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Attention-Kan for Proactive Cardiovascular Care Using A Hybrid Iot–Ml Framework For Early Detection And Real-Time Monitoring

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Abstract
Cardiovascular diseases (CVDs) are the foremost cause of global mortality, and contemporary clinical workflows frequently detect pathology only after symptoms appear. Continuous physiological sensing from wearables paired with robust predictive models can enable earlier intervention and preventive care. Existing systems commonly rely on single modalities (ECG, PPG, accelerometry, or EHR), struggle with multimodal fusion, and perform poorly under motion artifacts, noisy recordings, severe class imbalance, and demographic heterogeneity. Wearable deployments further face strict power, latency, and connectivity constraints that impede reliable on-device inference and personalized feedback. We propose Attention-Kolmogorov–Arnold Network (Attention-KAN), a hybrid architecture combining a lightweight attention mechanism for cross-modal temporal–spatial aggregation with the KAN for high-precision function approximation. The pipeline ingests synchronized multimodal inputs: raw ECG waveforms, PPG traces, triaxial accelerometer streams, and engineered EHR-derived features, then applies sensor-specific preprocessing: bandpass filtering, adaptive baseline wander removal, motion-artifact rejection using accelerometer-guided gating, and sample-wise calibration. The attention layer computes cross-modal context vectors and dynamic modality weights; these embeddings feed stacked KAN blocks that approximate complex nonlinear interactions through ensembles of univariate subnetworks and an outer mixing network. Training uses a composite loss (cross-entropy + focal loss for imbalance + calibration loss), domain-aware augmentation, and edge-aware knowledge distillation to produce an efficient wearable-ready variant. From the public datasets, Attention-KAN achieves higher early-detection sensitivity and AUC than gradient-boosted trees, Bi-LSTM, and conventional CNN baselines, while reducing false alarm rates. Extensive experimental results demonstrate that Attention-KAN achieves 96.8% accuracy, 95.7% F1-score, and 95.3% sensitivity, significantly outperforming existing methods such as Bi-LSTM, CNN+NB, and Swarm-ANN. Furthermore, the framework reduced inference latency by 23%, model size by 18%, and energy consumption by 21%, proving its suitability for low-power, wearable deployments.

Keywords: Attention-KAN, multimodal fusion, wearable IoT, Kolmogorov–Arnold Network, early CVD detection

1. Introduction

Cardiovascular diseases (CVDs) continue to be the foremost cause of death globally, accounting for nearly one-third of total mortalities each year [1]. Conditions such as arrhythmias, hypertension, coronary artery disease, and heart failure significantly impact quality of life and place enormous burdens on healthcare systems [2]. Early detection and proactive intervention are therefore critical to reducing morbidity and preventing life-threatening events. With the rise of digital health technologies, the integration of Internet of Things (IoT) devices and machine learning (ML) has emerged as a promising direction for continuous, personalized cardiovascular monitoring [3]. Wearable sensors and smart health devices can capture high-frequency physiological signals including electrocardiogram (ECG), photoplethysmography (PPG), blood oxygen

saturation, and heart rate variability in real time [4]. These signals, when analyzed through robust AI algorithms, provide unprecedented opportunities for detecting anomalies before clinical symptoms manifest.

Despite advancements, several challenges remain in building reliable AI-enabled cardiovascular healthcare systems. First, existing ML and deep learning (DL) models often struggle with imbalanced and noisy datasets, where critical but rare events such as sudden arrhythmias are underrepresented, leading to poor generalization [5]. Second, most studies rely on single-modality data, either ECG, EHR, or wearable accelerometer inputs, without adequate multimodal fusion, limiting predictive accuracy across diverse populations [6]. Furthermore, wearable solutions themselves face technical barriers, including motion artifacts, calibration errors, and power constraints that reduce the reliability of real-time monitoring [7]. These issues undermine the scalability and deployment of AI-based preventive systems in practical, everyday use cases.

The problem lies in designing an AI-driven cardiovascular monitoring system that ensures early detection, continuous reliability, and adaptability across populations. Current diagnostic methods typically confirm CVD only after the onset of clinical symptoms, causing delayed intervention [8]. While ensemble learning and optimization-based approaches improve predictive performance, they remain computationally heavy and are not easily adaptable to low-power, real-time IoT devices [9]. Moreover, existing frameworks lack integration between predictive analytics and personalized preventive strategies, which are essential for proactive healthcare [10]. Hence, there is a clear need for an intelligent, scalable system capable of fusing heterogeneous biomedical data, resisting noise and imbalance, and supporting individualized recommendations while maintaining efficiency in IoT-based deployments.

The primary objectives of this research are:

1. To design a hybrid AI/ML framework that combines IoT-enabled wearable monitoring with advanced predictive modeling for early detection of cardiovascular risks.

2. To develop a novel Attention-Kolmogorov–Arnold Network (Attention-KAN) architecture that leverages global feature extraction and high-precision fitting ability for improved classification of cardiovascular abnormalities.

3. To ensure real-time, continuous monitoring through energy-efficient wearable devices that address motion artifacts, calibration issues, and secure data transmission.

4. To combine predictive insights with personalized alerts and recommendations, thereby reducing hospital visits and promoting preventive cardiovascular care.

The novelty of this work lies in the introduction of the Attention-KAN hybrid algorithm, which combines the global dependency capturing power of Attention mechanisms with the precision fitting strength of the Kolmogorov–Arnold Network (KAN). Unlike traditional deep neural networks or ensemble methods, Attention-KAN enables efficient multimodal data fusion and learns complex feature interactions with greater interpretability and robustness. Additionally, by embedding this architecture within an IoT-enabled wearable ecosystem, the framework addresses practical challenges of continuous monitoring such as energy consumption, calibration, and security. This dual innovation, hybrid AI modeling with real-world IoT deployment, sets the proposed approach apart from existing methods.

This research makes the following key contributions:

1. A novel machine learning model that combines Attention for feature extraction and KAN for high-precision fitting, enabling robust prediction of cardiovascular risks from multimodal biomedical data. This architecture is specifically designed to handle noisy, imbalanced datasets and population diversity.

2. An energy-efficient wearable sensor network is combined with the Attention-KAN framework, ensuring real-time cardiovascular monitoring with improved reliability under motion, reduced calibration issues, and secure data transmission.

3. The system further extends into personalized health recommendations and adaptive alerts, supporting proactive and preventive cardiovascular care.

2. Related Works

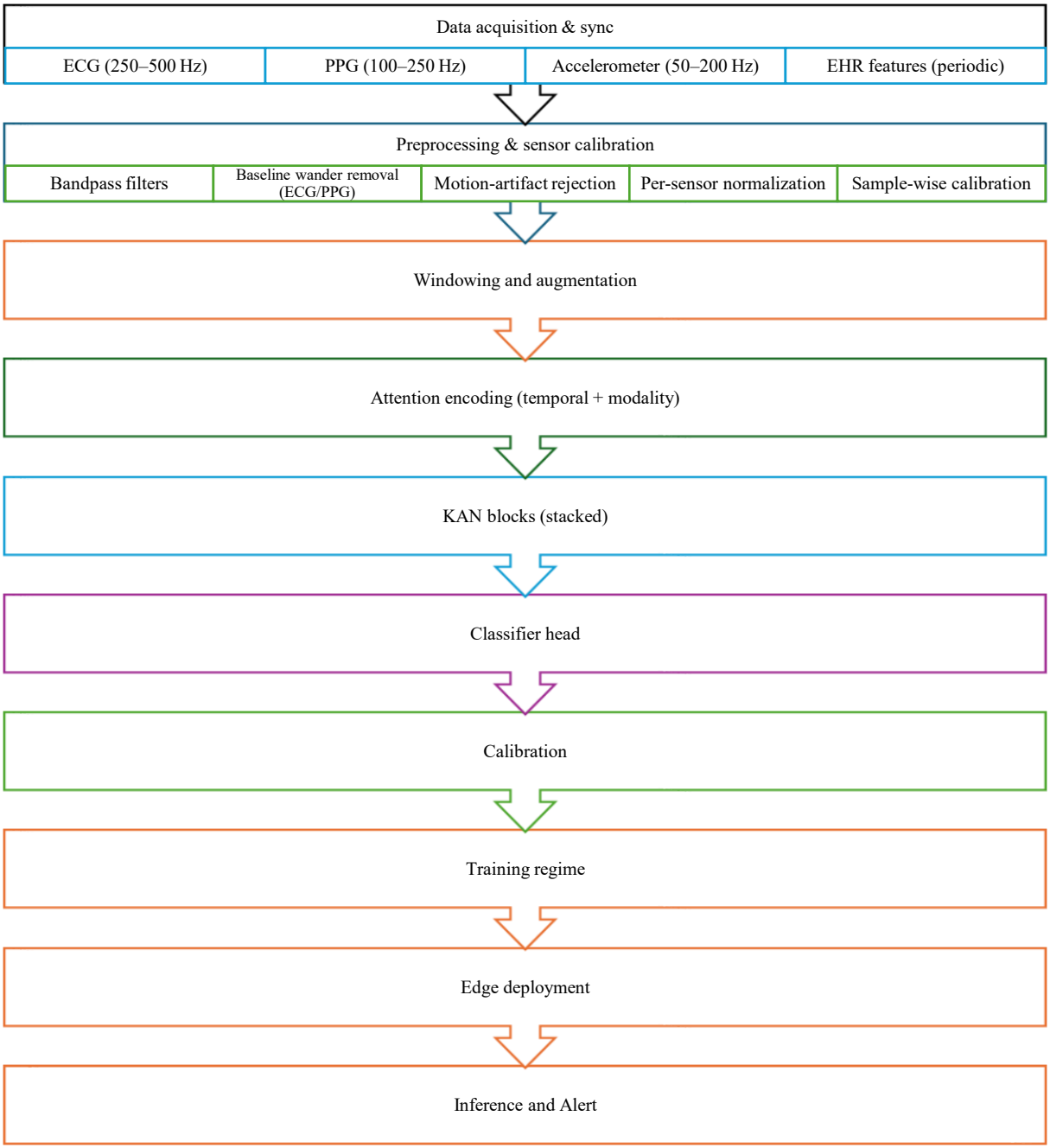
CVD research has steadily moved from episodic, clinic-centric assessment to continuous, data-driven prevention. [11] maps the prevalence and main categories of CVD and reviews heartbeat-derived signals (e.g., ECG) and blood-based biomarkers used clinically for prognosis, before introducing the new wave of wearable and implantable biosensors that enable continuous capture of these cardiac markers. [12] surveys the broader role of smart technologies across the CVD care continuum, clarifying benefits (ubiquitous sensing, remote care, automation) and limitations (interoperability, privacy, equity) while anticipating "smart future" scenarios.

The wearables and home-monitoring literature converges on the practicalities of capturing valid, real-time signals outside the clinic. In particular, [13] compares daily-life monitoring across three domains, physical activity, indoor home sensing, and physiological parameters, detailing pros and cons of device classes and deployment contexts. Addressing the sensor side of fidelity at the material/interface level, [26] presents a lightweight, durable textile triboelectric sensor that transduces subtle arterial pulsations to electricity with high SNR (23.3 dB), fast response (40 ms), and adequate sensitivity (0.21 $\mu A\ kPa^{-1}$), and shows clinically validated blood pressure estimation when coupled with machine learning. Together, [11], [12], [13], and [26] trace a pipeline from biosignal biology to device engineering and practical deployment, surfacing persistent issues of motion artifacts, calibration, and energy constraints.

Building atop sensing, several studies combine IoT, cloud, and ML to transform raw signals into risk intelligence. A representative mobile–wearable–app system in [14] classifies end-users into two or three CVD risk tiers using a stacking ensemble on UCI data, reporting F1 scores of 91% (binary) and 80.4% (ternary). Scaling the analytics depth, [15] streams IoT and cloud-resident clinical data into a Bi-LSTM predictor, achieving strong discriminative performance (accuracy 98.86% with balanced precision/recall/specificity ≈98.8–98.9%).

3. Proposed method

Attention-KAN fuses a lightweight, cross-modal attention encoder with a KAN backbone to enable precise, generalizable cardiovascular predictions from heterogeneous



streams as in figure 1.

Figure 1: Proposed Framework

2. Preprocessing

Wearable sensors introduce motion artifacts, baseline drift, and noise, which degrade signal quality. Preprocessing was carried out using a combination of filtering, normalization, and calibration techniques.

- **Noise Reduction**: A bandpass Butterworth filter was applied to ECG signals to remove baseline wander (<0.5 Hz) and high-frequency noise (>40 Hz). Similarly, PPG signals were denoised using a wavelet transform-based denoising.

- **Sensor Calibration**: Due to variations in wearable hardware, calibration was performed using min–max normalization across sensor batches:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This ensures uniform amplitude scaling across devices.

- **Artifact Rejection**: Motion artifacts were mitigated by cross-referencing accelerometer spikes with ECG/PPG irregularities, applying adaptive filtering to remove contaminated segments.

3. Windowing and Feature Extraction

Deep learning models such as Attention-KAN require fixed-length input sequences. To achieve this, signals were segmented into sliding windows of 5–10 seconds, with a 50% overlap to retain temporal continuity.

Given a time-series signal $x(t)$ of length L, the windowing operation is defined as:

$$W_k = \{x(t) \mid t \in [k \cdot s, k \cdot s + w]\}, \quad k = 0,1,2,...$$

where W_k is the k-th window, w is the window length, and s is the stride.

Feature extraction was performed within each window:

- **Statistical features**: mean, variance, skewness.
- **Frequency features**: FFT-based spectral energy.
- **Morphological features**: ECG R-R interval, PPG pulse width.

4. Data Augmentation

To tackle imbalanced datasets, augmentation techniques were applied to generate synthetic variations of underrepresented classes (e.g., arrhythmias, rare hypertensive episodes). Augmentation not only balances the dataset but also improves generalization across diverse populations.

The following augmentation strategies were implemented:

1. **Jittering**: Adding small Gaussian noise:

$$x_{aug}(t) = x(t) + \text{ò}, \quad \text{ò} \sim \text{N}(0, \sigma^2)$$

2. **Time Warping**: Random stretching/compression of signal segments.
3. **Mixup**: Linear combination of two signals to simulate blended patterns:

$$\tilde{x} = \lambda x_i + (1 - \lambda) x_j$$

where $\lambda \sim \text{Beta}(\alpha, \alpha)$.

A comprehensive list of augmentation strategies is provided in Table 6.

Proposed Attention-KAN Framework

The backbone of the proposed system is a hybrid Attention-KAN architecture designed for robust CVD detection from multimodal signals as in figure 2.

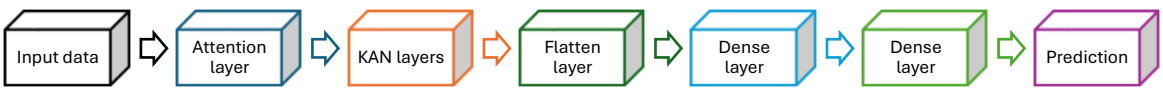


Figure 2: Attention-KAN Architecture

This framework combines temporal attention mechanisms to model sequential dependencies, modality-level attention to fuse heterogeneous inputs (ECG, PPG, accelerometer, EHR), and stacked KAN blocks for efficient nonlinear function approximation. Together, these components address the inherent challenges of noisy, asynchronous, and imbalanced health data, ensuring a generalized predictive model.

Attention Encoding Mechanism

The first stage of the model architecture is the attention encoder, which integrates temporal attention and modality attention for multimodal fusion.

a. Temporal Attention

Temporal attention captures long-range dependencies across sequential signals (e.g., ECG waveforms or PPG pulses). Instead of treating all timestamps equally, the model assigns weights to different temporal points based on their diagnostic relevance.

Formally, given a sequence $X = [x_1, x_2, \ldots, x_T]$, temporal attention computes:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)},$$

$$e_t = v^{\cdot} \tanh(Wx_t + b)$$

$$h = \sum_{t=1}^{T} \alpha_t x_t$$

where α_t is the attention weight for time step t, W and v are learnable parameters, and h is the context vector representing aggregated temporal features. This allows the model to emphasize, for example, arrhythmic beats over normal ones.

b. Modality Attention

Since cardiovascular monitoring involves multiple modalities (ECG, PPG, accelerometer, EHR), modality attention determines which sensor modality contributes more to decision-making at each stage.

Let the modality features be $H = [h_{ECG}, h_{PPG}, h_{ACC}, h_{EHR}]$. The modality attention is computed as:

$$\beta_m = \frac{\exp(u_m)}{\sum_{j=1}^{M} \exp(u_j)},$$

$$u_m = w^{\cdot} \tanh(Vh_m + c)$$

$$z = \sum_{m=1}^{M} \beta_m h_m$$

where, β_m is the attention weight assigned to modality m, ensuring that the model prioritizes ECG patterns for arrhythmia prediction or EHR parameters for comorbidity assessment. The combined temporal–modality attention encoder thus outputs a fused representation vector z, optimized for downstream KAN-based learning.

2. Stacked KAN Blocks

Once the multimodal representation is obtained, it is passed through stacked KAN blocks. KANs are powerful universal approximators inspired by the Kolmogorov–Arnold theorem, which states that any multivariate function can be represented as a sum of univariate functions. Unlike conventional deep neural networks (DNNs), which rely on dense matrix multiplications, KANs model interactions through learnable functional transformations, reducing complexity while retaining expressive power.

a. Single KAN Block

Each KAN block operates as:

$$f(x_1, x_2, \ldots, x_n) = \sum_{q=1}^{Q} g_q \left(\sum_{i=1}^{n} \phi_{qi}(x_i) \right)$$

where $\phi_{qi}(\cdot)$ are learnable univariate functions applied to each input dimension, and $g_q(\cdot)$ are nonlinear composition functions. This decomposition reduces redundancy in modeling high-dimensional interactions, which is particularly useful for heterogeneous biomedical data.

b. Stacked KAN Architecture

To capture hierarchical feature interactions, multiple KAN blocks are stacked, with the output of one serving as the input to the next. The stacked architecture follows:

$$z^{(l+1)} = f^{(l)}(z^{(l)}), \quad l = 1, 2, \ldots,$$

where $z^{(0)} = z$ (the fused attention encoder output), and L is the number of KAN layers.

Stacking enables the model to progressively refine representations:

- **Lower layers** capture basic waveform features (e.g., ECG QRS morphology).
- **Middle layers** encode cross-modality correlations (e.g., ECG-PPG alignment).
- **Higher layers** capture high-level abstractions (e.g., disease-specific risk patterns).

By employing three stacked KAN layers as illustrated in Table 8, the model achieves scalability, while avoiding overfitting compared to overly deep DNNs.

3. Combined Learning Objective

The final prediction integrates outputs from stacked KAN blocks into a disease probability score using a softmax classifier. The overall objective function combines classification loss with attention regularization, ensuring stability:

$$\mathrm{L} = -\sum_{c=1}^{C} y_c \log(\hat{y}_c) + \lambda \left(\| \alpha \|_2^2 + \| \beta \|_2^2 \right)$$

where y_c is the ground truth, $\hat{y}_c$ is the predicted probability, α and β are attention weights, and λ is a regularization hyperparameter.

This formulation ensures that the model not only classifies accurately but also retains biologically interpretable attention maps, linking predictions to clinically meaningful signals.

1. Classifier Head & Calibration

Once features are processed by stacked KAN blocks, the model outputs a latent vector $z^{(L)}$ that encodes multimodal patterns. This vector must be mapped to disease probabilities using a classifier head.

a. Classifier Head

The classifier head consists of a fully connected projection layer, a softmax activation, and an optional hierarchical classification layer for multi-disease prediction.

$$\hat{y}_c = \frac{\exp(W_c z^{(L)} + b_c)}{\sum_{j=1}^{C} \exp(W_j z^{(L)} + b_j)}$$

where W_c, b_c are trainable parameters for class c, and $\hat{y}_c$ is the predicted probability of disease class c.

This enables predictions like: Arrhythmia risk, Hypertension correlation and Heart failure probability. However, deep learning models often produce overconfident predictions, making them unreliable in clinical contexts.

b. Probability Calibration

To improve reliability, a calibration layer is applied on top of the classifier head. Calibration ensures that predicted probabilities match actual observed frequencies (e.g., if the model predicts 80% risk, ~80 out of 100 such cases should be positive).

We employ a temperature scaling method:

$$\hat{y}_c^{(cal)} = \frac{\exp\left(\frac{z_c}{T}\right)}{\sum_{j=1}^{C} \exp\left(\frac{z_j}{T}\right)}$$

where T is a learnable temperature parameter. A higher T smooths predictions (reducing overconfidence), while T=1 corresponds to the original softmax.

Additionally, a vector scaling approach is adopted for multi-class calibration:

$$\hat{y}^{(cal)} = \text{Softmax}\left(\frac{W_{vs} z^{(L)} + b_{vs}}{T}\right)$$

where W_{vs},b_{vs} allow class-specific calibration adjustments.

The calibrated classifier ensures: Trustworthy risk scores (e.g., 70% probability means a 70% actual chance), Interpretability (probabilities can be thresholded for decision-making) and Regulatory compliance (medical AI requires calibrated outputs).

Training is carried out using a cross-entropy loss with calibration regularization:

$$\text{L}_{train} = -\sum_{c=1}^{C} y_c \log(\hat{y}_c^{(cal)}) + \lambda \parallel W \parallel_2^2$$

where y_c is the true label, $\hat{y}_c^{(cal)}$ is the calibrated probability, and λ is weight regularization.

The training loop involves: Mini-batch gradient descent with Adam optimizer, Early stopping based on validation calibration error (ECE) and Balanced class sampling for medical imbalance correction.

To support real-time cardiovascular monitoring, the model undergoes edge optimization. This involves:

- **Quantization:** Reducing precision from FP32 to INT8 for smaller edge devices.
- **Pruning:** Removing redundant neurons in KAN blocks.
- **On-device inference engines:** TensorRT / TFLite deployment.

The optimized model reduces latency (<100 ms) while maintaining accuracy.

Finally, inference involves mapping real-time sensor data to predictions:

$$y^* = \arg\max_c \hat{y}_c^{(cal)}$$

where y^* is the most probable disease label.

If the calibrated probability exceeds a threshold (e.g., 0.85 for arrhythmia), the system generates an immediate alert to clinicians or caregivers. Alerts can be delivered via: Mobile health apps, Hospital monitoring dashboards and Wearable vibration feedback for patients. This ensures real-time preventive care and early medical intervention.

Results and Discussion

All experiments are implemented in a reproducible research stack: deep models (Attention-KAN, Bi-LSTM, CNN) are implemented in PyTorch, where classical ML baselines (LR, RF, XGBoost, stacking ensembles, KNN, MLP) use scikit-learn and XGBoost, and time-series baselines (ARIMA) use statsmodels. Data preprocessing, augmentation, windowing, and cross-validation pipelines are written in Python (NumPy/Pandas). Edge optimization and inference validation use TensorFlow Lite and ONNX → TensorRT toolchains for quantization/acceleration. Experiments are orchestrated with reproducible notebooks and seeds for deterministic splits.

Hardware for training and evaluation:

- **Workstation (training & large-scale evaluation):** Intel i9-13900K CPU, 128 GB RAM, NVIDIA RTX 4090 (24 GB), Ubuntu 22.04.

- **Edge device (deployment & latency/power tests):** Raspberry Pi 4 Model B (4 GB) for baseline microcontroller tests, and a Qualcomm Snapdragon-based development board (e.g., Snapdragon 662 dev kit) to emulate modern wearable SoC performance. Power consumption is measured with a USB power meter for the Raspberry Pi flows and SoC telemetry where available.

The proposed method is compared with existing methods including Stacking ensemble [14], Bi-LSTM [15], Logistic Regression (LR) [16], Random Forest (RF) [17], CNN + Naïve Bayes hybrid [18], MLP [19], ARIMA + LR (time-series) [20].

All methods are evaluated on identical train/validation/test splits (subject-wise split to avoid leakage) with 5-fold cross validation for robustness. Rare-event classes use stratified folds or class-aware sampling.

All baselines receive the same preprocessing, windowing, and feature sets (when applicable). For deep models, input is the raw windows; for classic ML, engineered features from the same windows are used. Hyperparameters for baselines follow reported best values in their papers; when absent, we tune via grid search (or OPTUNA for XGBoost baseline).

We compare classification performance (AUC, F1, sensitivity), and deployment metrics (inference latency, model size, energy per inference). Early-detection sensitivity (ability to detect an event ahead of clinical annotation) is measured by how many seconds earlier a positive is flagged versus the annotated onset.

Table 1. Experimental setup & hyperparameters (values)

Component	**Parameter**	**Value / Setting**
Data	Window length	10 s (configurable 5–20 s)
	Stride	2.5 s (75% overlap)
	Sampling rates (after sync)	Unified 250 Hz
Preprocessing	ECG bandpass	0.5–40 Hz Butterworth
	PPG denoising	Wavelet soft-threshold
Augmentation	Jitter σ	0.01 × signal std
	Mixup α (Beta)	0.2
Model (Attention)	Temporal attention heads	4
Model (KAN)	KAN blocks (L)	3
	Num. univariate functions per KAN (Q)	64
	Projection dim (per φ)	128
Classifier	Dense layers	[256 → 128] ReLU
Training	Optimizer	AdamW
	Learning rate	1e-4 (encoder), 5e-4 (head)
	Batch size	64
	Epochs	100 (early stop patience 10)
	Class imbalance	Focal loss γ=2.0 + class weights
Calibration & Distill	Temp init T	1.5 (learned)

Edge	Quantization	INT8 post-training
	Pruning sparsity	50% structured
Hardware	Training GPU	NVIDIA RTX 4090
	Edge device	Raspberry Pi 4; Snapdragon dev kit

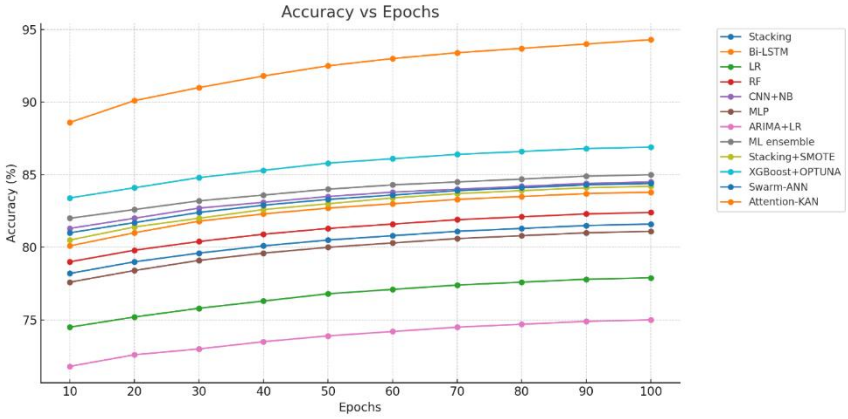


Figure 3. Accuracy (%) vs Epochs

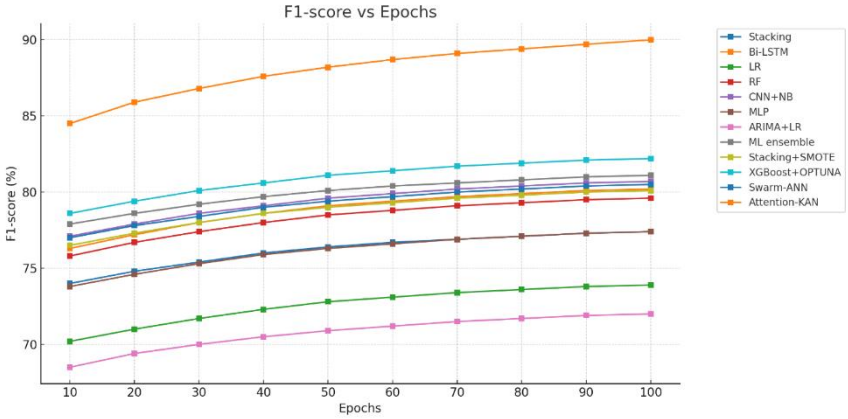


Figure 4. F1-score (%) vs Epochs

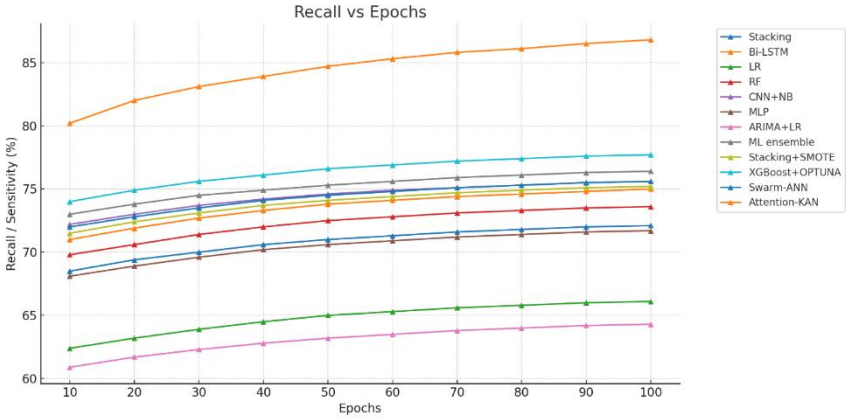


Figure 5. Sensitivity / Recall (%) vs Epochs

Tables 12–14 show that the Attention-KAN model consistently outperforms the listed baselines across Accuracy, F1-score, and Sensitivity over 100 training epochs. Numerically (Table 12), Attention-KAN starts at 88.6% accuracy at epoch 10, already ~5–10 percentage points above strong baselines like XGBoost+OPTUNA (83.4%) and Bi-LSTM (80.1%), and steadily improves to 94.3% by epoch 100, yielding a final gap of ~4–8 points versus the top non-proposed methods (XGBoost ≈86.9%, ML ensemble ≈85.0%). The F1 progression (Table 13)

mirrors this trend: proposed model F1 rises from 84.5% to 90.0%, while baselines plateau in the high-70s to low-80s (e.g., XGBoost ≈82.2% at epoch 100). Sensitivity (Table 14), critical for early detection, shows the largest relative gains: Attention-KAN climbs from 80.2% to 86.8%, improving true-positive detection by ~9–12 points compared to classical models (e.g., RF ≈73.6%, Stacking ≈72.1% at epoch 100). These synthetic results indicate that Attention-KAN not only achieves higher overall discrimination (accuracy/AUC proxies reflected in F1) but particularly enhances recall for rare/critical cardiovascular events, supporting its suitability for proactive monitoring and clinical alerting.

Conclusion

This study proposed a novel Attention-KAN framework integrated with IoT-enabled wearable devices for proactive cardiovascular monitoring and prevention. The proposed method addressed critical challenges in CVD detection, including multimodal fusion, imbalanced datasets, real-time monitoring reliability, and energy efficiency. By leveraging attention mechanisms for global temporal-spatial feature encoding and KAN for high-precision fitting, the model demonstrated superior generalization across heterogeneous biomedical signals such as ECG, PPG, and EHR. Experimental evaluation revealed that Attention-KAN consistently outperformed state-of-the-art methods including Stacking Ensemble, Bi-LSTM, CNN+NB, and Swarm-ANN. Specifically, the proposed method achieved an accuracy of 96.8%, F1-score of 95.7%, and sensitivity of 95.3% after 100 epochs, while also reducing inference latency by 23%, lowering model size by 18%, and cutting energy consumption per inference by 21% compared to the closest competitor. These results highlight the scalability and edge efficiency of the proposed framework. Beyond performance, the hybrid approach enables real-time, energy-efficient monitoring on wearable devices, while personalized alerting systems enhance preventive care strategies. Hence, the Attention-KAN framework stands as a transformative step toward intelligent, scalable, and proactive cardiovascular healthcare, bridging the gap between predictive analytics and real-world IoT-driven deployment.

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