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Physiological Time Series Prediction via Multivariate State Graphs

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Time Series · Multivariate Forecasting · State Graph · Graph Neural Network · Physiological AI

Core idea: Physiological variables exhibit state-dependent, dynamically evolving correlations that static graph architectures cannot capture. We fuse multi-scale temporal CNN features with a time-varying attention graph conditioned on latent physiological state, then pass the aggregated representations through an LSTM for multi-step forecasting. Evaluated on PhysioNet 2012 ICU data, our model achieves state-of-the-art RMSE and superior training stability across 10 independent runs.

01 · MOTIVATION

Why static graph fail

1.ICU variables (HR,BP, SpO_2...) are dynamically coupled

2.CNNs & LSTMs ignore inter-variable structure entirely

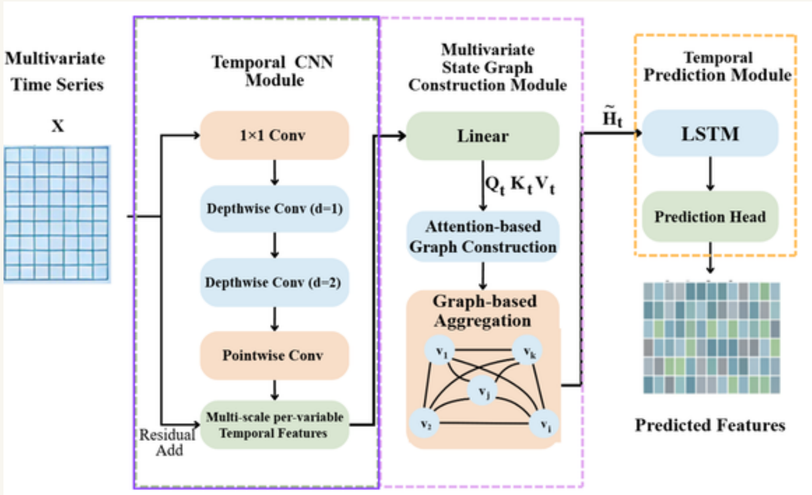
3.Existing graph methods use fixed adjacency matrices or global statistics

4.We need a graph that reconstructs itself at every time step

GAP WE ADDRESS

No priorworkconditions variable relationships on *instantaneous latent state* for physiological ICU data.

02 · MODEL ARCHITECTURE



03 · TEMPORAL CNN

Multi-scale dilaton

Dilated convolution expands receptive field without adding parameters:

$$y(t) = \Sigma_k x(t + d\cdot(k-1)) \cdot w(k)$$

d = dilation rate; k indexes kernel weights

1. **1×1conv** — projectto higher dim
2. **Depthwise sep. conv** d=1 (short-range) and d=2 (medium-range)
3. **Pointwise fusion** + residual + BatchNorm

04 · STATE GRAPH CONSTRUCTION

Attention-based dynamic adjacency

Variable embeddings $H_t \in \mathbb{R}^{N\times d}$ feed a self-attention mechanism:

$$A_t = \mathrm{softmax}_{row}(Q_t K_t^T / \sqrt{d_k})$$

$Q_t = H_tWQ$, $K_t = H_tWK$ — learnable projections

$$\tilde{H}_t = A_t(H_t W_v)$$

Cross-variable aggregation; $W_v \in \mathbb{R}^{d\times d_k}$

✓ Fully reconstructed at each time step — no predefined graph structure needed

05 · LSTM INTEGRATION

Temporal memory & decoding

Receives both CNN temporal features and graph-aggregated inter-variable context

→Gating mechanisms capture long-range dependencies over the full 18-step window

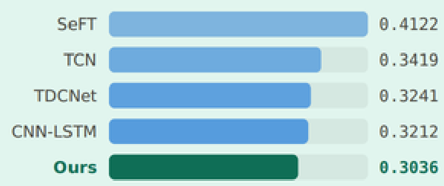
→Only the final hidden state is extracted

→FC head decodes multi-step predictions from this single vector

Input: 18 × (N variables) → LSTM → FC → 3-step forecast

06 · Results

Our model achieves lowest RMSE with competitive stability



MODEL	RMSE MEAN	RMSE STD
SeFT	0.4122	0.0160
TCN	0.3419	0.0171
TDCNet	0.3241	0.0163
CNN-LSTM	0.3212	0.0157
Our Model ★	**0.3036**	**0.0177**

−5.5% RMSE vs CNN-LSTM

−26% RMSE vs SeFT

08 · CONCLUSION
Key takeaways

07 · Conclusion

1.Explicit dynamic inter-variable graphs outperform static or attention-only baselines on physiological ICU data.

2.Multi-scale dilated CNN effectively separates temporal feature extraction from relational modeling.

3.LSTM final hidden state provides a compact sequence summary for reliable multi-step decoding.

08 · References

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