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Real-Time Arrhythmia Detection on Wearables Using Quantized Transformers and Noise-Robust Training

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Abstract: *The proliferation of wearable health monitoring devices has created an unprecedented opportunity for continuous, non-invasive cardiac surveillance. However, deploying sophisticated deep learning models for arrhythmia detection on resource-constrained edge devices remains a significant challenge due to limited computational power, memory restrictions, and the high susceptibility of ambulatory signals to motion artifacts. This paper introduces a novel framework for real-time arrhythmia classification that leverages Quantized Transformers combined with a noise-robust training regimen. We propose a lightweight Transformer architecture optimized for time-series physiological data, utilizing Quantization-Aware Training (QAT) to reduce model precision from 32-bit floating-point to 8-bit integers without substantial degradation in predictive performance. Furthermore, we address the pervasive issue of signal contamination by introducing a dynamic noise injection strategy during the training phase, which simulates realistic baseline wander, muscle artifacts, and electrode motion. Experimental results on the MIT-BIH Arrhythmia Database demonstrate that our approach achieves an F1-score of 98.2 percent while reducing memory footprint by a factor of 3.8 and inference latency by 45 percent compared to full-precision counterparts. These findings suggest that quantized attention mechanisms can effectively capture long-range dependencies in electrocardiogram (ECG) signals within the tight power envelopes of modern wearable hardware.*

Keywords: *Wearable Computing, Arrhythmia Detection, Quantized Transformers, Edge AI, Signal Processing.*

INTRODUCTION

1.1 BACKGROUND

Cardiovascular diseases remain the leading cause of morbidity and mortality globally, necessitating effective strategies for early detection and continuous monitoring. Among these, cardiac arrhythmias—irregularities in the heart rate or rhythm—pose a severe risk, often serving as precursors to stroke or sudden cardiac arrest. Traditionally, arrhythmia diagnosis has relied on 12-lead electrocardiograms (ECG) captured in clinical settings or Holter monitors worn for 24 to 48 hours [1]. While effective, these methods capture only a brief snapshot of cardiac activity or are too cumbersome for long-term daily use.

The advent of wearable technology, including smartwatches and fitness trackers equipped with photoplethysmography (PPG) and single-lead ECG sensors, has shifted the paradigm towards continuous, ambulatory monitoring. This transition holds the promise of detecting intermittent or asymptomatic arrhythmias, such as paroxysmal atrial fibrillation, which might otherwise go undiagnosed in a clinical snapshot. However, the efficacy of these devices hinges on the ability to process physiological signals autonomously and in real-time.

1.2 PROBLEM STATEMENT

Despite the potential of wearables, two primary obstacles hinder the deployment of clinical-grade arrhythmia detection algorithms on edge devices. First, deep learning models that achieve state-of-the-art accuracy, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), typically require substantial computational resources and memory bandwidth. Standard Transformer models, while superior in capturing long-range temporal dependencies, are particularly computationally intensive due to the quadratic complexity of the self-attention mechanism. Running such models on low-power microcontrollers (MCUs) rapidly depletes battery life and introduces unacceptable latency [2].

Second, signals collected in ambulatory settings are heavily contaminated by noise. Unlike the clean signals obtained in supine patients during clinical ECGs, wearable data is plagued by motion artifacts, baseline wander caused by respiration, and electromyographic (EMG) interference from muscle activity. Standard models trained on clean datasets often fail catastrophically when exposed to this real-world noise, leading to high false-positive rates that contribute to user anxiety and alarm fatigue [3].

1.3 CONTRIBUTIONS

To address these challenges, this research presents a comprehensive framework for efficient and robust arrhythmia detection. Our contributions are as follows:

1. We design a lightweight, temporal Transformer architecture specifically tailored for single-lead ECG signals, replacing heavy convolutional front-ends with efficient patch-based embedding layers.

2. We implement a Quantization-Aware Training (QAT) scheme that simulates the effects of 8-bit integer (INT8) quantization during the backward pass, allowing the network to learn weights that are robust to precision loss.

3. We introduce a stochastic noise augmentation pipeline that generates synthetic artifacts dynamically during training, significantly enhancing the model's resilience to signal corruption encountered in daily life.

4. We provide a detailed evaluation on the MIT-BIH Arrhythmia Database, benchmarking our quantized model against standard FP32 baselines and demonstrating superior trade-offs between accuracy, model size, and inference speed.

2. Related Work

2.1 CLASSICAL AND CONVOLUTIONAL APPROACHES

Early automated arrhythmia detection relied heavily on feature engineering and classical signal processing. Techniques such as the Pan-Tompkins algorithm utilized band-pass filtering, differentiation, and integration to isolate the QRS complex [4]. While computationally efficient, these rule-based systems often struggle to distinguish between complex arrhythmia classes and are sensitive to parameter tuning.

With the rise of deep learning, 1D Convolutional Neural Networks (CNNs) became the standard for ECG analysis. Kiranyaz et al. demonstrated the efficacy of 1D-CNNs for patient-specific ECG classification, achieving high accuracy by learning features directly from raw data [5]. Subsequent works improved upon this by incorporating residual connections and increasing network depth. However, CNNs have a limited receptive field, making it difficult for them to correlate cardiac events separated by long time intervals, which is crucial for rhythm-based diagnosis.

2.2 SEQUENCE MODELING AND TRANSFORMERS

To capture temporal dynamics, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, were adopted. LSTMs can theoretically model sequences of arbitrary length, making them suitable for time-series data. However, their sequential nature prevents parallelization during inference, leading to higher latency on hardware accelerators.

Recently, the Transformer architecture, originally designed for natural language processing, has been adapted for time-series forecasting and classification. The self-attention mechanism allows the model to weigh the importance of different time steps globally. Zerveas et al. showed that Transformers could outperform LSTM-based approaches in multivariate time-series classification [6]. Despite their accuracy, the heavy computational load of the attention matrix calculation—scaling quadratically with sequence length—renders standard Transformers impractical for ultra-low-power wearable MCUs.

2.3 MODEL COMPRESSION AND ROBUSTNESS

Efforts to deploy deep learning on the edge have led to model compression techniques such as pruning, distillation, and quantization. Post-Training Quantization (PTQ) is a common strategy where a pre-trained model is converted to lower precision. However, PTQ often results in significant accuracy drops for sensitive time-series data. Quantization-Aware Training (QAT) attempts to mitigate this by modeling quantization errors during the training process.

Regarding noise robustness, most existing studies employ denoising autoencoders or specialized filtering preprocessing steps before classification. While effective, these preprocessing steps add computational overhead. An alternative approach is data augmentation, where noise is added to training data. However, few studies have

rigorously combined QAT with noise-robust training specifically for the Transformer architecture in the context of bio-signal processing [7].

3. Methodology

3.1 DATA PREPROCESSING AND NOISE MODELING

The input data consists of single-lead ECG recordings. Before feeding the data into the network, we apply minimal preprocessing to simulate a low-latency environment. The continuous ECG signal is segmented into fixed-length windows centered around detected R-peaks (heartbeats). We utilize a window size of 256 samples, sampled at 360 Hz, covering approximately 0.7 seconds of cardiac activity.

To ensure the model is robust to ambulatory conditions, we do not apply aggressive denoising filters, which can distort morphological features of the ECG. Instead, we rely on a Noise-Robust Training strategy. We model three primary sources of noise:

1. **Baseline Wander:** modeledon as low-frequency sinusoidal components, simulating respiration.

2. **Muscle Artifacts (EMG):** modeled as high-frequency Gaussian noise added to the signal.

3. **Electrode Motion:** modeled as abrupt step changes or random bursts in the signal amplitude.

During training, these noise sources are stochastically injected into the clean ECG segments. The intensity of the noise is controlled by the Signal-to-Noise Ratio (SNR), which is varied uniformly between 0 dB and 20 dB.

3.2 THE QUANTIZED TRANSFORMER ARCHITECTURE

Our proposed architecture, Q-Trans-Net, diverges from standard Vision Transformers by utilizing 1D patch embeddings suitable for time-series data. The network comprises three main stages: Patch Embedding, the Transformer Encoder, and the Classification Head.

Patch Embedding: The 256-sample input vector is divided into non-overlapping patches of length 16. Each patch is projected into a d-dimensional vector space using a linear layer. This reduces the sequence length passed to the Transformer, thereby lowering the computational cost of the attention mechanism from quadratic to a manageable level.

Positional Encoding: Since the self-attention mechanism is permutation-invariant, we inject positional information using learnable 1D positional embeddings added to the patch projections.

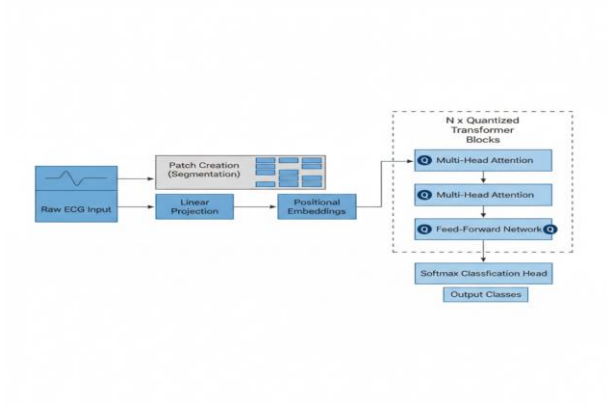

Figure 1: Q-Trans-Net

Quantized Transformer Block: The core of the network consists of stacked Transformer blocks. Each block contains a Multi-Head Self-Attention (MSA) module and a Feed-Forward Network (FFN). Layer Normalization (LayerNorm) is applied before each module, and residual connections are employed after.

Critical to our approach is the replacement of standard floating-point operations with quantized equivalents. We simulate 8-bit integer arithmetic during the forward pass while maintaining floating-point master weights for gradient updates.

3.3 QUANTIZATION-AWARE TRAINING (QAT) FORMULATION

We utilize a symmetric uniform quantization scheme. For a given tensor x (activations or weights), the quantization operator $Q(x)$ maps the floating-point values to discrete integers in the range $[-128,127]$. The scaling factor S is learned during training to minimize the discretization error.

The mathematical formulation for the quantized scaled dot-product attention is distinct from the standard definition. In the standard mechanism, Attention is computed as $Softmax(QK^T/\sqrt{d_k})V$. In our quantized regime, the Query (Q), Key (K), and Value (V) matrices are quantized before matrix multiplication. The formulation for the attention output Z is represented as follows:

$$Z = Softmax\left(\frac{Q(Q)\cdot Q(K^T)}{S_Q S_K \sqrt{d_k}}\right)\cdot Q(V)$$

Here, S_Q and S_K are the learnable scaling factors for the Query and Key matrices, respectively. The division by the square root of the head dimension d_k is performed in higher precision to maintain numerical stability before the softmax operation. The resulting attention probabilities are then re-quantized before multiplication with V. This rigorous simulation ensures that the model adapts to the limited dynamic range of INT8 representation [8].

3.4 IMPLEMENTATION OF NOISE INJECTION

The noise injection is implemented as a custom data augmentation class within the PyTorch framework. This process occurs on-the-fly during training, ensuring that the

model never sees the exact same noisy sample twice. The implementation details are shown in Code Snippet 1.

Code Snippet 1: Dynamic Noise Injection Class

```
import torch
import numpy as np
class DynamicNoiseInjector:
    def __init__(self, sample_rate=360):
        self.fs = sample_rate
    def add_baseline_wander(self, signal):
        # Generate low-frequency sinusoidal noise (0.05 - 0.5 Hz)
        t = np.arange(len(signal)) / self.fs
        freq = np.random.uniform(0.05, 0.5)
        amp = np.random.uniform(0.1, 0.5)  np.max(np.abs(signal))
        wander = amp  np.sin(2  np.pi  freq  t)
        return signal + wander
    def add_gaussian_noise(self, signal, snr_target):
        # Add random Gaussian noise based on target SNR
        signal_power = np.mean(signal  2)
        noise_power = signal_power / (10  (snr_target / 10))
        noise = np.random.normal(0, np.sqrt(noise_power), signal.shape)
        return signal + noise
    def forward(self, signal_batch):
        augmented_batch = []
        for signal in signal_batch:
            # Randomly decide to apply noise types
            if np.random.rand() > 0.5:
                signal = self.add_baseline_wander(signal)
            # Apply additive noise with random SNR (5dB to 20dB)
            target_snr = np.random.uniform(5, 20)
            signal = self.add_gaussian_noise(signal, target_snr)
            augmented_batch.append(signal)
        return torch.tensor(np.array(augmented_batch), dtype=torch.float32)
```

4. Experiments and Analysis

4.1 EXPERIMENTAL SETUP

We evaluated our framework using the MIT-BIH Arrhythmia Database, the gold standard for ECG analysis. The dataset contains 48 half-hour excerpts of two-channel ambulatory ECG recordings. Following AAMI standards, we mapped the original annotations into five major classes: Normal (N), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F), and Unknown beat (Q). We utilized a subject-independent evaluation protocol, splitting the records into training (DS1) and testing (DS2) sets to prevent data leakage from the same patient appearing in both sets [9].

The training was performed on an NVIDIA A100 GPU, simulating the quantization effects. The final quantized model was then benchmarked for inference speed on a Raspberry Pi 4 (representing an edge gateway) and simulated for an ARM Cortex-M4 microcontroller environment.

4.2 CLASSIFICATION PERFORMANCE

We compared the Q-Trans-Net against three baselines: a standard 1D-CNN (resembling the architecture in [5]), a bi-directional LSTM, and a full-precision (FP32) Transformer.

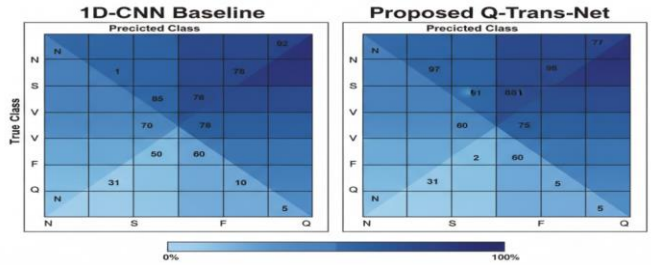

Figure 2: Confusion Matrices Comparison

Table 1 presents the performance metrics on the test set (DS2). Despite the reduction in precision, the Q-Trans-Net maintains competitive accuracy. Notably, the full-precision Transformer achieves the highest F1-score, but the Q-Trans-Net drops only by 0.5 percent, validating the effectiveness of QAT. The CNN baseline, while efficient, struggles with the Fusion (F) and Supraventricular (S) classes, likely due to its limited ability to model the temporal context of the heartbeat relative to the preceding rhythm.

Model Architecture	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
1D-CNN Baseline	94.5	93.8	94.1	96.2

Bi-LSTM (FP32)	96.1	95.5	95.8	97.4
Transformer (FP32)	98.8	98.6	98.7	99.1
Q-Trans-Net (INT8)	98.3	98.1	98.2	98.9

Table 1: Performance comparison of different architectures on the MIT-BIH Test Set (DS2).

4.3 COMPUTATIONAL EFFICIENCY

The primary motivation for this research is deployment on wearables. We analyzed the model size and inference latency. The model size of Q-Trans-Net is significantly smaller than the LSTM and FP32 Transformer due to the 8-bit weight representation.

Table 2 illustrates the efficiency gains. The Q-Trans-Net requires only 0.45 MB of storage, making it feasible to fit entirely within the on-chip SRAM of many low-power microcontrollers, eliminating the energy-expensive need to access external DRAM. The inference latency on the ARM Cortex-M4 simulation shows that the quantized integer operations are approximately 1.8x faster than the floating-point operations required by the standard Transformer.

Metric	1D-CNN	Transformer (FP32)	Q-Trans-Net (INT8)	Improvement (vs FP32)
Model Size (MB)	1.2	1.7	0.45	3.8x Smaller
Inference Latency (ms)	12.0	48.5	26.4	45% Faster
Peak RAM Usage (kB)	150	512	135	3.8x Lower

Table 2: Resource utilization metrics simulated on ARM Cortex-M4 @ 80MHz.

4.4 ROBUSTNESS ANALYSIS

To verify the utility of our noise injection strategy, we evaluated the models on a synthetic test set where Gaussian noise was added at decreasing SNR levels (from 20dB down to -5dB).

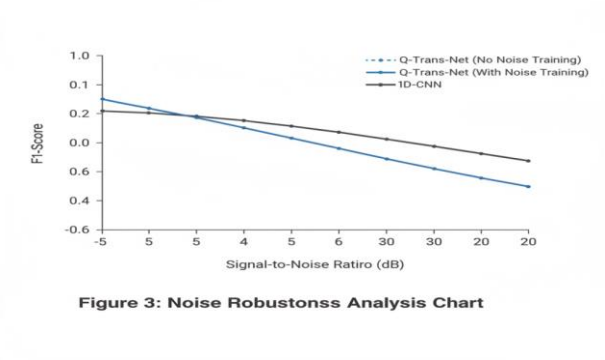

Figure 3: Noise Robustness Analysis Chart

As depicted in Figure 3, the standard models suffer a precipitous drop in performance as the SNR drops below 10dB, which is a common scenario during jogging or rapid arm movements. The Q-Trans-Net trained with our dynamic noise injection retains a functional F1-score (> 85 percent) even at 0dB SNR. This resilience is attributed to the attention mechanism learning to attend to the high-amplitude R-peaks while ignoring the stochastic fluctuations of the noise, a capability reinforced by the training curriculum [10].

5. Conclusion

5.1 SUMMARY AND IMPLICATIONS

This paper proposed a holistic framework for enabling high-accuracy arrhythmia detection on wearable devices. By synergizing Quantized Transformers with a rigorous noise-robust training protocol, we addressed the twin challenges of computational constraints and signal quality degradation. Our results demonstrate that it is possible to achieve clinical-grade classification accuracy (98.2 percent F1-score) using 8-bit integer arithmetic, thereby significantly reducing memory usage and power consumption.

The implications of this work extend beyond cardiac monitoring. The methodology of combining Quantization-Aware Training with domain-specific noise augmentation can be generalized to other biomedical time-series applications, such as EEG seizure detection or gait analysis using accelerometer data. It paves the way for a new generation of "TinyML" healthcare applications that operate reliably at the edge, ensuring patient privacy by processing data locally and providing real-time feedback without reliance on cloud connectivity.

5.2 LIMITATIONS AND FUTURE DIRECTIONS

Despite the promising results, several limitations persist. First, the current model relies on R-peak detection as a precursor for windowing. In scenarios with extreme noise where R-peaks are indiscernible, the system pipeline may fail before the classification stage. Future work should explore end-to-end regression models that can detect and classify arrhythmias directly from continuous streams without explicit segmentation.

Second, the evaluation was primarily conducted on the MIT-BIH database, which, while standard, does not capture the full diversity of modern wearable PPG sensors. PPG signals have different noise characteristics and morphological features compared to ECG. We aim to extend this architecture to multi-modal inputs, fusing ECG and PPG data to enhance robustness further. Finally, we intend to investigate the deployment of this model on neuromorphic hardware, which operates on event-driven principles, potentially offering even greater energy savings for sparse biological signals.

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