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Temporal-Aware and Memory Fusion-Based Non-Invasive Continuous Blood Pressure Prediction

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Abstract: *Aiming at the intermittent measurement limitations of traditional blood pressure monitoring methods and the insufficient feature fusion in existing deep learning models, this study proposes a hybrid model integrating Temporal Convolutional Network and Bidirectional Gated Recurrent Unit. The model captures multi-scale spatial features from photoplethysmography waveforms through TCN's dilated convolutions, models long-term hemodynamic temporal dependencies using BiGRU's bidirectional gating mechanism, and incorporates an attention mechanism for dynamic spatiotemporal feature fusion. Clinical dataset validation demonstrates that the model achieves MAE metrics of 2.59 mmHg and 3.32 mmHg for systolic and diastolic blood pressure prediction respectively, showing significant advantages over traditional machine learning methods and single deep learning models. This framework enables continuous blood pressure estimation with medical-grade accuracy while maintaining computational efficiency through synergistic learning of local waveform characteristics and global temporal patterns.*

Keywords: *Temporal Convolutional Network, Gated Recurrent Unit, Blood Pressure Prediction, Photoplethysmography Signals*

1. Introduction

Cardiovascular disease remains a major global health threat, with hypertension being a key predisposing factor. Studies reveal that many hypertensive individuals are undiagnosed, leading to preventable complications and delayed interventions. Traditional blood pressure monitoring methods are categorized as invasive or non-invasive [1]. Invasive techniques provide accurate real-time measurements but are clinically restricted to critical care due to operational complexity [2]. Recent advancements focus on deep learning for noninvasive continuous monitoring. Yen et al. [3] proposed a multi-scale CNN-LSTM hybrid model using filtered MIMIC II data, improving BP/HR estimation accuracy. Ma et al. [4] integrated ECG and PPG features via CNN, quantitatively analyzing waveform contributions to error reduction through activation visualization. Li et al. [5] enhanced LSTM stability with residual connections, significantly reducing MAE and RMSE in comparative trials.

Despite progress, challenges persist in model robustness and generalization. While SVM [6] and SVR [7] models achieved moderate accuracy, limitations in population diversity and feature depth hinder clinical applicability. Current machine learning approaches require further refinement to address these constraints.

Building upon the aforementioned research foundation, this study proposes a hybrid blood pressure prediction model integrating Temporal Convolutional Networkand Gated Recurrent Unit. This architecture achieves feature extraction from long-term Photoplethysmography sequences through temporal awareness and memory fusion mechanisms. The model employs dilated convolutions in TCN to capture local spatial features and leverages GRU's gating mechanism to model long-term dependencies within temporal sequences. Compared to conventional models, this framework demonstrates enhanced capability to discern comprehensive and nuanced features in PPG signals during blood pressure data processing, thereby yielding precise and reliable blood pressure prediction results.

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2. Non-invasive Continuous Blood Pressure Prediction

Photoplethysmography (PPG) enables noninvasive continuous blood pressure monitoring by capturing pulsatile blood volume changes in peripheral arteries (e.g., fingers/wrists) through photoelectric sensors [8]. During cardiac cycles, arterial volume fluctuations alter blood's light absorption, which PPG converts into waveform signals via optical-electrical transduction. Critical morphological features and pulse transit time extracted from PPG waveforms encode hemodynamic patterns correlated with blood pressure. Deep learning models leverage these spatiotemporal features to establish robust PPG-BP mapping, achieving cuffless continuous estimation through integrated signal processing and hierarchical feature learning.

3. Conventional Approaches

Traditional cuff-based methods like oscillometry [9] and Korotkoff auscultation [10] dominate blood pressure monitoring. Oscillometry detects cuff pressure oscillations via sensors, offering simplicity and speed, while Korotkoff auscultation identifies SBP/DBP through vascular sound analysis with higher accuracy. However, both provide only intermittent readings, failing to track dynamic BP fluctuations. To enable continuous prediction, classical machine learning approaches [11] extracted time-domain PPG features but achieved limited accuracy. Deep learning advances address these limitations through hierarchical feature fusion. ANN-LSTM hybrids [12] combined morphological and temporal waveform analysis, outperforming traditional models, yet faced generalization constraints. Transfer learning frameworks integrating GRU-CNN architectures [13] further improved accuracy via pretraining on large clinical datasets, demonstrating the potential of adaptive spatiotemporal modeling for continuous BP estimation.

4. Methods

4.1 Spatial Feature Extraction

The TCN, a specialized variant of CNN, effectively addresses sequential modeling tasks through causal convolutional operations [14]. Unlike conventional RNNs, TCNs—as illustrated in Figure.1.—enable parallel computation, significantly enhancing computational efficiency and excelling in long-sequence processing through their superior capability to capture long-range dependencies.

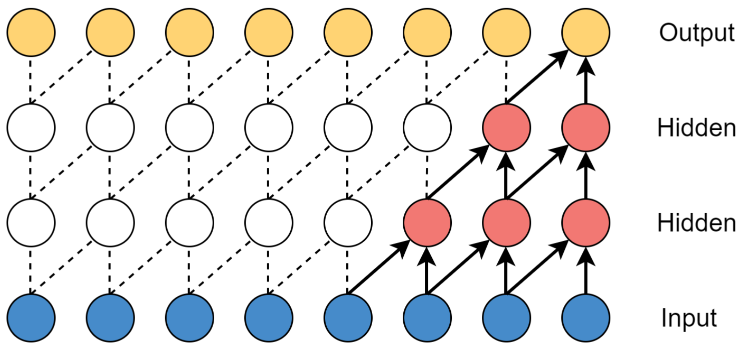

Figure 1 Temporal convolution process

Researchers have introduced dilated convolution, a technique that expands the receptive field by interleaving dilation gaps between kernel elements. This spatial sparsity enables explicit control over input sampling intervals, thereby empowering the model to capture long-range dependencies in sequential data with extended time-span correlations. The mathematical formulation of dilated convolution is expressed as:

$$y[t]=\sum_{k=0}^{K-1} w\,[k]\cdot x[t-d\cdot k] \tag{1}$$

Where d denotes the dilation rate. By adjusting d, we can dynamically control the receptive field dimensions to accommodate diverse sequential data patterns and task requirements. Through the utilization of convolution layers and dilated convolutions, TCN can effectively extract localized spatial

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features from PPG signal windows.

4.2 Temporal Feature Extraction

The Gated Recurrent Unit (GRU) [15] addresses gradient vanishing/explosion and computational inefficiency in traditional RNNs through streamlined gating mechanisms. Unlike standard RNNs constrained by sequential backpropagation and information overload, GRU builds on LSTM's "forgetting mechanism" by merging gates into a unified update-reset architecture. This simplification reduces parameters while retaining temporal modeling capacity, enabling faster convergence and prioritized feature learning in long sequences.

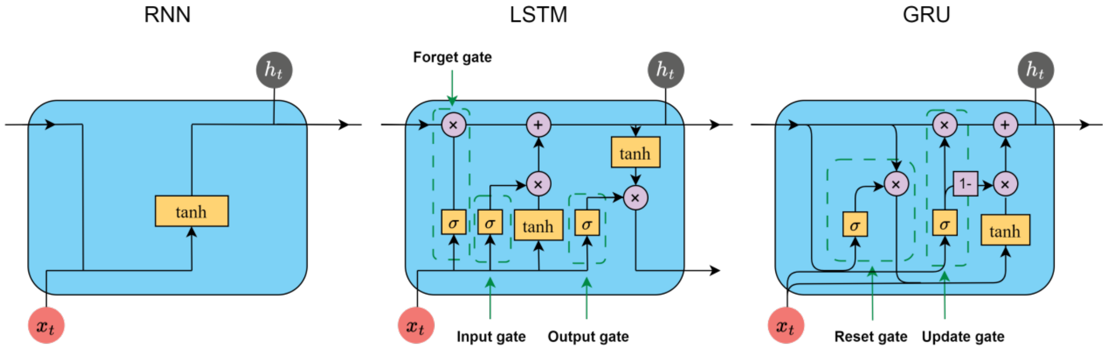

Figure 2 Structure diagram of RNN, LSTM, and GRU

As illustrated in Figure 2 through comparative architectural visualization, GRU significantly streamlines the gating units compared to LSTM to enhance predictive efficiency. The GRU architecture employs two essential gates:

(1) Reset Gate r_t The mathematical formulation is:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{2}$$

Let W_r denote the weight matrix of the reset gate, which constitutes a set of learnable parameters whose dimensionality is determined by the concatenated dimensions of the input vector x_t and hidden state h_{t-1}. The candidate hidden state $\tilde{h}_t$ is derived through the reset gate operation as:

$$\tilde{h}_t = \tanh(W \cdot [r_t \cdot h_{t-1}, x_t] + b) \tag{3}$$

(2) Update Gate z_t The governing equation is:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{4}$$

Let W_z represent the update gate's weight matrix — analogous to W_r in the reset gate — whose dimensionality is jointly determined by the input vector x_t and preceding hidden state h_{t-1}. The resultant current hidden state h_t is computed through adaptive blending:

$$h_t = z_t \cdot h_{t-1} + (1 - z_t) \cdot \tilde{h}_t \tag{5}$$

In blood pressure prediction, GRU's recurrent architecture excels at processing prolonged PPG sequences by autonomously extracting temporal features. Its update and reset gates dynamically regulate information flow, prioritizing relevant historical patterns and current signal characteristics. The hidden states act as adaptive memory units, preserving critical PPG temporal signatures through continuous refinement via gate-controlled mechanisms, ensuring vital hemodynamic information retention during sequence analysis.

4.3 Model Architecture

Based on the theoretical analysis of TCN and GRU, this study employs TCN for spatial modeling and BiGRU for temporal modeling. By integrating the dual advantages of spatial and temporal feature

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extraction, we have developed a combined TCN-GRU model for non-invasive blood pressure prediction. The overall architecture of the model is illustrated in Figure. 3.

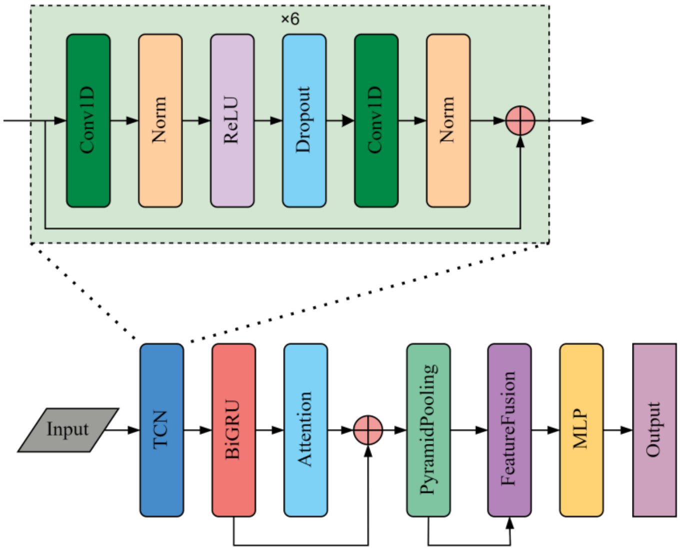

Figure 3 General framework of the model

The proposed TCN-BiGRU model combines temporal convolutional networks and bidirectional gated units for blood pressure prediction. TCN employs dilated 1D convolutions (kernel=3, stride=1) with residual connections and ReLU activation to extract hierarchical spatiotemporal features from 2100-length PPG sequences, while layer normalization and 20% dropout ensure stable training. Simultaneously, BiGRU processes these features through reset/update gates, adaptively fusing historical and current states to model long-term hemodynamic dependencies. Attention mechanisms dynamically weight salient temporal patterns, with fused features projected through fully-connected layers for final BP estimation. This architecture synergizes TCN's localized waveform analysis with BiGRU's context-aware temporal modeling, achieving efficient multi-scale fusion without compromising physiological interpretability. The governing equations are as follows:

$$Attention(Q,K,V) = softmax\left(\frac{Q \cdot K^T}{\sqrt{d_k}}\right) \cdot V \tag{6}$$

The lengthy feature sequence is subsequently compressed into a fixed dimensionality through adaptive average pooling, as formalized in Equation (7), where the dimension parameter k governs the feature reduction to 16 dimensions. This operation preserves temporal characteristics across multiple granularities while achieving dimensional compaction.

$$P^{(k)} = \frac{1}{\lfloor T/k \rfloor} \sum_{i=1}^{\lfloor T/k \rfloor} C_{(i-1)l:ik} \tag{7}$$

The hierarchically extracted features are concatenated to achieve complementary integration of global characteristics and local patterns, with the final prediction accomplished through a two-layer fully connected network. The synergistic integration of TCN and BiGRU enables the model to concurrently capture localized spatial features and process long-range temporal dependencies, significantly enhancing blood pressure estimation accuracy in our application.

5. Experiment and analysis

5.1 Experimental Datasets

This study utilizes the Guilin Hospital dataset [16], containing 657 PPG segments from 219 adults, each providing three consecutive 2.1-second recordings. Demographic and physiological parameters were included. Preprocessing removed non-numerical identifiers and standardized input dimensions by truncating sequences exceeding 2,100 samples. Spatial-temporal features were extracted via TCN's

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dilated convolutions (spatial) and BiGRU's bidirectional processing (temporal), with final BP estimates generated through multimodal feature fusion. The comprehensive data processing workflow is formally illustrated in Figure.4.

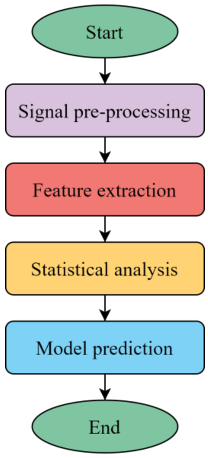
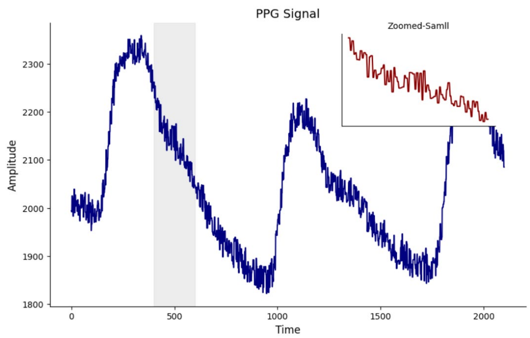
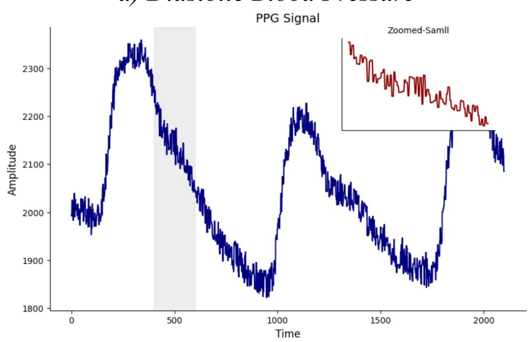


Figure 4 Flow chart of data reading and selection



a) Diastolic Blood Pressure



b) Systolic Blood Pressure

Figure 5 Visualizes the waveform

This study chronologically visualizes waveform segments from individual subjects, as shown in Figure 5. The results demonstrate distinct data periodicity, complete morphological integrity of waveforms, and effective noise reduction, confirming the success of preprocessing steps.

5.2 Experimental setup

This experiment was conducted based on the PyTorch deep learning framework. The dataset was partitioned into training and test sets in a 7:3 ratio, with a batch size of 32 and 50 training epochs. The Adam gradient descent method was employed with an initial learning rate $\alpha=0.001$. The Adam optimizer can adaptively adjust the learning rate during training to facilitate faster and more stable model convergence. The model's loss function was Mean Absolute Error (MAE), and the final evaluation metrics used to assess the model performance were MAE and Root Mean Squared Error (RMSE).

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5.3 Evaluation Metrics

In this study, both MAE and Root RMSE were employed as evaluation metrics. The MAE formula is expressed as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{8}$$

The other metric, RMSE, is formulated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{9}$$

The combined use of MAE and RMSE enables comprehensive assessment: MAE reflects average error magnitude while RMSE emphasizes the influence of larger errors. This dual-metric approach provides critical references for model refinement during training and ensures thorough evaluation of blood pressure prediction performance through complementary error analyses.

5.4 Experimental result

Table 1 Experimental Results

Algorithm	Experimental Results	
	Systolic Blood Pressure	Diastolic Blood Pressure
MLP	MAE: 38.6283 RMSE: 6.2152	MAE: 20.7500 RMSE: 4.5552
Random Forest	MAE: 15.6360 RMSE: 3.9542	MAE: 8.4590 RMSE: 2.9084
RNN	MAE: 26.1193 RMSE: 5.1107	MAE: 8.8128 RMSE: 2.9686
LSTM	MAE: 44.0318 RMSE: 6.6356	MAE: 8.8688 RMSE: 2.9781
GRU	MAE: 23.9240 RMSE: 4.8912	MAE: 8.8535 RMSE: 2.9755
TCN	MAE: 50.7840 RMSE: 7.1263	MAE: 25.1062 RMSE: 5.0106
Transformer	MAE: 38.1419 RMSE: 6.1759	MAE: 8.6347 RMSE: 2.9385
TCN+GRU	MAE: 2.5881 RMSE: 6.1862	MAE: 3.3208 RMSE: 7.7975

As shown in Table 1, TCN+GRU achieves the lowest MAE (2.5881) and RMSE (6.1862) for systolic blood pressure (SBP) prediction, reducing MAE by 89.2% and 93.2% compared to standalone GRU (23.9240) and Transformer (38.1419), respectively, while being the only model to achieve an RMSE below 6.2. For diastolic blood pressure (DBP), TCN+GRU maintains dominance with MAE=3.3208 and RMSE=7.7975, reducing DBP MAE by 61.5% compared to the second-best Transformer (8.6347) and delivering the sole RMSE under 8.0. These results confirm TCN+GRU's complementary strengths in long-sequence feature extraction (TCN) and temporal dynamics modeling (GRU), surpassing conventional approaches.

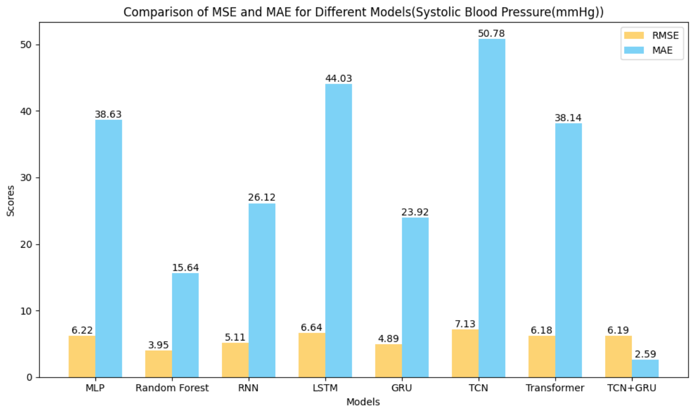

Figure 6 Systolic blood pressure visualization results

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The visual comparisons of MAE and RMSE values for systolic blood pressure prediction across multiple models are shown in Figure 6. Experimental results demonstrate that the TCN+GRU model achieves significantly superior performance in SBP prediction, obtaining the lowest error metrics among all comparative models with an MSE of 6.19 and MAE of 2.59. These findings confirm the TCN+GRU architecture's optimal capability in balancing prediction accuracy with effective error minimization.

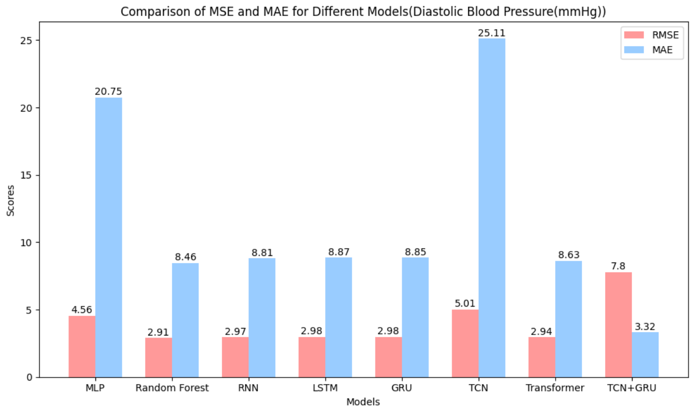

Figure 7 Diastolic blood pressure visualization results

The visual comparisons of MAE and RMSE values for diastolic blood pressure prediction across multiple models are shown in Figure 7. The experimental results demonstrate that the GRU+TCN architecture achieves optimal performance in DBP prediction, attaining an RMSE of 7.8 and MAE of 3.32. These metrics are significantly lower than those of the baseline TCN model (RMSE 25.11) and represent the smallest composite errors in cross-model evaluation. This substantiates the structural efficacy of GRU+TCN in temporal feature integration, enabling more precise capturing of intricate patterns in diastolic pressure fluctuations while maintaining robust error suppression capabilities.

5.5 Result analysis

This study validates the TCN+GRU hybrid model's superiority in noninvasive blood pressure prediction, achieving significantly lower MAE/RMSE for SBP and DBP compared to conventional methods. While shallow architectures like MLP fail to capture PPG's spatiotemporal complexity, TCN leverages dilated convolutions and residual connections to extract localized spatial features, while GRU's gated mechanisms model long-term hemodynamic dependencies. Integrated through attention-augmented feature fusion, the framework synergizes TCN's spatial sensitivity with GRU's temporal awareness, addressing standalone models' limitations. The architecture's hierarchical spatiotemporal learning enables precise BP estimation, demonstrating deep learning's advantage in decoding PPG signal intricacies.

6. Conclusion

This study demonstrates the TCN+GRU hybrid model's superior accuracy in noninvasive continuous blood pressure prediction, outperforming conventional methods and standalone models by effectively processing PPG spatiotemporal features through integrated spatial-temporal learning. While enhancing computational efficiency, challenges persist in large-scale processing and cross-population generalization. Future work will prioritize: 1) architectural optimization for reduced complexity, 2) multimodal physiological signal fusion, and 3) transfer learning frameworks for clinical adaptability. These strategies aim to strengthen robustness and accelerate clinical translation of cuffless BP monitoring systems.

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