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## Hybrid Neural Network Models for Time-Series Biomedical Signal Forecasting

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## Abstract

Biomedical signals such as ECG, EEG, and respiratory waveforms are highly nonlinear and temporally dependent, making accurate forecasting difficult. This work introduces a Hybrid Neural Network(HNN) integrating multi-level signal decomposition, deep temporal modeling, and neuromorphic dynamics for biomedical time-series prediction. The framework combines Empirical Mode Decomposition(EMD) for adaptive denoising, a CNN-LSTM attention module for temporal feature learning, and a fine-tuned Liquid Neural Network(LNN) for time dependent forecasting. Bayesian Optimization and self-supervised cross signal pretraining further enhance model performance. Experiments on MIT-BIH Arrhythmia and MIMIC-IV waveform datasets demonstrate that HNN outperforms CNN, LSTM, and Transformer baselines in RMSE and $R^2$, while retaining interpretability via attention maps. Findings highlight HNN as a generalized and efficient solution for biomedical signal forecasting and real-time clinical decision support.


## Tables

TABLE I
ECG forecasting (MIT-BIH). Mean ± std over 5 runs.

| Method | RMSE ↓ | MAE ↓ | $\mathbf{R^2}$ ↑ | Corr ↑ |
|---|---|---|---|---|
| CNN | 0.123 | 0.088 | 0.842 | 0.909 |
| LSTM | 0.120 | 0.084 | 0.859 | 0.917 |
| EMD+CNN–LSTM | 0.112 | 0.08 | 0.881 | 0.931 |
| HNN | 0.097 | 0.072 | 0.911 | 0.950 |

TABLE II
Multimodal Forecasting (MIMIC-IV)

| Method | RMSE↓ | MAE↓ | $R^2$↑ |
|---|---|---|---|
| CNN | 0.168±0.006 | 0.124±0.005 | 0.802±0.012 |
| LSTM | 0.161±0.004 | 0.118±0.004 | 0.826±0.011 |
| Transformer | 0.157±0.005 | 0.116±0.004 | 0.835±0.010 |
| Graph-ARNN | 0.149±0.003 | 0.109±0.003 | 0.847±0.009 |
| EMD+CNN–LSTM | 0.152±0.004 | 0.111±0.004 | 0.849±0.008 |
| HNN (ours) | 0.137±0.003 | 0.101±0.003 | 0.882±0.008 |

## Methods/Results

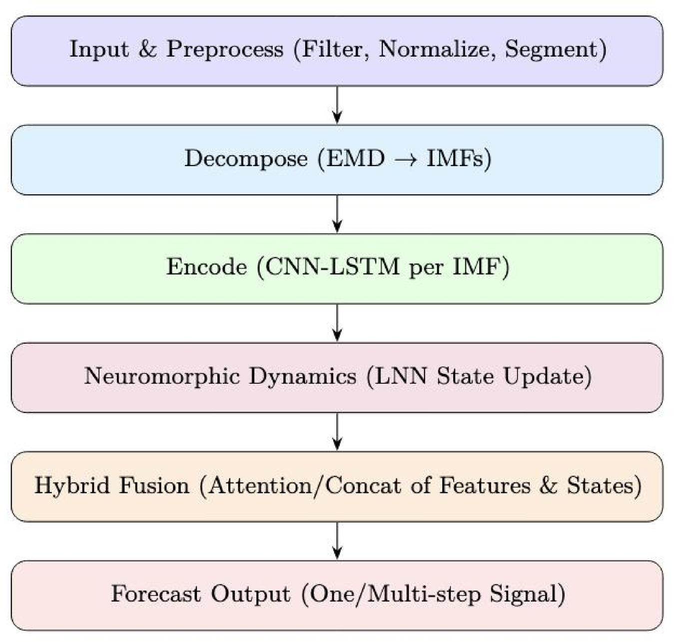
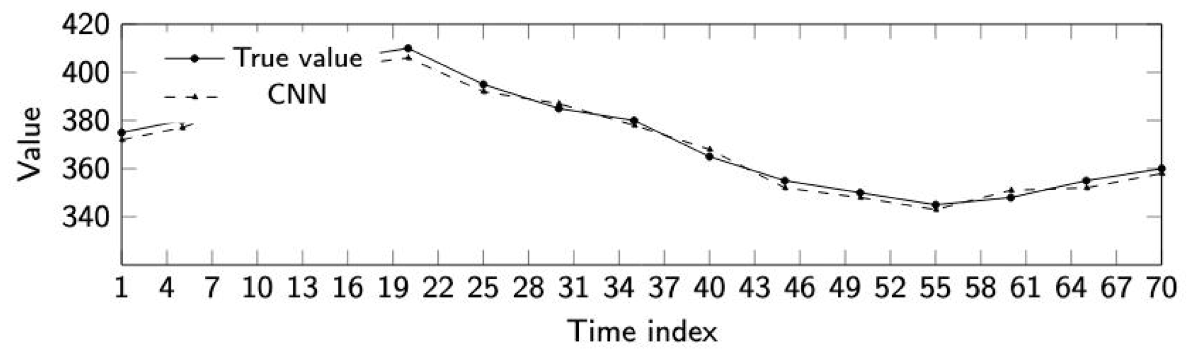



Fig. 1. Hybrid Neural Network Workflow

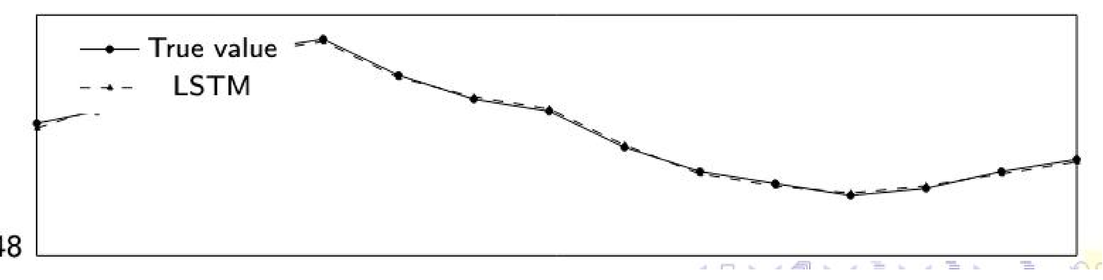
## Figures

The figure presents two centrally aligned illustrations comparing deep-learning models for ECG signal prediction.
In subfigure (a), the convolutional neural network (CNN) demonstrates its capability to approximate the true ECG values across time indices, showing a close overlap between predicted and actual signals.
Subfigure (b) depicts the performance of the long short-term memory (LSTM) model, which similarly tracks the temporal variations of the ECG waveform with high fidelity.
Both illustrations remain within the designated typing area and are placed near their initial reference point in the text. Captions are omitted according to the formatting guideline, though each subfigure is clearly labeled for ease of interpretation.

[b]0.48
(a) CNN prediction of ECG




(b) LSTM prediction of ECG




[b]0.48

## Conclusions

This paper introduced a HNN for biomedical time-series forecasting that integrates EMD-based decomposition, CNN–LSTM temporal encoding, and a lightweight LNN forecaster within a unified framework. The combination effectively reduces non-stationarity and captures both morphological and physiological dynamics. Experiments on MIT-BIH and MIMIC-IV datasets show that HNN surpasses standard deep learning baselines in RMSE, MAE, and $R^2$ for both single and multi-step prediction. Ablation studies confirm the complementary contributions of EMD, LNN, and attention fusion, while cross modality tests demonstrate strong generalization under varying noise and sampling conditions.