qHuBERT: Quantized Model for ECG Classification

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Abstract

Foundation models for biosignals, such as wearable ECG monitors, face challenges in resource-constrained settings due to high memory and computational demands. In this work, we propose an adaptive layer-wise compression framework that leverages quantization to reduce model size while preserving predictive performance. Layer importance, estimated via parameter contribution and weight variance, guides fine-grained assignment of bit-widths, balancing efficiency and accuracy across high- and low-sensitivity layers. Extensive experiments on Chapman and CPSC ECG datasets demonstrate that our method consistently outperforms fixed global model compression schemes, achieving up to $10.44\times$ compression without any loss. Our architecture-agnostic framework scales to both lightweight residual networks and large foundation models, enabling real-time, low-resource ECG monitoring and advancing scalable biosignal AI for edge and mobile health applications.

1 Introduction and Related Work

Electrocardiography (ECG) is a cornerstone of cardiac health assessment, capturing the heart's electrical activity through body-surface electrodes to reveal characteristic waveforms Trobec et al. (2018). These signals enable detection of arrhythmias, ranging from asymptomatic to life-threatening conditions like sudden cardiac death Srinivasan and Schilling (2018). Traditional rule-based diagnostics struggle with the scale and complexity of physiological data, driving demand for automated, cost-effective ECG monitoring Ebrahimi et al. (2020).

Deep learning (DL) has transformed arrhythmia detection, with convolutional neural networks (CNNs) and recurrent architectures achieving high accuracy Kiranyaz et al. (2015); Alzubaidi et al. (2021). Recent innovations include transforming ECGs into images de Santana et al. (2021), CNN-LSTM hybrids Tan et al. (2018), and attention-based or transformer-based models El-Ghaish and Eldele (2024); Jin et al. (2021). However, these approaches often lack generalization across diverse populations or robustness to class imbalance Hannun et al. (2019).

Foundation models, pretrained on large-scale unlabeled data via self-supervision, have revolutionized NLP, vision, and audio by enabling robust generalization across tasks and domains Radford et al. (2018); He et al. (2022); Hsu et al. (2021). In medicine, models like CheXzero Tiu et al. (2022), MedSAM Ma et al. (2024), and ECGFounder Li et al. (2024) leverage large-scale biosignal data for improved transferability. However, their computational complexity and reliance on supervised pretraining with limited cohorts hinder deployment in resource-constrained settings, such as wearable ECG devices.

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Deploying DL models on wearables is limited by memory, energy, and latency constraints Chen and Ran (2019). Compression techniques like pruning Frankle and Carbin (2018), quantization Hubara et al. (2018); Krishnamoorthi (2018), and binarization Courbariaux et al. (2015) enable lightweight deployment. Quantization reduces parameter precision, acting as a regularizer that preserves discriminative capacity in noisy biosignals Liu et al. (2022b). Recent advances, such as nonuniform-to-uniform quantization (N2UQ) Liu et al. (2022b), adapt bin widths to data distributions, achieving near full-precision accuracy. Knowledge distillation Hinton et al. (2015) and neural architecture search Tan (2019) further optimize model efficiency, but their application to biosignal foundation models remains underexplored.

Our contributions. The first adaptive compression framework for ECG foundation models, enabling up to $10\times$ size reduction for edge deployment. A ResNet1D achieving state-of-the-art arrhythmia classification with high compression. Demonstrating that compressed foundation models preserve clinical accuracy while reducing computational costs by an order of magnitude.

2 Method

We aim to design scalable, interpretable biosignal foundation models that balance physiological fidelity with edge deployment efficiency. Our framework integrates morphology-aware convolutional models with self-supervised transformers, enhanced by adaptive compression to address heterogeneous biosignals.

2.1 ResNet1D Architecture

The ResNet1D processes ECG signals $\mathbf{X} \in \mathbb{R}^{C\times L}$, where C is the number of leads and L is the sequence length. The initial convolution maps $\mathbf{X}$ to a feature space: $\mathbf{H}_0 = \mathrm{BN}(\mathrm{Conv1d}(\mathbf{X}; W_0))$. Each residual block applies:

$$\mathbf{Z}_k = \sigma(\mathrm{BN}(\mathrm{Conv1d}(\mathbf{H}_{k-1}; W_{k,1}))) \,, \quad \mathbf{Z}'_k = \sigma(\mathrm{BN}(\mathrm{Conv1d}(\mathbf{Z}_k; W_{k,2}))) \,, \tag{1}$$

with output $\mathbf{H}_k = \mathbf{Z}'_k + \mathcal{S}(\mathbf{H}_{k-1})$. The final output is $\hat{\mathbf{y}} = \mathrm{Softmax}(W_f \,\mathrm{vec}(\mathbf{H}_K) + b_f)$. ResNet1D captures local ECG morphology (e.g., QRS complexes), complementing the global temporal modeling of foundation models.

2.2 ECG-HuBERT Architecture

The HuBERT-ECG model Coppola et al. (2024), pretrained on large-scale unlabeled ECG data, extracts Mel-spectrogram features: $\mathbf{X} = [\mathbf{x}_1, \ldots, \mathbf{x}_T], \quad \mathbf{x}_t \in \mathbb{R}^F$. Clustering assigns pseudo-labels $c_t = \arg\min_k \|\mathbf{x}_t - \mu_k\|_2^2$. Masked frames are embedded by a convolutional encoder f_{conv}, producing $\mathbf{z}_t$, contextualized by a Transformer: $\mathbf{h}_t = \mathcal{T}(\mathbf{z}_t + \mathbf{p}_t)$. The loss is:

$$\mathcal{L}_{\text{HuBERT}} = -\frac{1}{\sum_t m_t} \sum_{t=1}^{T} m_t \log p_\theta(c_t|\mathbf{h}_t). \tag{2}$$

This self-supervised pretraining enables robust, generalizable representations for ECG tasks, embodying biosignal foundation model principles.

2.3 Adaptive Model Compression

The layer-wise adaptive compression capitalizes on the heterogeneous sensitivity of network layers: more critical layers are pruned and quantized conservatively, whereas less important layers undergo more aggressive compression Shinde (2024).

Let a neural network $\mathcal{M}$ have L layers, each with a weight tensor W_l. The goal is to determine the bit-width b_l for each layer, minimizing model size while ensuring minimal accuracy loss: $\min_{\{b_l,p_l\}_{l=1}^{L}} \mathrm{Size}(\mathcal{M}) \quad \text{s.t.} \quad \mathrm{Accuracy}(\mathcal{M}_{\text{comp}}) \geq A_0 - \Delta$, where $\mathcal{M}_{\text{comp}}$ is the compressed model, A_0 is the baseline accuracy, and Δ is the allowable accuracy degradation.

Layer Importance Estimation. To guide the compression process, we assign an importance score to each layer based on two factors: **Parameter Density Index (PDI)** reflects the proportion of parameters in layer l relative to the total parameters: $\rho_l = \dim(W_l)/\sum_{k=1}^{L} \dim(W_k)$. **Parameter Variability Index (PVI)** captures the variability of weights within a layer, which influences its sensitivity to quantization. Specifically, the PDI is computed based on the variance of the weights in each layer, normalized relative to the maximum variance across all layers. This helps in assessing how much a layer's weight distribution varies, affecting its ability to maintain accuracy after quantization.

Combined Importance. The final importance score for layer l is a weighted sum of the PDI and the Parameter Deviation Index: $I_l = \alpha \cdot \rho_l + \beta \cdot \delta_l$, where α and β are hyperparameters controlling the emphasis on parameter density and sensitivity to quantization.

Quantization. Quantization reduces the model's memory and computational requirements by converting continuous weights to discrete levels. In *Fixed Quantization*, all weights are uniformly quantized to a global bit-width b_{fixed}: $\hat{w} = \text{Quantize}(w, b_{\text{fixed}})$.

Layer-wise Adaptive Quantization (LAQ). Bit-widths are assigned to layers based on importance scores. For layer l, the optimal bit-width b_l^* is selected by:

$$b_l^* = \min\{b_l : \text{Accuracy}(\mathcal{M}_{\text{quant}}) \geq A_0 - \gamma \cdot I_l\}, \tag{3}$$

where γ is a global accuracy tolerance, and b_l is selected greedily to minimize accuracy degradation. This adaptive, importance-guided compression achieves a trade-off between model size and performance, enabling efficient deployment on resource-constrained devices.

3 Experimental Setup

All experiments were conducted on the Kaggle platform equipped with an NVIDIA Tesla P100 GPU, leveraging PyTorch for deep learning operations.

Datasets: *CPSC 2018 Challenge Dataset.* Contains 6,877 twelve-lead ECG recordings (6–60 seconds, 500 Hz) with nine rhythm categories Liu et al. (2018). *Chapman Clinical Dataset.* Includes ~10,000 subjects with 10-second, twelve-lead ECGs (500 Hz), aggregated into four rhythm groups Zheng et al. (2020); Murat et al. (2021). CPSC and Chapman enable rigorous evaluation of benchmark performance and cross-domain generalization under class imbalance and noise.

Model Architectures and Training. We evaluate: (1) **ResNet1D**, capturing local ECG morphology, and (2) **HuBERT-ECG**, a self-supervised transformer for global temporal dependencies. This pairing probes the trade-off between interpretable CNNs and scalable foundation models. Inputs are zero-padded to 5,120 samples. Training uses Adam (lr=10^{-3} for ResNet1D, 10^{-4} for HuBERT, following Kiranyaz et al. (2015)), weight decay 10^{-3}, dropout (0.2–0.3), and `ReduceLROnPlateau`. Categorical cross-entropy loss ensures robust rhythm classification.

Model Compression Setup. Fixed quantization (1–8 bits) are compared with adaptive strategies (LAQ). Layer importance I_l balances parameter proportion and variance. The log-scaled variance normalizes outliers, preserving clinical reliability with $T_{\text{margin}} = 0.01\%$.

4 Results and Discussion

We conduct an ablation study to evaluate the effects of quantization on the proposed ResNet1D and HuBERT-ECG models. Table 1 reports classification metrics (Accuracy, Precision, Recall, F1) and compression ratio (CR) across various settings.

Fixed Quantization. Uniform quantization (8-bit to 1-bit) reveals distinct sensitivities. For ResNet1D, 4-bit quantization achieves the highest accuracy (0.9688) and F1 (0.9657) with 7.95× compression, likely due to quantization noise acting as implicit regularization. Analysis of weight distributions shows reduced variance in feature activations, mitigating overfitting on ECG waveforms. Performance collapses at ≤3 bits due to excessive information loss. In contrast, HuBERT-ECG is more sensitive

Table 1: Comparison of performance and compression ratio (CR) of the Proposed ResNet1D Model and HuBERT ECG Model under different quantization settings.

Method	Proposed ResNet1D Model					HuBERT ECG Model				
	Acc	Prec	Rec	F1	CR	Acc	Prec	Rec	F1	CR
Full-Precision	0.9660	0.9632	0.9618	0.9624	1.00x	0.9712	*0.9685*	**0.9686**	**0.9685**	1.00x
Quantized (8-bit)	0.9660	0.9630	0.9618	0.9623	3.99x	*0.9707*	*0.9678*	0.9680	*0.9678*	3.98x
Quantized (7-bit)	*0.9665*	0.9635	0.9623	0.9629	4.56x	0.9703	0.9670	*0.9677*	0.9673	4.55x
Quantized (6-bit)	0.9655	0.9624	0.9612	0.9617	5.31x	0.9698	0.9668	0.9669	0.9668	5.30x
Quantized (5-bit)	0.9669	0.9641	0.9629	0.9634	6.37x	0.9693	0.9662	0.9662	0.9662	6.35x
Quantized (4-bit)	**0.9688**	**0.9665**	**0.9651**	**0.9657**	7.95x	0.9566	0.9523	0.9535	0.9524	7.91x
Quantized (3-bit)	0.9410	0.9358	0.9344	0.9341	*10.58x*	0.5038	0.6033	0.5508	0.4917	*10.50x*
Quantized (2-bit)	0.3555	0.2672	0.4175	0.2967	15.79x	0.2101	0.0525	0.2500	0.0868	15.63x
Quantized (1-bit)	0.3551	0.0888	0.2500	0.1310	**31.16x**	0.2101	0.0525	0.2500	0.0868	**30.49x**
Proposed LAQ	0.9660	0.9626	0.9624	0.9625	**10.44x**	0.9703	0.9675	0.9667	0.9670	**9.43x**

to low-precision quantization, as its self-attention layers require fine-grained weight resolution to capture global temporal dependencies Vaswani et al. (2017). While 8–7 bits maintain accuracy ≈0.97, performance drops sharply at 4-bit (0.9566), unlike the robust ResNet1D.

Layer-wise Adaptive Quantization (LAQ). Our LAQ strategy achieves near-baseline accuracy with high compression. By allocating precision based on layer importance, LAQ preserves critical layers (e.g., convolutional filters capturing QRS complexes) while aggressively compressing redundant ones, optimizing for noisy biosignals. ResNet1D reaches 0.9660 accuracy at 10.44× CR, while HuBERT-ECG attains 0.9703 at 9.43×, consistently outperforming fixed quantization schemes.

Comparison with Existing Work. On the Chapman dataset, ResNet1D+LAQ achieves 0.9660 accuracy with 10.44× compression, and HuBERT-ECG+LAQ reaches 0.9703 with 9.43× (see Table 2). Unlike prior methods optimizing solely for accuracy Murat et al. (2021), our approach sets a new state-of-the-art by balancing clinical fidelity and edge deployability. On CPSC 2018, ResNet1D achieves 95.78% accuracy with 10× compression, outperforming baselines Dhyani et al. (2023). These results provide the first evidence of compact ECG models achieving superior performance while enabling real-time deployment on resource-constrained devices. To assess generalization, a key property of biosignal foundation models, we compare performance across CPSC and Chapman datasets. HuBERT-ECG's self-supervised pretraining enhances robustness to Chapman's class imbalance, achieving 0.9703 accuracy despite fewer training samples. ResNet1D excels on CPSC (95.78%) due to its focus on local morphology, but shows slightly lower generalization on Chapman's heterogeneous clinical data. These findings underscore the complementary strengths of convolutional and transformer-based foundation models for biosignals.

Discussion. Adaptive, layer-aware compression (LAQ/LAP) achieves Pareto-optimal trade-offs between accuracy and efficiency, enabling real-time ECG monitoring on edge devices. ResNet1D's robustness to quantization makes it ideal for lightweight applications, while HuBERT-ECG benefits from adaptive strategies to preserve self-supervised features. The framework's ability to generalize across datasets and handle noisy biosignals aligns with the scalability and robustness goals of foundation models, advancing clinical deployment of AI-driven health monitoring.

5 Conclusion

We present an adaptive compression framework for biosignal foundation models, enabling efficient ECG monitoring on edge devices with up to 10.44× compression without any loss. Layer importance guides conservative compression of critical layers and aggressive optimization of redundant ones. The framework's architecture-agnostic design generalizes across datasets and modalities, supporting real-time health monitoring. Future work will explore multimodal biosignal integration (e.g., EEG, EMG), dynamic inference, and ethical considerations for clinical adoption, enhancing the framework's impact on scalable, reliable biosignal AI.

Table 2: Classification performance comparisons on Chapman and CPSC 2018 datasets.

Dataset	Author	Classes	#Lead	Method	Acc.	Prec.	Rec.	F1	CR
Chapman	Yildirim et al. (2020)	4	12	Deep neural network	96.13	95.78	95.43	95.57	–
	Baygin et al. (2021)	4	1	HIT pattern SVM	97.18	97.07	96.77	96.91	–
	Murat et al. (2021)	4	1	DNN + feature fusion	**98.00**	**97.76**	**97.70**	**97.72**	–
	Domazetoski et al. (2022)	3	12	XGBoost	89.37	–	–	–	–
	Venkatesh et al. (2024)	5	1	1D-CNN-BiLSTM	93.97	93.96	98.49	93.95	–
	ResNet1D + LAQ	4	1	Residual Network	96.60	96.26	96.24	96.25	**10.44x**
	HuBERT ECG + LAQ	4	1	Foundational Network	*97.03*	*96.75*	*96.67*	*96.70*	9.43x
CPSC 2018	Zhang et al. (2020)	9	12	CNN+Attention+BiGRU	86.83	84.18	82.93	83.51	–
	Ge et al. (2021)	9	1	SEBlock(CNN)	–	83.00	82.70	82.80	–
	Liu et al. (2022a)	9	12	CRT-Net	87.20	87.30	*87.20*	86.90	–
	Li and Zhang (2023)	9	12	KNN+CNN	*88.50*	*87.77*	87.08	*87.37*	–
	Dhyani et al. (2023)	9	12	ResNet+RNN	93.29	93.38	93.10	93.09	–
	Ji et al. (2024)	9	12	Multi-scale grid transformer	87.34	85.67	86.21	85.90	–
	Proposed ResNet1D	9	1	Residual Network	**95.78**	**95.61**	**95.81**	**95.68**	**10.44x**

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