Research and Experiment with Some Activation Functions in Sleep Stage Classification Using Deep Learning Methods

Tan Thuy Trang, Nguyen Thi Hong, Duong Phi Long
Faculty of Information Systems, University of Information Technology, Vietnam National University Ho Chi Minh City, Vietnam.
Correspondence: Duong Phi Long, longdp@uit.edu.vn
Received: 14/1/2024, revised: 7/5/2024, accepted: 28/5/2024
Digital Object Identifier: 10.32913/mic-ict-research-vn.v2024.n1.1269

Abstract: Sleep disorders are becoming increasingly complex in today's society. Analyzing sleep structure provides valuable information about sleep types, sleep cycles, and variations in different stages. However, manual sleep stage classification is challenging and time-consuming, limiting its clinical use. Deep learning methods have demonstrated promise for automated sleep stage classification, but they face challenges such as class imbalance and the need for interoperability. This paper investigates three deep learning methods, TinySleepNet, TS-TCC, and CA-TCC, using the Expanded Sleep-EDF dataset. The results indicate that TinySleepNet performs well overall, achieving an accuracy of around 80%, while TS-TCC and CA-TCC also perform relatively well with accuracies of around 70%. All three methods classify the Wake stage effectively, with accuracies reaching up to 90%, but struggle with the N1 stage, where accuracy falls below 60%. We propose methods to address these challenges, including the use of GELU, PReLU, LeakyReLU, and SinLU activation functions, which can handle negative values as alternatives to the original ReLU function, and the result can increase from 0.2-1%. Additionally, we have developed a sleep stage classification tool based on these methods.

Keywords: *sleep stage classification, TinySleepNet, TS-TCC, CA-TCC.*

Tiêu đề: **Nghiên cứu và thử nghiệm một số hàm kích hoạt trong phân lớp giai đoạn giấc ngủ sử dụng các phương pháp học sâu**

Tóm tắt: Rối loạn giấc ngủ ngày càng trở nên phức tạp trong xã hội ngày nay. Phân tích cấu trúc giấc ngủ cung cấp thông tin quý giá về các loại giấc ngủ, chu kỳ giấc ngủ và sự biến đổi trong các giai đoạn khác nhau. Tuy nhiên, việc phân loại giai đoạn giấc ngủ thủ công gặp nhiều khó khăn và tốn nhiều thời gian, hạn chế việc áp dụng trong lâm sàng. Các phương pháp học sâu đã cho thấy triển vọng trong việc phân loại giai đoạn giấc ngủ tự động, nhưng vẫn gặp phải những thách thức như mất cân bằng giữa các lớp và nhu cầu về khả năng liên kết dữ liệu. Bài báo này nghiên cứu ba phương pháp học sâu, TinySleepNet, TS-TCC và CA-TCC, sử dụng bộ dữ liệu Expanded Sleep-EDF. Kết quả cho thấy TinySleepNet hoạt động tốt nhất với độ chính xác khoảng 80%, trong khi TS-TCC và CA-TCC cũng hoạt động tương đối tốt với độ chính xác khoảng 70%. Cả ba phương pháp đều phân loại giai đoạn Wake hiệu quả với độ chính xác lên đến 90%, nhưng gặp khó khăn với giai đoạn N1, khi độ chính xác chỉ dưới 60%. Chúng tôi đề xuất các phương pháp để giải quyết những thách thức này, bao gồm sử dụng các hàm kích hoạt GELU, PReLU, LeakyReLU và SinLU, có khả năng xử lý các giá trị âm, thay thế cho hàm ReLU gốc và kết quả có thể tăng từ 0,2-1. Ngoài ra, chúng tôi đã phát triển một công cụ phân loại giai đoạn giấc ngủ dựa trên các phương pháp này.

Từ khóa: *phân lớp giai đoạn giấc ngủ, TinySleepNet, TS-TCC, CA-TCC.*

I. INTRODUCTION

Sleep is a basic human need and has a profound impact on every aspect of daily life. During sleep, the body regenerates and restores energy. Lack of sleep or poor quality sleep can cause fatigue, impaired concentration, weakened immune function, and increase the risk of cardiovascular disease, diabetes, hypertension, and obesity [1]. Sleep also has a significant impact on mood and emotions. Lack of sleep or poor quality sleep can cause anxiety, depression, mental stress, and difficulty concentrating, affecting memory and learning. Research shows that adequate, good-quality sleep improves concentration, memory, and problem-solving abilities, stimulating work performance and creativity. Conversely, poor sleep can affect weight and overall health, increase hunger, reduce concentration and reaction time, increase the risk of accidents, and reduce work performance [2].

Understanding sleep structure is vital for assessing sleep quality, identifying issues, and developing treatment strategies. Good sleep is crucial for health and cognitive function, while sleep disorders are increasingly common and need prompt treatment to minimize their impact on health and quality of life [2]. A night's sleep consists of 4 to 5 cycles, each lasting about 90 to 110 minutes and progressing through the stages: N1, N2, N3, N2, and REM [3]. The Wake stage is when a person is alert and can interact with the environment. The N1 stage, also known as Light Sleep, represents 5% of total sleep time and is characterized by theta waves with low voltage on EEG recordings. This stage marks the transition from wakefulness to sleep, with more than 50% of alpha waves being replaced with low-amplitude mixed-frequency (LAMF) activity. Muscle tone is present in the skeletal muscle, and breathing is regular. The N2 stage, or Deeper Sleep, accounts for 45% of total sleep and is marked by a drop in heart rate and body temperature. Sleep spindles and K complexes, indicative of neuronal firing in various brain regions, are observed in EEG recordings. This stage is also when teeth grinding, or bruxism, occurs. The N3 stage, or Deepest Non-REM Sleep, makes up 25% of total sleep and is characterized by delta waves, which have the lowest frequency and highest amplitude. This stage is the most restorative, with mental fog often experienced upon awakening. Finally, REM sleep accounts for 25% of total sleep and is associated with dreaming. While the brain is highly active during this stage, similar to wakefulness, the skeletal muscles are atonic and without movement. This stage is also characterized by irregular breathing and increased brain oxygen use. [4].

In recent years, many studies have utilized neural network models for the classification of sleep stages in various medical conditions. These studies have primarily focused on the analysis of sleep cycle patterns and spectral power to accurately classify sleep stages. Additionally, some research has incorporated heart rate and respiration data to aid in the diagnosis of sleep-related breathing disorders [6], [7]. These studies focus on utilizing deep learning methods that employ machine learning techniques to extract features for sleep stage classification. Depending on the specific methods and approaches, the choice of signal channels and neural network models for analysis varies. For example, the paper "Automatic sleep stage classification based on two-channel EOG and one-channel EMG" [8] discusses sleep stage classification using Electrooculogram (EOG) and Electromyogram (EMG) signals. In contrast, the EOGNET method introduced in 2021 only uses EOG (Electrooculogram) signals [9]. Other methods like DeepSleepNet [10], SleepEEGNet [11], and AttnSleep [12] utilize Electroencephalogram (EEG) signals. EEG signals are commonly used in sleep stage classification tasks because they are highly interpretable, providing essential information about the patient's sleep state [13]. Therefore, in this paper, we survey studies that employ EEG signals for sleep stage classification, including TinySleepNet [14], TS-TCC [15], and CA-TCC [16]. We conducted experiments on the Sleep EDF Expanded dataset [17] and evaluated these methods based on criteria such as F1-score and Accuracy. These results assess the potential of machine learning applications in sleep stage classification, contributing to further research and the enhancement of sleep quality in the future.

II. RESEARCH METHODOLOGY

Classification of sleep stages using deep learning based on raw EEG signals is a research topic that has attracted significant attention from the scientific community. Approaches to this problem involve utilizing deep neural networks to extract features from EEG signals and classify sleep stages based on various models, including CNNs (convolutional neural networks), and RNNs (recurrent neural networks), and their combinations. Furthermore, data augmentation techniques have been applied to improve model generalization, including weak and strong data augmentation. Adversarial learning models have also been employed to extract features from EEG signals, such as the "Temporal Contrasting" and "Contextual Contrasting" modules.

1. TinySleepNet

TinySleepNet is a deep learning model that was proposed in the paper "TinySleepNet: An Efficient Deep Learning Model for Sleep Stage Scoring based on Raw Single-Channel EEG" by Supratak et al. (2020) [14]. TinySleepNet is a deep learning model designed for classifying sleep stages using single-channel EEG signals. It integrates a convolutional neural network (CNN) to extract spatial features and long short-term memory (LSTM) to process temporal data, enabling the model to capture the continuity of sleep stages. This model is an improved version of the DeepSleepNet method [10], with the main difference being that it uses only one CNN branch instead of two branches like the DeepSleepNet [10] architecture. As a result, TinySleepNet has fewer model parameters than existing models, requiring less training data and computational resources. The first part of the network consists of four convolutional layers, two max-pooling layers, and a dropout layer. These layers

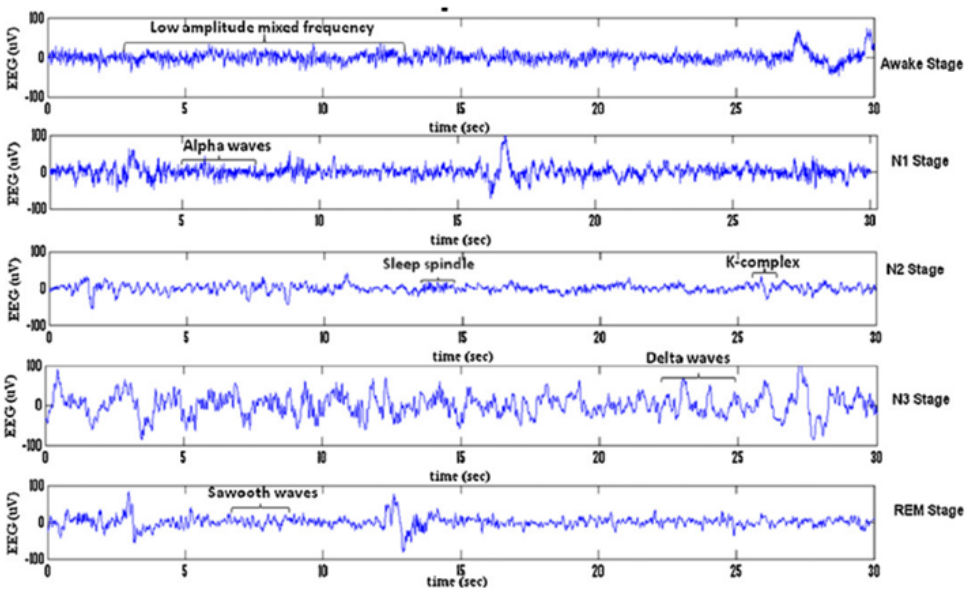

Figure 1. EEG signals for different sleep stages [5].

are used to extract time-invariant features from the original EEG signal. The convolutional layer converts each segment of the EEG signal into a feature vector, denoted as (a_i). In the preprocessing stage, EEG signals are normalized and segmented into smaller segments. The model is trained using the Cross-Entropy loss function and optimized with the Adam optimizer. This is done through a convolutional network, denoted as CNN, where are the learnable parameters of the network. The size of (a_i) varies depending on the sampling rate of the input EEG signal. Figure 2 describes the overall structure of TinySleepNet.

2. TS - TCC

This paragraph introduces a representation learning method for time series data called Temporal and Contextual Contrasting (TS-TCC), which was proposed in the paper "Time-Series Representation Learning via Temporal and Contextual Contrasting" by Eldele et al. (2021) [15]. TS-TCC uses Strong Augmentation and Weak Augmentation to create two different perspectives of the input data. Then, it uses a Temporal Contrasting module to explore the temporal characteristics of the data by simulating an autoregressive model. Autoregressive models use historical information and contextual contrast modules to optimize their predictive ability. Experimental results show that a simple model trained on features learned by TS-TCC can perform almost as well as a model trained with supervision. In addition, TS-TCC is highly effective when there are only a limited number of labeled examples and can also be used for

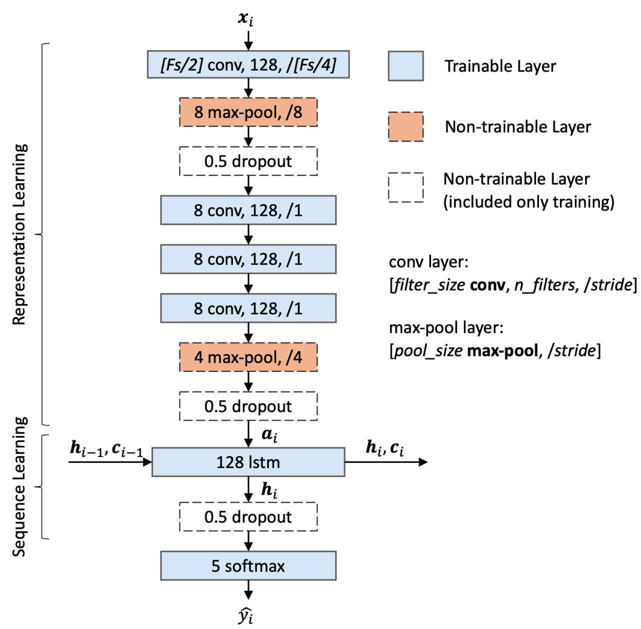

Figure 2. Overview structure of TinySleepNet [14].

transfer learning. For example, by using only 10% labeled data, TS-TCC can achieve performance similar to that of a supervised model. Figure 3 represents the overall structure of TS-TCC [15].

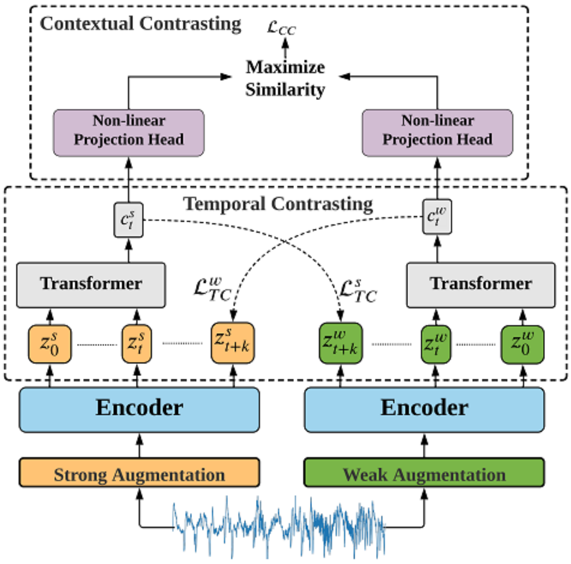

Figure 3. Structure of TS-TCC [15]

3. CA-TCC

In their 2022 paper titled "Contrastive Representation Learning for Semi-supervised Time-Series Classification", Eldele et al. proposed a second variant of TS-TCC, Class-Aware TS-TCC (CA-TCC), which is specifically aimed at semi-supervised learning [16]. This variant uses a combination of labeled and unlabeled data to improve the representation learned from TS-TCC. In the first stage of the semi-supervised learning process, the TS-TCC model is trained on unlabelled data. In the second stage, the pre-trained encoder is fine-tuned using labeled data. In the third stage, the unlabeled data is assigned pseudo labels by using a retuned TS-TCC encoder. Finally, in the fourth stage, the semi-supervised model is trained using the labeled and pseudo-labeled data. Figure 4 represents the four semi-supervised training stages of CA-TCC.

III. EXPERIMENT AND EVALUATE

1. Dataset

In this research, we utilized PHYSIONET's openly available polysomnography signal data source, Expanded Sleep-EDF (ES-EDF) [17]. The dataset encompasses recordings of polysomnographic signals (PSG) that have been annotated with sleep stages. The dataset features a range of signal types, such as electroencephalography (EEG) signals, electrooculography (EOG) signals, and electromyography (EMG) signals. The dataset is organized into two file formats: PSG.EDF files, which contain recordings of polysomnographic signals, and Hypnogram.EDF files, which contain labels for the sleep stages of each recording.

These Hypnogram.EDF files, which are of immense value to our research. These files supply the sleep stage labels, effectively providing a roadmap of the various sleep stages. The stages represented include wakefulness (W), transition to sleep (N1), deep sleep (N2, N3, N4), and Rapid Eye Movement (REM) sleep.

Additionally, the Hypnogram.EDF files include annotations for movement time (Movement(M)), unknown events (UNKNOWN), and timestamps for the signals obtained during each stage of sleep corresponding to the PSG file [4]. Each EDF and Hypnogram file has a header that identifies the patient (anonymized by gender and age), details about the recording (specifically the period recorded), and characteristics of the signal.

The data used for all three methods TinySleepNet, TS-TCC, and CA-TCC are labeled data, after extracting the EEG signal channel FPZ-CZ [18], the data is stored as NPZ file to facilitate data processing and analysis by converting waveform data into numbers, in which x has 3000 attributes and y has 5 labels which are 0, 1, 2, 3, 4 corresponding to wake stage W, sleep stage N1, sleep stage N2, sleep stage N3, sleep stage REM. Also at this step, remove the epochs labeled Movement(M) and UNKNOWN and combine phase 4 into phase 3 because they have similar characteristics [19]. We proceed to divide the data into 2 sets of train and test with a ratio of 8:2, then continue to divide the train set into a train set and a validation set with a ratio of 8:2 based on the criterion of balancing the ratio of stages in the group. Accordingly, the training set has 98 NPZ files, the validation set has 24 NPZ files and the test set has 31 files. Each file will have a duration of 86400s after removing the Movement and unknown stages. The remaining time will be divided into epochs of 30 seconds, and sleep scoring will be performed on each epoch. Additionally, for TS-TCC and CA-TCC, there is an additional step of converting data into PT files.

Table I
STATISTICS ON THE NUMBER OF EPOCHS AND FILES OF EACH DATA SET

Data set	Number of files	Number of epochs
Training set	98	158383
Validation set	24	34390
Testing set	31	37096

After training the TinySleepNet, TS-TCC, and CA-TCC methods using the training set specified in Table I, we performed an experimental evaluation by re-testing with the testing set specified in Table I. The testing set includes 31 samples, which were evaluated using criteria including

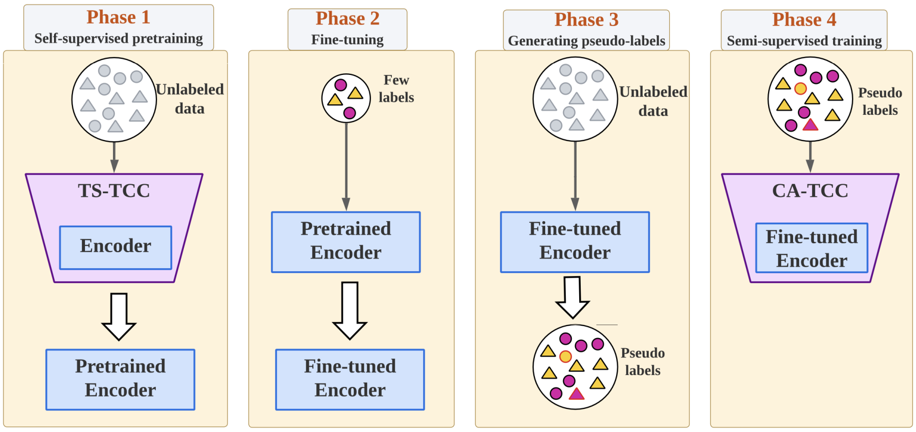

Figure 4. 4 stages of semi-supervised training of CA-TCC [16]

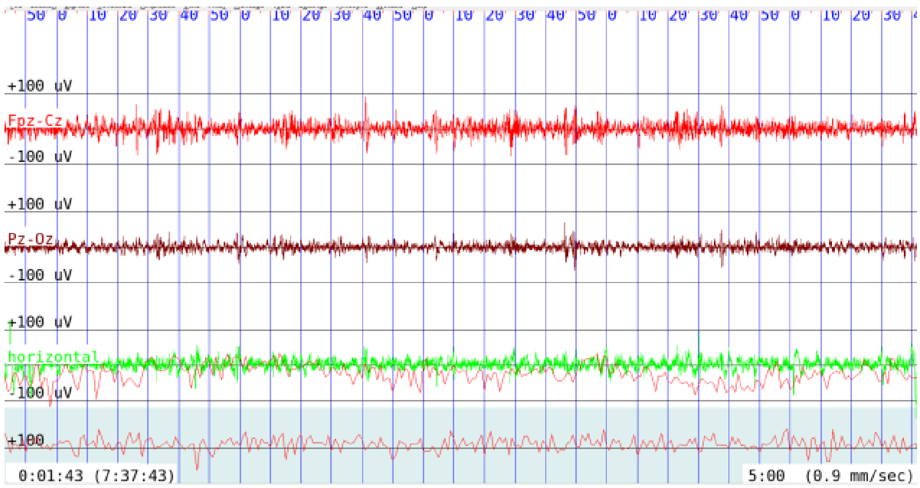

Figure 5. Image illustrating the signal of an EDF file

Table II
STATISTICS ON THE NUMBER OF EPOCHS OF EACH PERIOD IN EACH DATA SET

Stage	W	N1	N2	N3	REM
Training set	55304	16979	54873	10613	20614
Validation set	13260	3418	11808	2289	3615
Testing set	10647	4543	14259	2426	5221

accuracy and F1-score. The results are shown in Tables III and IV.

2. Evaluation criteria

In this article, we applied two criteria to evaluate the effectiveness of sleep stage classification models, specifically Accuracy and Weighted-averaged F1-score (Macro-Avg.F1). Macro-Avg.F1 is a popular criterion for evaluating the performance of models on imbalanced datasets.

We customized the training parameters in comparison to the original paper to align with our data and research approach.

3. Evaluate

After using the methods to train the model, experiment with testing the models on the previously divided testing set. The Accuracy and Macro-Avg.F1 results of the methods are shown in Table III.

Table III
TABLE OF ACCURACY AND MACRO-AVG.F1 RESULTS IN EACH METHOD

Methods	Accuracy	Macro-Avg.F1
TinySleepNet	**81.88%**	**77.64%**
TS-TCC	75.37%	68.84%
CA-TCC	75.52%	69.16%

The results have demonstrated, that the methods achieve relative efficiency on the dataset. CA-TCC achieved an Accuracy of 75.52% and Macro-Avg. F1 is 69.16%, TS-TCC achieved an Accuracy of 75.37%, and Macro-Avg.F1 is 68.54%. The TinySleepNet method has a high compatibility performance with an Accuracy of 81.88% and Macro-Avg.F1 of 77.64%, showing the most accurate classification ability among the methods.

Table IV
COMPARISON OF ACCURACY AND F1-SCORE FOR EACH STAGE IN EACH METHOD

Methods	Metric	Stages				
		W	N1	N2	N3	REM
CA-TCC	Accuracy	91.45	38.15	78.35	74.28	60.33
	F1-score	87.50	36.28	80.55	72.18	65.26
TS-TCC	Accuracy	91.43	35.26	80.24	75.19	61.98
	F1-score	87.79	36.25	81.61	71.26	66.44
TinySleepNet	Accuracy	91.85	54.61	85.16	77.63	78.52
	F1-score	92.08	53.20	84.88	76.82	81.09

The results in Table IV show that the three deep learning methods all performed pretty well in classifying each sleep stage. However, there were some differences in performance between the methods and between the sleep stages:

- **Stage W:** The TinySleepNet method achieved the highest results with an accuracy of 91.85% and an F1-score of 92.08%. The TS-TCC and CA-TCC methods also yielded good results with accuracies above 80%.
- **Stage N1:** The CA-TCC and TS-TCC methods yield low results: accuracy and F1-score of only around 30%. The TinySleepNet method yields average results, with accuracy and F1-score above 50%. This indicates that the methods still face many difficulties in classifying stage N1.
- **Stage N2:** Stage 2 is a stage with quite good performance when the accuracy is from 75% and the F1-score of the methods is all above 80%.
- **Stage N3:** TinySleepNet shows relatively good performance in classifying stage N3, with an accuracy and F1-score of around 75%. TS-TCC and CA-TCC also achieve fairly good performance in classifying this stage, with accuracy and F1-score of around 70%. These methods have relatively good performance in detecting stage N3.
- **REM Stage:** TinySleepNet still maintains relatively good performance in classifying the REM stage, with an accuracy of 78.52% and an F1-score above 80%. Meanwhile, TS-TCC and CA-TCC face more difficulties and have lower performance, with accuracy and F1-score only reaching around 60%. These two methods can classify the REM stage at an average level and need further improvement to achieve higher accuracy.

The evaluation results indicate that the effectiveness of classification methods depends on each specific stage and exhibits significant variability.

Classification methods' efficacy varies across sleep stages. Classifying N1 is challenging due to its resemblance with other stages and short duration. W and N2 stages are less complex to classify due to distinct features. However, N3 and REM stages, despite their distinct characteristics, pose classification difficulties.

Regarding neural network architecture, different models perform differently. TinySleepNet, with its simple structure, effectively classifies stages like W, N2, and N3. TS-TCC and CA-TCC, having complex architectures, excel in classifying challenging stages like N1 and REM.

Performance improvement requires collecting more data for all stages, especially N1 and REM. Also, improving training data quality by removing noise and filtering inaccurate data, researching new methods for learning complex features, and handling noise in data is essential. Further research is needed on larger and more diverse datasets as performance may vary.

4. Testing improvement

In EDF to NPZ conversion, data is stored as a 3000-value array, each value representing an epoch of EEG signals from the FPZ-CZ channel, which can be positive or negative. The activation function, often using Rectified Linear Unit (ReLU), is crucial for deep learning performance, impacting learning capacity, stability, and computational load. While ReLU reduces costs and speeds up training, it can cause inactive neurons if input is negative, potentially affecting network performance. We conducted a survey and experiment on several different activation functions on the hidden layer to replace ReLU in the process of using methods to train the model such as LeakyReLU [20], PReLU [21], GELU [22], SinLU [23]

The Leaky ReLU function is defined by the formula $f(x) = max(\alpha x, x)$, where α is a small positive constant, typically set between 0.01 and 0.3. Unlike ReLU, which outputs 0 for negative inputs, LeakyReLU produces a small negative value. This slope helps alleviate the "dying ReLU" problem that ReLU can experience when the input is too negative. [20]

The PReLU function is also defined by the formula $f(x) = max(\alpha x, x)$. However, unlike Leaky ReLU, the α parameter is not fixed but is instead learned during training. This allows PReLU to learn hidden features and create more complex decision boundaries than ReLU. As a result, PReLU can be more effective at learning and representing complex data. [21]

The GELU function can be approximated by the following formula: $GELU(x) = 0.5x(1 + Tanh((2/\pi)(x + 0.044715x^3)))$. GELU is constructed based on the Gaussian cumulative distribution function, which allows it to have continuous properties and the ability to approximate non-linear functions while avoiding the dead state problem that occurs in ReLU. ReLU has a derivative of 0 for negative or zero values, while GELU has a non-zero derivative in this case.[22].

The SinLU function is defined by the formula $SinLU(x) = (x+asinbx)\cdot\sigma(x)$. It is a continuous activation function that helps to maintain the continuity of the SinLU derivative and prevents the vanishing gradient problem. Additionally, SinLU has a buffer zone on the negative side of the X-axis, similar to the GELU function. When the input is within this buffer zone, SinLU allows for a non-zero derivative, which helps to stabilize the training of the model. [23]

Table V
COMPARISON TABLE OF RESULTS
BETWEEN ACTIVATION FUNCTIONS

	ReLU	PReLU	LeakyReLU	GELU	SinLU
Accuracy					
TinySleepNet	81.88	81.18	80.33	**82.04**	80.90
TS-TCC	75.37	**75.57**	75.24	74.44	73.43
CA-TCC	75.52	**75.69**	75.23	74.39	74.04
Macro-Avg.F1					
TinySleepNet	**77.64**	75.85	76.24	76.91	75.07
TS-TCC	68.84	**69.43**	68.8	68.54	67.96
CA-TCC	69.3	**69.5**	69.2	68.52	68.47

Based on the data in Table V, the performance of TinySleepNet, TS-TCC, and CA-TCC can be compared when using different activation functions and key evaluation metrics such as Accuracy and Macro-Avg.F1:TinySleepNet achieves the best results with all activation functions, with the highest Accuracy score of 82.04% when using the GELU activation function. TS-TCC and CA-TCC have lower accuracy, with TS-TCC achieving the highest accuracy of 75.57% when using the PReLU activation function, and CA-TCC achieving the highest accuracy of 75.69% also with the PReLU activation function.

In terms of Macro-Avg.F1, TinySleepNet also achieves the best results with the highest score of 77.64% when using the ReLU activation function. TS-TCC and CA-TCC have lower scores, with TS-TCC achieving the highest score of 69.43% when using the PReLU activation function, and CA-TCC achieving the highest score of 69.5% also with the PReLU activation function.

The results show that TinySleepNet performs better than TS-TCC and CA-TCC in both evaluation metrics. ReLU can help the TinySleepNet model learn faster and avoid the issue of vanishing gradients, which can explain why it achieves the highest accuracy. GELU is a smooth non-linear activation function that can help improve the learning ability of neural networks. GELU can help the TinySleepNet model capture more complex patterns, which may explain why it achieves the highest Macro-Avg.F1 score. The TS-TCC and CA-TCC models perform best when using PReLU, as this activation function effectively utilizes negative input values by allowing the gradient to be learned during training. The slope for negative values is learned during the training process. This allows the neural network to learn the most appropriate slope for each neuron, enhancing the model's ability to capture complex patterns, and providing the highest accuracy TS-TCC and CA-TCC.

5. Sleep stages classification tool

We have developed a tool for classifying sleep stages based on 3 methods: TinySleepNet, TS TCC, and CA TCC. For each method, we select the model with the best performance to incorporate into the tool. This tool is built on the Flask framework, providing a simple interface to process EDF files and predict sleep stages using classification models trained with TinySleepNet, TS-TCC, and CA-TCC methods. Uploading raw EDF file (a standard format for sleep data) alongside the file containing its correct sleep stage labels. Then, data processing and classification are performed, feeding it into each pre-trained sleep stage classification model. The tool then presents the sleep stage predictions generated by each model. To make the comparison even more intuitive, it utilizes chart.js to create compelling statistical charts. These charts visually represent the accuracy level of each model, allowing you to see at a glance which one reigns supreme for your specific data. Figure 6 shows the screen after analyzing an EDF file containing 20 epochs. Tool links: https://link.uit.edu.vn/sleepstage

IV. CONCLUSION

The performance of TinySleepNet, TS-TCC, and CA-TCC models was evaluated using various activation functions and metrics such as Accuracy and Macro-Avg.F1. TinySleepNet emerged as the best overall performer, achieving the highest Accuracy of 82.04% with the GELU activation function, and the highest Macro-Avg.F1 of 77.64% with the ReLU activation function. TS-TCC and CA-TCC, while performing well, showed lower scores with their best performance using the PReLU activation function (Accuracy of 75.57% and 75.69%, respectively, and Macro-Avg.F1 of 69.43% and 69.5%, respectively).

The efficacy of classification methods varies significantly across different sleep stages. The N1 stage remains

Figure 6. Classification results and comparison from sleep stage classification tool

particularly challenging to classify, with accuracy below 60% due to its short duration and similarity to other stages. In contrast, W and N2 stages achieve higher accuracy rates (80%-90%) due to their distinct features. N3 and REM stages, despite having clear characteristics, still pose classification challenges, with accuracy rates ranging from 60% to 80%.

ReLU activation helps TinySleepNet in avoiding vanishing gradients, resulting in the highest Macro-Avg.F1 score, while GELU activation enhances its ability to capture complex patterns, achieving the highest Accuracy. PReLU activation is most effective for TS-TCC and CA-TCC, facilitating the learning of appropriate slopes for negative input values and improving pattern recognition. However, all three models face difficulties in accurately classifying the N1 stage.

To address these challenges, we propose the use of a Fuzzy Ensemble using the Gompertz function to combine the three methods to improve the reliability of the sleep stage classification. By integrating the strengths of multiple models, the ensemble approach can potentially achieve higher accuracy and better generalization performance compared to using a single model alone. The Gompertz function will allow me to capture the relationships between the EEG features and the sleep stages, which is crucial given the complexity of the underlying physiological processes. This integrated approach should make the overall sleep staging system more reliable and less prone to errors, which is important for real-world applications in sleep medicine and cognitive neuroscience research.

In summary, while exploring different activation functions can improve model performance, the increase is not significant. Future research should focus on enhancing data preprocessing and classification for the N1 stage, developing user-friendly tools with customizable functions, and investigating comprehensive systems suitable for combining classification results. These advances will enhance sleep stage classification using EEG signals from the FPZ-CZ channel and open new research directions. This paper presents the results of the author's graduation thesis research, which explored effective methods for sleep stage classification through the development of research content, experiments, and tools.

ACKNOWLEDGEMENT

This research was supported by The VNUHCM-University of Information Technology's Scientific Research Support Fund.

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Tan Thuy Trang received an engineering degree in Information Systems from the University of Information Technology, Vietnam National University, Ho Chi Minh City, Vietnam in 2023.
Email: 19522384@gm.uit.edu.vn

Nguyen Thi Hong received an engineering degree in Information Systems from the University of Information Technology, Vietnam National University, Ho Chi Minh City, Vietnam in 2023.
Email: 19521550@gm.uit.edu.vn

Duong Phi Long has been working as a Lecturer in the Faculty of Information Systems of the University of Information Technology - Vietnam National University Ho Chi Minh City since 2012. He received her Master of Science degree from the University of Information Technology - Vietnam National University Ho Chi Minh City. His area of interest is Machine Learning, Deep Learning, Computer Vision, and Bioinformatics
Email: longdp@gm.uit.edu.vn