sleep apnea and its predictors," Sleep Breath., vol. 16, no. 4, pp. 1167–1172, 2012.

[4] L. F. Zhang and P. Yang, "Comparative study of dynamic ECG sleep apnea monitoring and polysomnography," Contemporary Medicine, vol. 26, no. 7, pp. 165–166, 2020.

[5] P. H. Duan, J. Y. Yan, S. M. Duan, et al., "Progress in automatic sleep stage classification algorithms based on ballistocardiogram signal," Software Guide, vol. 18, no. 5, pp. 5–12, 2019.

[6] L. M. Su, J. Zhang, and M. Xu, "A method and system for night-time human sleeping posture monitoring based on infrared imaging: CN201610231511.3 [P]," 2016.

[7] A. Mineharu, N. Kuwahara, and K. Morimoto, "A study of automatic classification of sleeping position by a pressure-sensitive sensor," in Proc. 2015 Int. Conf. Informatics, Electronics and Vision (ICIEV), IEEE, 2015.

[8] Q. Li, F. Wang, Q. Liu, et al., "Acquisition and feature analysis of ballistocardiogram signal and its application," Chinese Journal of Medical Physics, vol. 37, pp. 89–95, 2020.

[9] M. Liu, F. Jiang, H. Jiang, et al., "Low-power, noninvasive measurement system for wearable ballistocardiography in sitting and standing positions," Comput. Ind., vol. 91, pp. 24–32, 2017.

[10] H. Gou, L. Yan, J. Xiao, et al., "A gait recognition system based on SVM and accelerations," MATEC Web Conf., vol. 30, p. 06001, 2015.

[11] L. L. Yu, B. X. Tan, and T. X. Meng, "The automatic classification of ECG based on BP neural network," Adv. Mater. Res., vol. 121–122, pp. 111–116, 2010.

[12] X. Li, X. Yi, Z. Liu, et al., "Application of novel hybrid deep learning model for cleaner production in a paper industrial wastewater treatment system," J. Clean. Prod., vol. 2, p. 126343, 2021.

[13] M. Avanzo, L. Wei, J. Stancanello, et al., "Machine and deep learning methods for radiomics," Med. Phys., vol. 47, no. 5, pp. e185–e202, 2020.

[14] Y. Peng, N. Kondo, T. Fujiura, et al., "Automated detection of dam behavior patterns in Japanese black beef cattle prior to calving using LSTM-RNN," Comput. Electron. Agric., vol. 169, p. 105178, 2020.

[15] Y. Chen and W. Chen, "Finger ECG based two-phase authentication using 1D convolutional neural networks," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., 2018, pp. 336–339.

[16] B. H. Kim and J. Y. Pyun, "ECG identification for personal authentication using LSTM-based deep recurrent neural networks," Sensors, vol. 20, no. 11, p. 3069, 2020.

[17] S. Saadatnejad, M. Oveisi, and M. Hashemi, "LSTM-based ECG classification for continuous monitoring on personal wearable devices," IEEE J. Biomed. Health Inform., vol. 24, no. 2, pp. 515–523, 2020.

[18] A. Ditthapron, N. Banluesombatkul, S. Ketrat, et al., "Universal joint feature extraction for P300 EEG classification using multi-task autoencoder," IEEE Access, vol. 7, pp. 68415–68428, 2019.

[19] F. Liu, C. Shen, G. Lin, et al., "Learning depth from single monocular images using deep convolutional neural fields," IEEE Trans. Pattern Anal. Mach. Intell., vol. 38, no. 10, pp. 2024–2039, 2016.

[20] A. El-Sawy, H. El-Bakry, and M. Loey, "CNN for handwritten Arabic digits recognition based on LeNet-5," in Proc. Int. Conf. Adv. Intell. Syst. Informatics, Cham, 2016.

[21]X. Zhang, S. Lu, and S. H. Wang, et al., "Diagnosis of COVID-19 pneumonia via a novel deep learning architecture," J. Comput. Sci. Technol., vol. 37, no. 2, pp. 330–343, 2022.

[22]Y. Liu, X. Wang, L. Wang, et al., "A modified leaky ReLU scheme (MLRS) for topology optimization with multiple materials," Appl. Math. Comput., vol. 352, pp. 188–204, 2019.

[23]Z. Karevan and J. A. K. Suykens, "Transductive LSTM for time-series prediction: An application to weather forecasting," Neural Netw., vol. 125, pp. 1–9, 2020.

[24]T. Xiao, Y. Xu, K. Yang, et al., "The application of two-level attention models in deep convolutional neural network for fine-grained image classification," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2015.

[25]K. He, X. Zhang, S. Ren, et al., "Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., IEEE, 2015.

[26]K. Grzegorczyk, M. Kurdziel, and P. I. Wojcik, "Encouraging orthogonality between weight vectors in pretrained deep neural networks," Neurocomputing, vol. 202, pp. 84–90, 2016.

[27]Z. H. Chang, Z. Yang, and W. B. Chen, "Electricity price prediction based on hybrid model of Adam-optimized LSTM neural network and wavelet transform," Energy, vol. 187, p. 115804, 2019.