RESEARCH ARTICLE

Research on dynamic identification of traditional Chinese medicine constitution and personalized health care by integrating lightweight deep learning with wearable perception

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Traditional Chinese medicine (TCM) constitution can reflect the physiological state and disease tendency of the human body and is an important basis for carrying out personalized health and wellness interventions in TCM. Traditional questionnaire identification belongs to static subjective evaluation, which is difficult to capture the dynamic evolution of physical fitness. The existing intelligent identification models have many parameters, making it difficult to adapt to the computing power consumption limitations of wearable terminals, and generally lacking a complete business loop from monitoring to health intervention. This research constructed a lightweight intelligent identification system based on wearable 24-hour time-series physiological signals, realizing dynamic discrimination of TCM constitution and personalized home health recommendations. The study took multidimensional physiological time-series data as input, used MobileNetV2-BiLSTM lightweight hybrid network to mine spatiotemporal features, established the corresponding relationship between physiological indicators and nine types of TCM constitution, built an integrated framework for identifying and recommending health and wellness, and verified it through comparative experiments. The results showed that the model had a classification accuracy of 91.68%, a parameter size of 6.24M, a single frame inference speed of 9.76 ms, a wearable terminal power consumption of 12.19 mA, a dynamic recognition accuracy of 90.17%, and an average improvement rate of 31.68% in physical bias after home intervention. Its comprehensive performance was better than the comparative model. This lightweight solution could achieve dynamic and objective identification of TCM constitution under the wearable end, forming a complete identification and health care closed-loop, and providing technical reference for home and grassroots intelligent TCM health care work.

Keywords: lightweight deep learning algorithm; wearable sensing devices; dynamic identification; personalized health care.

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Introduction

Traditional Chinese medicine (TCM) constitution identification is an important foundation for achieving personalized health care and disease prevention and has significant application value in public health management and clinical diagnosis and treatment [1]. The current TCM constitution assessment relies heavily on traditional questionnaire scales, which have limitations such as strong subjectivity, static single assessment, and difficulty in continuous tracking and cannot adapt to the real-time and dynamic needs of modern health management [2]. With the rapid development of smart wearable technology, devices such as

smartwatches and wristbands can stably collect multi-dimensional physiological timing signals such as heart rate, blood oxygen, body temperature, and sleep rhythm, providing reliable data support for objective identification of physical fitness. Existing clinical research has confirmed that heart rate and heart rate variability (HRV) can reflect the balance between "heart-qi" and the autonomic nervous system; blood oxygen levels correlate with the sufficiency of "qi and blood"; skin temperature can distinguish between "cold" and "heat" states within the body; and sleep rhythms correspond to the fluctuations of "yin and yang". By integrating these various indicators, it is possible to comprehensively characterize the specific imbalances associated with the nine constitutional types in TCM [3]. Meanwhile, the application of lightweight deep learning in wearable terminals can achieve lightweight deployment, providing a feasible technical path for physiological feature mining and dynamic recognition. Integrating wearable perception, lightweight deep learning and TCM constitution recognition to carry out dynamic recognition and personalized health research has important practical necessity and application prospects [4].

In the field of intelligent identification of TCM constitutions, mainstream research relies on questionnaires and static tongue-image data, integrating machine learning and deep learning models to achieve the classification of these constitutions. Large sample studies have confirmed that different constitutions have differentiated quantitative image features of tongue images, which can be used to determine constitution based on static tongue images. However, this method lacks temporal physiological information and is difficult to capture the dynamic evolution of constitution [5]. Part of the machine learning research on constitution recognition is based on modeling of hand diagnosis images to achieve objective discrimination of constitution, but it has not been adapted for wearable temporal physiological signals [6]. The intelligent TCM identification model has been validated in specific gynecological diseases such as perimenopausal syndrome, but existing models mostly focus on a single disease syndrome and lack a universal identification scheme for the nine basic constitutions [7]. Zhang *et al*. explored physical biomarkers from the perspective of metabolomics to provide biological basis for objective identification, but did not construct a real-time inference model, which was unable to support dynamic health intervention closed-loop [8]. In the field of health monitoring, Mei *et al*. used a multi-sensor fusion scheme to achieve continuous collection and transmission of vital signs, improving the timeliness and integrity of health data. However, a correlation model between time-series data and TCM constitution was not constructed [9]. Xie *et al*. used wearable devices to track signs of chronic and infectious diseases, using traditional deep networks without low-power and lightweight modifications, which could not meet the long-term operation needs of terminals [10]. Research combined lightweight models with wearable data only achieved rough classification of general health risks without incorporating specialized modeling of the nine constitution theories of TCM [11]. Yang *et al*. showed through visual analysis that wearable devices were developing towards a closed-loop direction of dynamic monitoring, risk assessment, and personalized intervention, but had not proposed a closed-loop implementation path for TCM constitution [12]. Although significant progress has been made, there are still several key limitations. The existing digital identification methods for TCM constitution rely heavily on static data such as scales and tongue images, and lack continuous tracking of temporal physiological changes, making it difficult to reflect the dynamic evolution of constitution [13]. Most deep learning models have complex structures and large computational loads, making them unable to adapt to the low computing power and low power consumption operating conditions of wearable terminals. End to end deployment and real-time inference are difficult to achieve [14]. Most studies focus on long-term collection of physiological signals. However, they are mostly

applied to general health monitoring and have not established an effective correlation between physical sign data and TCM constitution status. A complete application loop of monitoring-identification-intervention has not yet been formed [15]. In addition, existing research generally lacks the internal correlation between the five basic physiological indicators and the nine types of TCM constitution and lacking the scientific mechanism explanation. Various studies have insufficient depth in exploring temporal physiological characteristics, resulting in significant limitations in identification accuracy and practicality for home use.

This research constructed an intelligent health and wellness technology system that combined lightweight deep learning and wearable perception to achieve objective and dynamic discrimination of TCM constitution and establish an integrated monitoring and intervention solution for home scenarios. The study used 24-hour wearable time-series physiological signals as input data sources to construct a MobileNetV2 BiLSTM lightweight hybrid network. By combining the theory of Qi, blood, yin and yang in TCM, this study elucidated the corresponding mechanisms between five physiological indicators and nine types of constitution. Probability classification and temporal sliding window weighting algorithms were designed to dynamically quantify constitution discrimination, and a personalized health recommendation mechanism was constructed using feature similarity algorithms. The model's recognition accuracy, lightweight performance, and actual effectiveness of health interventions were validated through multiple control experiments and multidimensional indicators. This study addressed the limitations of existing research, specifically regarding static recognition, challenges in end-to-end deployment, and the lack of closed-loop health management and provided new technical solutions for home smart TCM health care and grassroots health management. It also provided a theoretical and experimental reference for research on the objective identification of TCM patterns based on time-series physiological signals.

Materials and methods

Overview of the overall research system

The entire intelligent health care system of this study included six linkage modules. The wearable physiological data acquisition module was responsible for 24-hour continuous heart rate HRV, blood oxygen, body temperature, and sleep timing signal collection. The data preprocessing module completed filtering, interpolation, and standardization cleaning. The MobileNetV2 BiLSTM hybrid network module completed spatiotemporal feature extraction and physical fitness probability output. The dynamic recognition module determined the type of constitution and quantified the degree of bias based on probability vectors. The personalized health recommendation module relied on similar algorithms to output dietary therapy, exercise, and lifestyle adjustment plans. The closed-loop feedback module sent back the health and wellness effects, as well as new physiological data, to achieve continuous iterative optimization of the model and recommended solutions. Each module was connected in the order of data flow to form a complete "perception, processing, inference, identification, recommendation, feedback" system.

Data collection and preprocessing

A total of 282 healthy and sub healthy subjects including 131 males and 151 females, aged 18 to 60 years old, covering nine types of normal and biased constitutions were involved in this study. All data were collected by using Xiaomi Band 8 and Xiaomi Watch S3 smartwatch (Beijing Xiaomi Mobile Software Co., Ltd., Beijing, China) for 24-hour continuous monitoring with the sampling intervals for heart rate, HRV, temperature of 5 seconds, the blood oxygen of 10 seconds, and the sleep state of 30 seconds. Data preprocessing methods such as wavelet filtering for denoising, linear interpolation for missing values, temporal

resampling alignment, outlier removal, and Z-score standardization were applied to eliminate interference and unify dimensions. Ultimately, a standardized and reliable temporal physiological dataset was constructed. All procedures of this research were approved by the Medical Ethics Committee (Zibo Polytechnic University, Zibo, Shandong, China). Based on the theories of qi and blood, yin and yang, and organs in TCM, as well as existing clinical research results, heart rate + HRV reflected the state of qi rise and fall and the balance of yin and yang in the autonomic nervous system. Individuals with Qi deficiency/yang deficiency exhibited high resting heart rate and low HRV values. People with yin deficiency experienced significant fluctuations in heart rate at night. The daily heart rate of people with qi depression fluctuated significantly. The heart rate of the peaceful population was stable, and the HRV range was moderate. The skin surface temperature was used to distinguish the body's cold and hot imbalances, corresponding to yin and yang deficiency and excess. People with yang deficiency had lower skin temperature throughout the day, while people with yin deficiency and damp heat had a consistently high body surface temperature. The temperature of the skin was stable with no significant cold or heat shift. Blood oxygen saturation characterized the degree of whole-body Qi and blood filling and microcirculation patency. People with blood stasis and phlegm dampness had low and fluctuating mean blood oxygen levels. The blood oxygen level of the peaceful substance remained stable within the standard range with minimal fluctuations, while individuals with yin deficiency exhibited mild fluctuations in blood oxygen levels. Sleep rhythm reflected the balance of yin and yang in the human body. People with yin deficiency had difficulty falling asleep and were prone to waking up at night. People with phlegm dampness tended to feel drowsy and sleep long. People with Qi deficiency tended to have more dreams and shallow sleep, while people with depression experienced delayed sleep. People with peaceful and regular daily routine showed sufficient deep sleep. A single indicator could only determine the single dimension of cold and heat or qi and blood, and the coupling of multiple temporal indicators could fully distinguish the nine types of physical combination characteristics. All indicators of special properties fluctuated significantly with the environment. Overall, heart rate, HRV, skin temperature, blood oxygen, and sleep corresponded to the four major dimensions of TCM evaluation, including heart qi, cold and heat, qi and blood, and yin and yang. Each type of biased constitution had a unique pattern of abnormal combinations of multiple indicators. Special constitution and mixed constitution could also be distinguished by the fluctuation differences of multiple indicators.

Construction of lightweight MobileNetV2 BiLSTM model

MobileNetV2 backbone network adopted PyTorch Hub (https://pytorch.org/hub/) for public pre-training implementation. The BiLSTM temporal module was constructed using the recurrent neural network modules built into PyTorch's torch.nn package and did not directly utilize pre-trained weights from Hub. This architecture was compatible with both static questionnaires and dynamic physiological inputs and could simultaneously meet the training requirements of lightweight deployment and multigroup control experiments. The model body consisted of MobileNetV2 feature extraction module, BiLSTM temporal modeling module, and fully connected output layer. MobileNetV2 used depth-wise separable convolution and inverse residual structure to reduce parameter count and computational overhead. BiLSTM synchronously extracted context dependent information of physiological temporal data through forward and backward bidirectional loop structures, providing more comprehensive temporal features for dynamic recognition of physical constitution. The output layer used Softmax activation function to complete the classification and biased state recognition of nine basic constitutions. The model utilized MobileNetV2 to encode spatial features of the preprocessed temporal input data X_{in}, obtaining deep level features as below.

$$F_m = MobileNetV2(X_{in}) \quad (1)$$

where X_{in} was standardized temporal input. F_m was spatial feature. The feature was input into the BiLSTM unit for bidirectional temporal modeling, and the temporal hidden layer feature was output as follows.

$$H_t = BiLSTM(F_m, H_{t-1}) \quad (2)$$

where H_t was a temporal hidden state. The physical fitness classification results were obtained through fully connected layer mapping and probability normalization as follows.

$$\hat{Y} = Soft\,max(\,FC(H_t)) \quad (3)$$

where $\hat{Y}$ was the probability output of physical fitness classification. Model training adopted multiclass cross entropy loss function as below.

$$L_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_{i,k}\, log(\,\hat{y}_{i,k}) \quad (4)$$

where N was the number of samples. K was the number of physical fitness categories. $y_{i,k}$ was the true label. $\hat{y}_{i,k}$ was the model prediction probabilities. The training used the AdamW optimizer and further compressed the model through pruning and quantization to meet the requirements of end-to-end deployment. The control group experiment only adjusted the input layer data format to adapt to static questionnaire quantitative data, while the model backbone structure remained unchanged.

Dynamic identification mechanism of TCM constitution

Based on the probability vector of physical fitness prediction output from the network, a complete dynamic recognition quantification rule was established. The classification criteria for constitution in this study referred to the "Classification and Determination of Traditional Chinese Medicine Constitution", which is an industry standard published by the Chinese Society of Traditional Chinese Medicine (Beijing, China) and defines nine basic constitutions as calm, qi deficiency, yang deficiency, yin deficiency, phlegm dampness, damp heat, blood stasis, qi depression, and special constitution. Based on probability values, the classification was determined, and the degree of bias was quantified. The time series sliding window algorithm was introduced to capture the long-term dynamic changes of constitution. Setting the model output probability vector as $\hat{Y} = [\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_9]$, where $\hat{y}_k$ was the predicted probability value corresponding to the k-th constitution, the basis for determining the type of constitution was based on the matching degree of physiological characteristics learned by the model. The higher the fit between physiological temporal characteristics and a certain type of constitution pathology or physiological representation, the higher the probability of the model outputting a predicted constitution. This served as the core basis for classifying constitutions with the specific determination formula as follows.

$$Type = \arg\max_{k\in\{1,\ldots,K\}} \hat{y}_k \quad (5)$$

The physique category corresponding to the maximum predicted probability was selected as the final judgment of the subject's physique type. At the level of judging the degree of physical bias, the quantitative evaluation was completed by using the difference between the maximum predicted probability and the second highest predicted probability as below.

$$Dev = \hat{y}_{max} - \hat{y}_{submax} \quad (6)$$

where $\hat{y}_{max}$ had the highest predicted probability among the nine types of constitution, while $\hat{y}_{submax}$ had the second highest predicted probability. Based on actual identification needs, a clear evaluation interval was defined. When Dev ≥ 0.3, the physical characteristics of the subjects were distinct, indicating a typical single constitution. When 0.1 ≤ Dev < 0.3, there were cross characteristics in physical constitution, which was classified as a mixed constitution. When Dev < 0.1, the probability distribution of

various constitutions was uniform, and the constitution state was in a fluctuating and unstable state. To overcome the limitations of static single recognition, this research introduced a time-series sliding window weighting algorithm to track the trend of physical fitness fluctuations and achieve dynamic trend analysis as follows.

$$\hat{Y}_t^* = \sum_{i=t-N+1}^{t} \omega_i \cdot \hat{Y}_i \quad (7)$$

where N was the sampling length of the sliding window. ω_i was the weight coefficient corresponding to different temporal nodes. $\hat{Y}_i$ was the probability result of single time constitution recognition. By smoothing the recognition error caused by short-term physiological data through this method, the subtle changes in physical fitness over time could be accurately captured.

Personalized health and wellness program recommendation mechanism

Based on the physical fitness recognition results after temporal weighting correction, a health knowledge base covering three types of conditioning schemes of dietary therapy, daily living, and exercise was constructed, and a feature similarity matching algorithm was designed to adapt to the conditioning schemes. The algorithm took the probability vector of physical fitness throughout the entire period as input and dynamically adjusted the focus of health care based on real-time bias, forming a complete intervention chain of physiological monitoring, physical fitness discrimination, personalized program matching, and long-term dynamic optimization. Using the time series corrected constitution recognition result $\hat{Y}_t^*$ as the matching benchmark, a mapping relationship between constitution features and health care plans was established and used feature similarity calculation to complete the optimal health care plan screening as below.

$$S = 1 - \frac{1}{K}\sum_{k=1}^{K} |\hat{y}_{tk} - z_{mk}| \quad (8)$$

where S was the similarity between physical condition and fitness plan. $\hat{y}_{tk}$ was the recognition probability of the k-th physical condition at time t. z_{mk} was the fitness adaptation feature vector corresponding to the m-th fitness plan. The higher the similarity value, the higher the fitting between fitness plan and the current physical condition, and the system prioritized the push of high fitness plans. Meanwhile, based on the degree of physical bias and temporal fluctuations in different time periods, the focus direction of recommended content should be dynamically adjusted to achieve flexible changes in health care plans.

Experimental setup

The software environment was built based on the PyTorch deep learning framework equipped with physiological signal processing tools and end-to-end model deployment environment. Based on the multidimensional physiological temporal signals collected, nine types of constitution were manually annotated by professional TCM practitioners according to the "Classification and Determination of Traditional Chinese Medicine Constitution", forming a labeled standard dataset. The model evaluation using classification performance indicators of precision, recall, F1 value and was calculated as follows.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Precision = \frac{TP}{TP+FP} \quad (10)$$

$$Recall = \frac{TP}{TP+FN} \quad (11)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (12)$$

where TP was the true case. TN was the true negative case. FP was the false positive case. FN was the false negative case. Lightweight deployment indicators of single sample inference time, terminal operating power consumption, and model parameter quantity were also evaluated. To ensure fairness, consistency, and validation of the comprehensive performance of

the lightweight MobileNetV2 BiLSTM model in this study, five typical models were selected as controls, which included pure CNN model, pure LSTM model, MobileNetV3-LSTM, EfficientNet-B0-LSTM, and Swin Transformer Tiny BiLSTM. The MobileNetV3, EfficientNet-B0, and Swin Transformer Tiny backbone networks were obtained from the PyTorch Hub. The basic components of CNN and LSTM were built based on the built-in torch.nn module in PyTorch. All models were trained by using unified parameters with batch size of 32, maximum iteration round of 100, initial learning rate of 1×10^{-3}. The optimizer used AdamW, and loss function used multiclass cross entropy loss. Based on these settings, two levels of testing schemes were tested to complete model validation. Basic performance comparison experiments were conducted at the first level, comparing the proposed model with five comparison models in a unified dataset and experimental environment, and quantitatively evaluating the comprehensive performance of the model from four dimensions including classification accuracy, model complexity, inference efficiency, and training convergence. The second level performed application testing for practical application scenarios, focusing on three dimensions of device adaptation, dynamic recognition, and health recommendation. Objective quantitative indicators were used to test the actual application effects of the model in wearable terminal deployment, physical fitness dynamic tracking, and personalized health intervention scenarios.

Results

Dataset and model convergence basic data

The results showed that the samples were mainly concentrated in the middle range with heart rate, HRV, blood oxygen saturation, and body surface temperature as 78.15%, 72.63%, 87.32%, and 80.48%, respectively. The proportion of low and high segments in each indicator was at a relatively low level. The data integrity rate of the dataset was between 97.95% and 99.31%. The mean values of heart rate, HRV, blood oxygen saturation, and body surface temperature were 75.86 ± 9.31, 44.92 ± 10.85, 97.05 ± 1.03, and 36.55 ± 0.41, respectively. The dispersion degrees of heart rate and HRV were relatively higher, while that of blood oxygen saturation and surface temperature were relatively low. The overall dataset quality met the input conditions of the model. The model in this study underwent 80 rounds of iterative training and converged by the 48th round. After 80 iterations, the training loss was 0.107, and the validation loss was 0.198. The training and validation losses decreased synchronously and tended to stabilize with no significant differentiation between the two. There was no significant overfitting phenomenon in the model.

Model basic performance test

The basic performance comparison of each model demonstrated that the indicators of proposed model were all higher than those of the other compared models. The classification accuracy of proposed model increased by 9.34% and 7.51% compared to the pure CNN and pure LSTM single models, respectively. Compared with MobileNetV3-LSTM and EfficientNet-B0-LSTM, the proposed model also showed an accuracy advantage. Compared with Swin Transformer Tiny BiLSTM, the accuracy of proposed model was 2.15% higher (Figure 1).

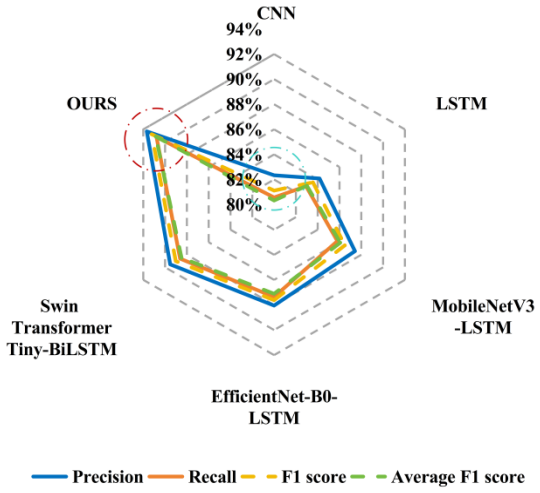


Figure 1. Comparison of core classification performance indicators among various models.

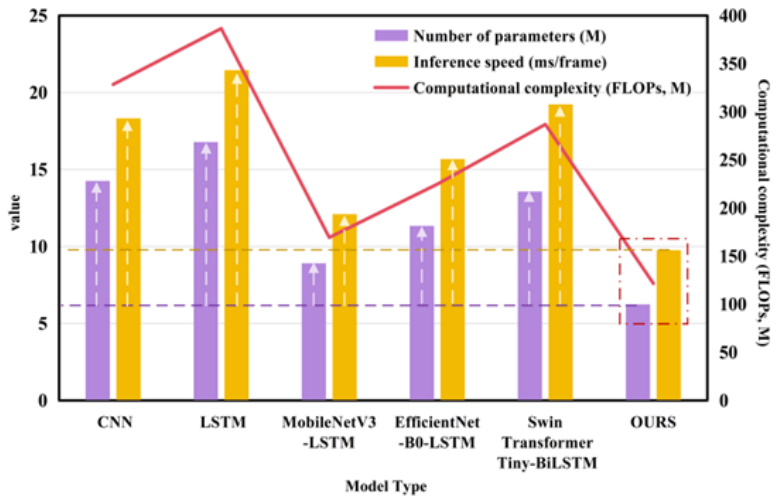


Figure 2. Comparison of complexity and inference speed of each model.

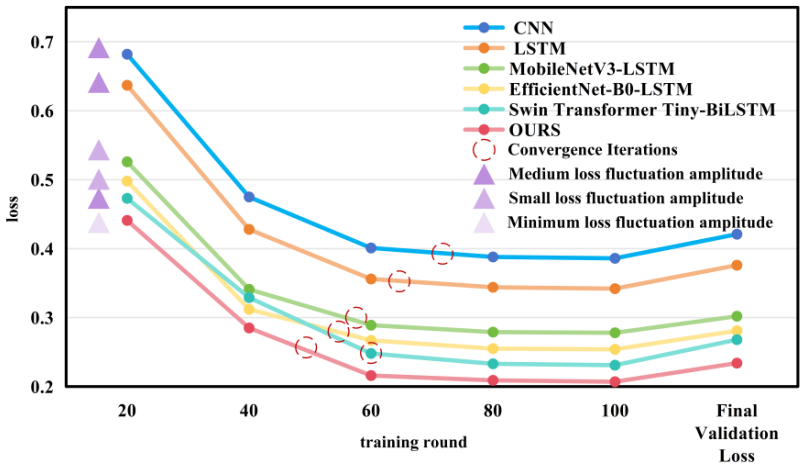


Figure 3. Comparison of convergence of training loss and validation loss for each model.

The comparison between model complexity and inference speed demonstrated that the parameter count of the proposed model was only 6.24M, while the computational complexity was 121.55M FLOPs, and the inference speed was 9.76 m/s per frame. Compared with heavy-duty models such as Swin Transformer Tiny BiLSTM, the proposed model reduced the number of parameters by 54% and improved inference speed by 49% (Figure 2). Compared with a single model, the proposed model achieved a significant reduction in the amount of calculation while improving the accuracy. The comparison of training loss and validation loss convergence for each model showed that, under the same training rounds of 20, 40, 60, and 80, the training loss of proposed model was lower than the other five comparison models with a faster descent speed and smoother convergence process. Pure CNN and pure LSTM single model feature extraction had high loss and slow convergence speed in the same round. The training curve of Swin Transformer Tiny BiLSTM model exhibited oscillations. The proposed model reached complete convergence around 48 rounds, and the loss remained basically unchanged after 80 rounds with no significant fluctuations throughout the entire process (Figure 3).

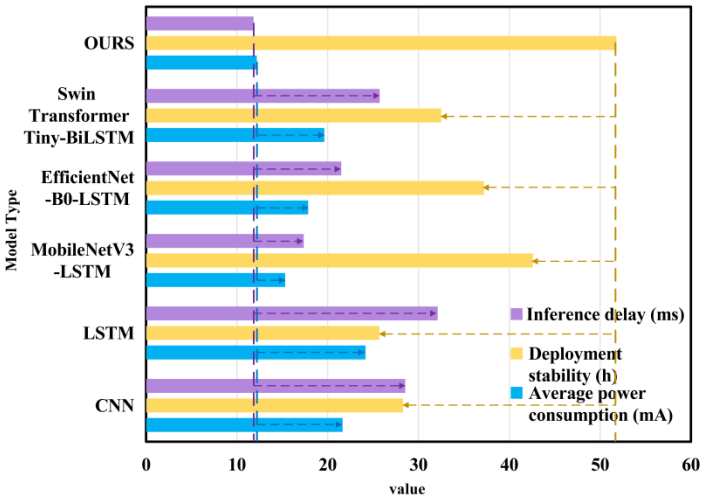


Figure 4. Comparison of wearable terminal deployment performance of various models.

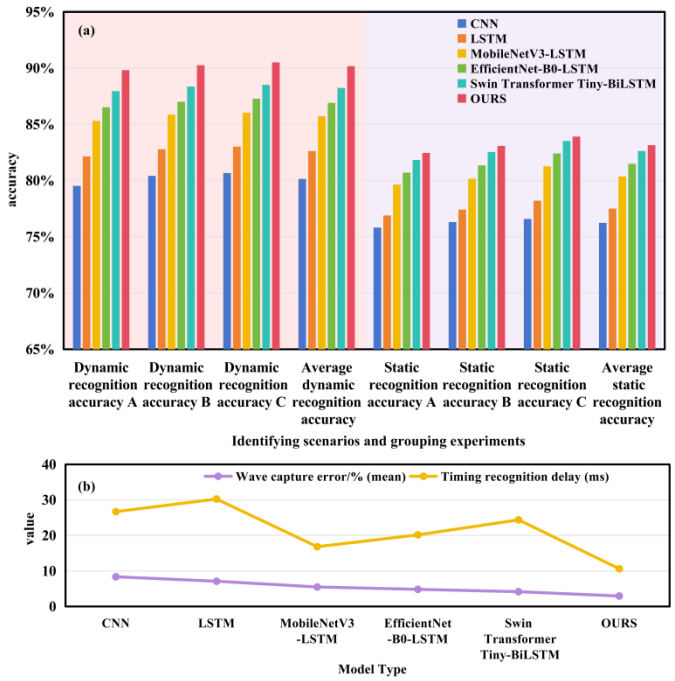


Figure 5. Comparison of dynamic recognition performance of physical fitness.

Model application performance

The comparison of the deployment performance of wearable terminals among various models showed that the average power consumption of proposed model was only 12.19 mA, while the inference delay was 11.83 ms, and the fault free stable operation time was as long as 51.8 h. Pure CNN and pure LSTM models demonstrated high power consumption and weak operation stability, while Swin Transformer class models had a larger number of parameters and computational overhead (Figure 4). The comparison of dynamic recognition performance of physical constitution showed that the average dynamic recognition accuracy of the proposed model was 90.17%. The dynamic recognition

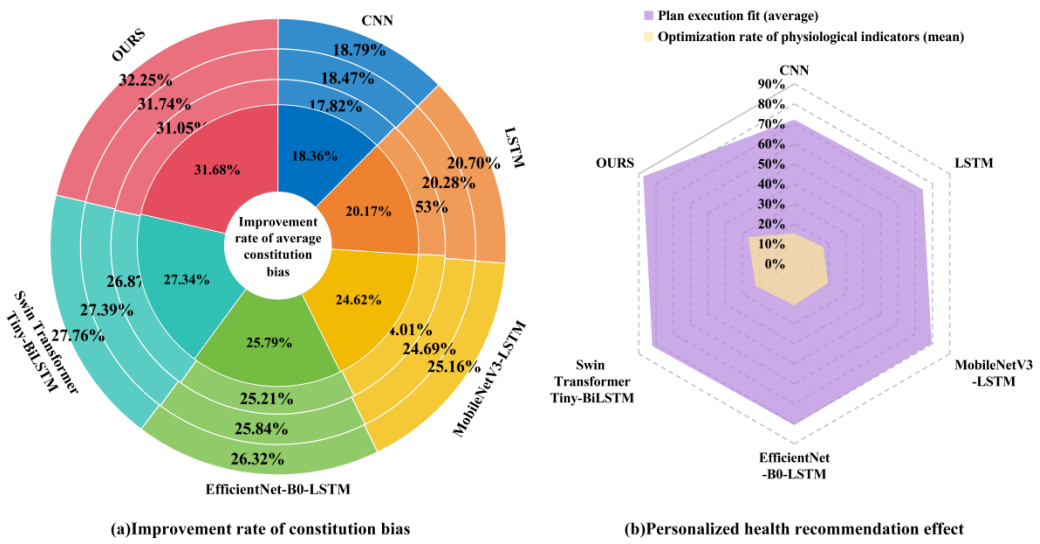


Figure 6. Comparison of health and wellness recommendation effects among various models.

accuracy of all models was significantly higher than that of static questionnaire recognition (Figure 5a). The fluctuation capture error of the proposed model was as low as 2.95%, and the time series recognition delay was only 10.62 ms (Figure 5b). The overall mean of the fit of the plan execution and the optimization rate of physiological indicators was used to evaluate the practicality of the recommendation. The improvement rate of constitution bias in proposed model remained above 31% in three independent intervention experiments with an average improvement rate of 31.68%, significantly higher than that of all comparison models (Figure 6a). The proposed model had a fit rate of 87.42% for the execution of recommended solutions and a physiological index optimization rate of 26.79%, both of which were better than that of all compared models (Figure 6b).

Discussion

Model structure and internal mechanism analysis

The results demonstrated that the proposed MobileNetV2 BiLSTM hybrid network, which adopted a dual layer fusion architecture of MobileNet for spatial feature extraction and BiLSTM for temporal correlation before and after mining, was suitable for collecting time-related physiological data from wearable devices. Compared with a single network, the proposed model could simultaneously consider global static features and long-term dynamic change information, thus significantly improving classification accuracy. The combination of depth-wise separable convolution with model pruning and quantization strategies could significantly reduce redundant calculations, leading to a synchronous decrease in model parameter count, inference latency, and terminal power consumption. This lightweight architecture allowed the model to run continuously for 51.8 hours on low-power devices with a capacity of 12.19 mA, solving the pain points of traditional deep learning models being unable to adapt to wearable hardware computing power and power constraints. The convergence curve showed that convergence could be completed in 48 rounds without oscillation throughout the entire process. The core reason was that the spatiotemporal dual feature fusion mechanism reduced the risk of overfitting model and had stronger robustness to small sample and noisy physiological data. The time series sliding window weighting algorithm

could smooth out the recognition bias caused by single time data collection with a dynamic recognition accuracy of 90.17% and a fluctuation capture error of 2.95%, which proved that continuous time series monitoring could fully capture the long-term evolution law of human physical fitness compared to a single static questionnaire. Health and wellness matching algorithm based on high-precision time series recognition output could adjust the conditioning plan in real time according to the degree of constitution bias. The average bias improvement rate of the three intervention experiments was 31.68%, and the fit of the plan was 87.42%, verifying that the complete closed-loop of time series recognition personalized health and wellness had real home intervention value, while the control model lacked dynamic time series modeling, had insufficient recognition accuracy, and had poor targeted matching of health care plans, resulting in limited intervention effects in the end.

Horizontal comparative analysis with existing similar studies

The current mainstream digital identification solutions for TCM constitution mostly rely on static questionnaires and offline data modeling of tongue images with the accuracy mostly below 85%. Most traditional networks have not been optimized for lightweight, and the parameter count generally exceeds 20M, making it difficult to deploy on wearable terminals. Meanwhile, the inference delay of existing related methods is often higher than 20 ms, and the power consumption is higher than 18 mA, which cannot meet the requirements of long-term continuous monitoring. In addition, most existing related research only focuses on building physical fitness classification algorithms and lacks quantitative verification of the effectiveness of health interventions. This research took 24-hour continuous multidimensional temporal physiological signals as input and built a lightweight spatiotemporal fusion network, which improved the recognition accuracy while significantly reducing the hardware overhead of the model. Power consumption was controlled in proposed model, breaking through the limitations of traditional solutions that cannot perform real-time calculations on the end side and can only perform static evaluations once. At the level of health and wellness intervention, existing similar studies can only achieve a biased improvement level of 20% to 25%, while the average improvement effect of this study reached 31.68%, which was significantly better than existing results. Through synchronous optimization from the three levels of underlying time-series data, lightweight network, and implementation of health and wellness closed-loop, the overall practicality and scene adaptability were stronger, and it was more suitable for the promotion and use of smart TCM health and wellness at home grassroots level. Compared with existing research on offline physical fitness identification, this study used long-term physiological data to achieve dynamic tracking of physical fitness, breaking away from the limitations of traditional static questionnaire single evaluation. Further, this study adopted a lightweight network architecture that balanced the practical constraints of identification accuracy and real-time computing of wearable terminals. Furthermore, the study established a complete "recognition and regulation" health and wellness closed-loop, which could provide new technical ideas for smart TCM health and wellness at home grassroots level.

However, there were still several small-scale constraints in this study. The study only used a single brand of wearable devices to collect physiological signals during the data collection stage, and the differences in hardware sampling accuracy among different manufacturers were not included in the variable control. The length of the temporal sliding window was only fixed with a single parameter, and no multi-window scale ablation experiments had been conducted to compare the optimal values. The health and wellness intervention cycle was uniformly fixed in duration without setting up short-, medium-, and long-term gradient intervention groups to analyze the changes in effectiveness. Therefore, subsequent small-scale control experiments can

be targeted and improved. In addition, there were inherent limitations at the systemic level. The subject sample was collected from a single center with limited sample size. The distribution of nine types of physical fitness samples was uneven, and the proportion of some physical fitness samples such as those with special characteristics was relatively low. The study lacked hierarchical data sets of chronic diseases such as diabetes and cardiovascular and cerebrovascular diseases, and the impact of various interferences on the model under complex home environment still needs further systematic verification. Future research should include multi-center sample collection and expansion of stratified datasets for chronic diseases. The model's robustness modules need optimization, targeted health management programs should be iteratively developed, and the model size needs further compression. Furthermore, the algorithm should be integrated with wearable devices and mini-programs to improve the system's clinical adaptability and practical application value.

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