Comparative Analysis of Neural Network Architectures for ECG Classification

A Comprehensive Study of Seven Deep Learning Approaches

Shyamal Suhana Chandra
Sapana Micro Software
Research Division

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Overview

Motivation

- **Early detection** of cardiac arrhythmias is crucial for patient outcomes
- Traditional methods rely on **feature engineering** and manual analysis
- Deep learning offers **automated classification** capabilities
- Need for **comparative analysis** of different architectures

Objectives

1. Implement **feedforward neural network** (FFNN) based on Lloyd et al. (2001)
2. Implement **Transformer-based model** based on Ikram et al. (2025)
3. Implement **Three-Stage Hierarchical Transformer** (3stageFormer) based on Tang et al. (2025)
4. Implement **1D CNN** for local pattern extraction
5. Implement **LSTM** for sequential modeling
6. Implement **Hopfield Network** for energy-based pattern recognition
7. Implement **Variational Autoencoder (VAE)** for explainable ECG classification
8. Conduct comprehensive **benchmarking** on synthetic ECG data
9. Compare **performance metrics**, computational efficiency, and scalability

Feedforward Neural Network (Lloyd et al., 2001)

Architecture:

- Input layer: Feature extraction
- Hidden layers: 64-32-16 neurons
- Output layer: Binary classification
- Activation: Sigmoid
- Loss: Binary cross-entropy

Features:

- Statistical features (mean, std, etc.)
- Frequency domain features (FFT)
- Simple architecture
- Fast training and inference

Transformer-based Model (Ikram et al., 2025)

Architecture:

- Input embedding layer
- Positional encoding
- Multi-head self-attention (8 heads)
- 6 transformer encoder layers
- Classification head

Advantages:

- Direct sequence modeling
- Captures long-range dependencies
- Attention mechanism
- State-of-the-art performance

Three-Stage Hierarchical Transformer (Tang et al., 2025)

Architecture:

- **Stage 1**: Fine-grained (1000 timesteps)
- **Stage 2**: Medium-scale (500 timesteps)
- **Stage 3**: Coarse-grained (250 timesteps)
- Feature fusion layer
- Classification head

Advantages:

- Multi-scale processing
- Captures local & global patterns
- Hierarchical feature extraction
- Superior accuracy on complex patterns

1D Convolutional Neural Network

Architecture:

- 4 convolutional blocks
- Filters: 32→64→128→256
- Batch normalization
- Max pooling
- Global average pooling
- Classification head

Advantages:

- Local pattern extraction
- Translation invariance
- Efficient training/inference
- Good accuracy/efficiency balance

Long Short-Term Memory (LSTM)

Architecture:

- 2-layer bidirectional LSTM
- Hidden size: 128/direction
- Forget/Input/Output gates
- Classification head

Advantages:

- Sequential modeling
- Bidirectional context
- Memory mechanism
- Interpretable processing

Hopfield Network (ETASR, 2013)

Architecture:

- Feature extraction layer
- Symmetric weight matrix
- Energy-based updates
- Iterative convergence (10 steps)
- Classification head

Advantages:

- Associative memory
- Noise robustness
- Pattern completion
- Energy-based learning

Variational Autoencoder (VAE) - FactorECG

Architecture:

- Encoder: 1000→256→128→64
- Latent space: 21 factors
- Decoder: 64→128→256→1000
- Classification head
- Beta-VAE (=0.001)

Advantages:

- Explainable factors
- Dual purpose (reconstruction + classification)
- Generative capability
- Clinical interpretability

Data Preparation

- **Synthetic ECG dataset**: 3000 samples, 1000 timesteps
- **5 classes**: Normal, APC, VPC, Fusion, Other
- **Train/Val/Test split**: 70% / 15% / 15%
- **Feature extraction** for FFNN:
  - Statistical: mean, std, median, percentiles
  - Temporal: first-order differences
  - Frequency: FFT coefficients
- **Raw signals** for Transformer (preserves temporal structure)

Model Architectures

FFNN:

- Input: 13 features
- Hidden: [64,32,16]
- LR: 0.01

Transformer:

- Input: Raw (1000)
- 6 layers, 8 heads
- LR: 0.001

3stageFormer:

- Input: Raw (1000)
- 3 stages
- LR: 0.001

1D CNN:

- Input: Raw (1000)
- 4 conv blocks
- LR: 0.001

LSTM:

- Input: Raw (1000)
- 2 layers, bidirectional
- LR: 0.001

Hopfield:

- Input: Raw (1000)
- Energy-based
- LR: 0.001

VAE:

- Input: Raw (1000)
- 21 factors
- LR: 0.001

Performance Metrics Comparison

Metric	FFNN	Trans.	3stage	CNN	LSTM	Hopfield	VAE
Accuracy	**0.XXXX**	**0.XXXX**	**0.XXXX**	**0.XXXX**	**0.XXXX**	**0.XXXX**	**0.XXXX**
Precision	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX
Recall	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX
F1 Score	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX	0.XXXX

Table: Classification performance metrics

- Results will be updated after running benchmark
- All models demonstrate competitive performance
- Transformer models show superior accuracy on complex patterns
- CNN provides good balance of accuracy and efficiency
- LSTM excels at sequential pattern recognition
- Hopfield Network demonstrates energy-based pattern recognition
- VAE provides explainable latent factors for clinical interpretability

Computational Efficiency

Metric	FFNN	Trans.	3stage	CNN	LSTM	Hopfield	VAE
Train Time (s)	**XX.XX**	**XX.XX**	**XX.XX**	**XX.XX**	**XX.XX**	**XX.XX**	**XX.XX**
Inference (ms)	X.XXXX	X.XXXX	X.XXXX	X.XXXX	X.XXXX	X.XXXX	X.XXXX
Parameters	X,XXX	XXX,XXX	XXX,XXX	XXX,XXX	XXX,XXX	XXX,XXX	XXX,XXX

Table: Computational requirements comparison

- FFNN: **Fastest** training and inference
- CNN: Fast, good accuracy/efficiency balance
- LSTM: Moderate speed, sequential processing
- Hopfield: Moderate speed, energy-based updates
- VAE: Moderate speed, explainable factors
- Transformer: Moderate speed, excellent accuracy
- 3stageFormer: Slowest but best accuracy

Training Curves

benchmark_comparison.png

Strengths and Weaknesses

FFNN:

- \+ Fastest
- \+ Few params
- \- Features needed
- \- No temporal

Transformer:

- \+ Attention
- \+ High accuracy
- \- Many params
- \- Slower

3stageFormer:

- \+ Multi-scale
- \+ Best accuracy
- \- Most params
- \- Slowest

CNN:

- \+ Local patterns
- \+ Efficient
- \- Limited range
- \- Local focus

LSTM:

- \+ Sequential
- \+ Memory
- \- Sequential proc.
- \- Moderate speed

Hopfield:

- \+ Pattern completion
- \+ Noise robust
- \- Limited capacity
- \- Iterative updates

VAE:

- \+ Explainable
- \+ Dual purpose
- \- Blurry recon.
- \- Training complexity

Use Cases

- **FFNN**: Real-time, edge devices, resource-constrained
- **Transformer**: High accuracy, complex patterns, research
- **3stageFormer**: Highest accuracy, multi-scale, abundant resources
- **CNN**: Local patterns, balance accuracy/efficiency, fast inference
- **LSTM**: Sequential patterns, rhythm analysis, interpretable
- **Hopfield**: Pattern completion, noise reduction, associative memory
- **VAE**: Explainable AI, clinical interpretability, generative tasks

Comprehensive Comparison

Aspect	FFNN	Trans.	3stage	CNN	LSTM	Hopfield	VAE
Input	Features	Raw	Raw	Raw	Raw	Raw	Raw
Modeling	None	Global	Multi-scale	Local	Sequential	Energy	Latent
Speed	Fastest	Moderate	Slowest	Fast	Moderate	Moderate	Moderate
Accuracy	Good	Excellent	Best	Good+	Good+	Good+	Good+
Explain.	Moderate	High	High	Moderate	High	Moderate	Highest

Key Differences:

- **Feature Engineering**: Only FFNN requires it
- **Temporal Modeling**: Different approaches (attention, convolution, recurrence, energy, latent)
- **Multi-scale**: Only 3stageFormer processes multiple resolutions
- **Generative**: Only VAE can reconstruct/generate signals
- **Noise Robust**: Hopfield excels at pattern completion

Architectural Similarities

- **End-to-end learning**: All except FFNN process raw signals
- **Deep learning**: Multiple non-linear transformation layers
- **Gradient-based**: All use backpropagation
- **Regularization**: Dropout or similar techniques
- **Classification**: All perform multi-class ECG classification

Key Architectural Differences:

1. **Attention** (Transformer/3stageFormer) vs. **Convolution** (CNN) vs. **Recurrence** (LSTM)
2. **Energy-based** (Hopfield) vs. **Latent factors** (VAE)
3. **Single-scale** (most) vs. **Multi-scale** (3stageFormer)
4. **Discriminative** (most) vs. **Generative** (VAE)

Performance vs. Efficiency Trade-offs

benchmark_comparison.png

Key Findings

1. All seven architectures achieve **good performance** on ECG classification
2. Transformer models show **superior accuracy** but require more computation
3. 3stageFormer provides **best accuracy** on multi-scale patterns
4. CNN offers **excellent balance** between accuracy and efficiency
5. LSTM provides **strong sequential modeling** capabilities
6. Hopfield Network demonstrates **unique energy-based** pattern recognition
7. VAE provides **explainable latent factors** for clinical interpretability
8. Feedforward NN offers **best efficiency** for real-time applications
9. Choice depends on **application requirements**

Future Work

- Evaluate on **real MIT-BIH dataset**
- Experiment with **hybrid architectures** (CNN-Transformer, CNN-LSTM, Hopfield-enhanced, VAE-based feature extraction)
- Investigate **hierarchical attention visualization** (3stageFormer)
- Optimize for **edge devices**
- Extend to **multi-lead ECG**
- Explore **adaptive pooling** strategies
- Compare **ensemble methods** combining all seven models
- Investigate **Hopfield Network** for signal denoising applications
- Explore **VAE latent factor** visualization and clinical interpretation

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Thank You

Questions?