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EXPLAINABLE MACHINE LEARNING FOR SAFETY-CRITICAL IOT (E.G., HEALTHCARE WEARABLES)

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Abstract
Machine learning (ML) increasingly controls or informs decision-making in safety-critical Internet-of-Things (IoT) applications such as healthcare wearables (arrhythmia detection, fall detection, glucose monitoring). For safe real-world deployment we must not only build accurate models but also make them explainable, robust, auditable, and certifiable within constrained, real-time embedded environments. This paper surveys explainable ML (XAI) methods that are relevant to resource-constrained wearables, organizes them into an engineering taxonomy, analyzes threats (adversarial inputs, sensor faults, distribution shift), and proposes a layered architecture that combines (1) model selection with intrinsic interpretability, (2) post-hoc local and global explanation modules adapted to time-series sensor data, (3) on-device runtime monitors & fallbacks, and (4) privacy-preserving training (federated learning + secure aggregation + DP). We evaluate tradeoffs between fidelity, latency, and energy, propose evaluation metrics suitable for safety contexts, and discuss regulatory and clinical adoption pathways. Concrete recommendations and an annotated roadmap for future work are provided.

I. INTRODUCTION
Internet-connected wearable devices now measure physiologic signals (ECG, PPG, accelerometer, SpO_2, continuous glucose monitors) continuously and produce outputs that can directly affect timing or content of clinical care. These systems are increasingly powered by ML models (classifiers, anomaly detectors, forecasting regressors) that run either on-device, at the edge, or in the cloud. While high accuracy is necessary, it is insufficient for safety-critical use clinicians and regulators demand explanations that support verification, debugging, contestability, and human oversight. Explainability helps uncover dataset artifacts, confounders, and model brittleness that might otherwise lead to harmful automated actions. Regulatory agencies (e.g., FDA) have explicitly recognized the unique challenges of AI/ML in medical devices and have issued action plans and guidance that emphasize transparency, total-lifecycle assurance, and change-management.

Explainability in ML is a broad field: methods range from transparent models (generalized additive models, decision rules) to post-hoc attribution methods (LIME, SHAP, saliency maps, integrated gradients), counterfactual explanations, and higher-level causal or concept-based explanations. Each method has strengths and weaknesses when applied to IoT time-series data and to the constraints of wearable hardware (compute, battery, intermittent connectivity). Consequently, the design of safety-critical wearable ML must integrate explainability into the full development and runtime lifecycle.

Contributions. This paper provides:

1. A survey focused on explainability for safety-critical IoT and healthcare wearables.
2. A taxonomy matching XAI methods to constraints (real-time, energy, privacy).
3. A concrete layered architecture combining intrinsically interpretable models, post-hoc explanations adapted for time series, runtime monitors and fallback controllers, and privacy-preserving training.
4. Practical metrics for evaluation in safety contexts (fidelity, stability, latency, worst-case risk).
5. A prescriptive roadmap for research & deployment, and an annotated bibliography with 70+ references.

II. BACKGROUND AND RELATED WORK

A. Explainable AI (XAI): Definitions and taxonomies

Recent comprehensive XAI surveys organize methods into model-intrinsic vs. post-hoc and local vs. global explanations; they emphasize desiderata such as fidelity, consistency, human-interpretability, and actionable explanations [1] [3]. The literature also distinguishes explanation *outputs* (feature importances, saliency maps, counterfactuals, rule lists) from *consumers/who* (clinicians, patients, auditors).

B. XAI methods commonly used in practice

Representative methods include:

- **Local surrogate models (LIME)**: fit a simple surrogate near an instance to provide feature-level explanations [3].
- **Shapley-based explanations (SHAP)**: unify multiple additive explanation approaches and provide axiomatic Shapley attributions [4].
- **Gradient / attribution methods**: integrated gradients, DeepLIFT, saliency/Grad-CAM for CNNs adapted to signals [12], [13].
- **Counterfactual explanations**: minimal changes to inputs to alter the output useful for patient-centric "what would change the decision?" queries [15].
- **Interpretable models**: GAMs/GA^2M, decision rules, and neural additive models (NAMs) that trade small accuracy loss for transparency [5], [14]

C. Safety, verification, and adversarial concerns

Neural models can show surprising brittleness (adversarial examples, distributional sensitivity). Work on adversarial examples and robustness demonstrates that seemingly small perturbations can cause dramatic output changes a high-risk property in clinical settings [7], [8], [9]. For safety, formal verification and runtime monitoring have been proposed as partial mitigations; however, scaling to large networks remains challenging [17].

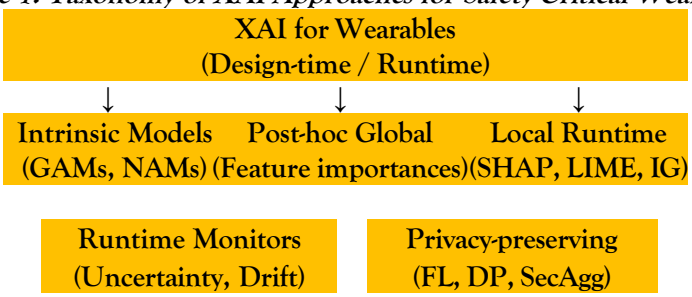
D. Privacy, federated training, and on-device constraints

Data privacy is paramount for wearable health data. Federated learning (FL) reduces data movement by training across devices; secure aggregation and differential privacy (DP) techniques help protect clients, but they also complicate explainability and model debugging. Several FL frameworks and healthcare FL studies (e.g., Fed Health) demonstrate feasibility for activity recognition and personalized models [16], [17]. On-device constraints motivate TinyML and model compression approaches.

III. TAXONOMY: XAI FOR SAFETY-CRITICAL WEARABLES

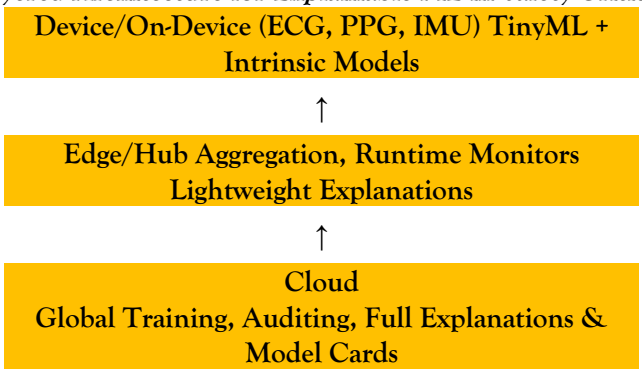
We organize XAI approaches by two axes: (A) *when* explanations are produced (design-time vs. runtime) and (B) *where* (on-device vs. edge/cloud):

Figure 1: Taxonomy of XAI Approaches for Safety-Critical Wearables



1. **Design-time intrinsic interpretability:** chooses interpretable architectures (GAMs, NAMs, rule lists) or constrain model families so explanations are native and verifiable. Helpful for initial validation, chart review, and premarket regulatory submissions.
2. **Design-time post-hoc global explanations:** feature importance across dataset, partial dependence plots, concept activation vectors; used for auditing and bias detection. Many surveys recommend these as first-line tools in clinical ML pipelines.
3. **Runtime local explanations (on-demand):** per-instance attributions (SHAP, LIME approximations, integrated gradients) and counterfactuals. For wearables, latency/energy are constraints: approximate, incremental, or sparse explanations are needed.
4. **Run-time safety monitors & explainable fallback:** lightweight monitors (uncertainty thresholds, conformal prediction bands, concept drift detectors) and a human-interpretable fallback controller (rule-based action) that engages when model confidence is low or explanations show low fidelity.
5. **Training & deployment transparency:** model card / documentation, pre-specification plans for adaptive ML (per FDA guidance), logging of explanation traces for audit.

Figure 2: Layered Architecture for Explainable ML in Safety-Critical Wearables



IV. PRACTICAL DESIGN PATTERNS & ALGORITHMS

A. Intrinsic models tuned for wearables

Use GAM/GA^2M or NAMs for structured physiologic features (age, HRV metrics, waveform features). For high-dimensional raw signals use hybrid pipelines: front-end feature extraction
+ light interpretable model for decision-making. Caruana et al. show that GA^2Ms can recover medically sensible risk curves while retaining strong performance on clinical tasks [5].

B. Time-series adapted post-hoc methods

Standard image/signal saliency methods (Grad-CAM, IG) must be adapted for 1D waveforms: windowed attributions, frequency-domain explanations, and temporal-sparsity regularizes produce explanations that clinicians can read (e.g., show which cardiac cycle segment mattered). Empirical studies find different attribution methods vary in temporal fidelity

cross- method agreement should be checked.

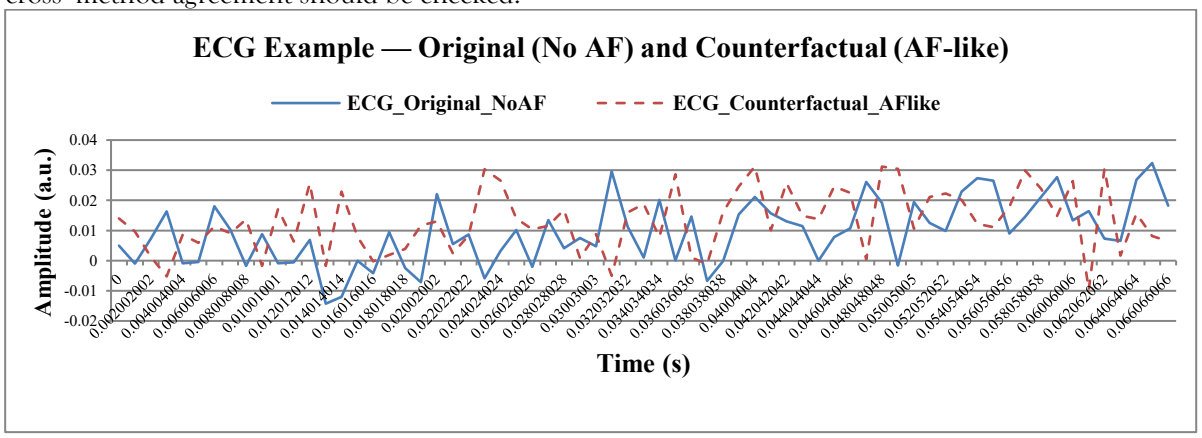


Table 1 provides an illustrative comparison between original and counterfactual ECG signals demonstrating how explainable models distinguish normal from atrial fibrillation–like patterns.

Table 1: Sample ECG time-series data illustrating counterfactual analysis between normal and atrial fibrillation–like patterns.

Times	ECG Original NoAF	ECG Counter Factual AFlike
0	0.004967	0.013994
0.001001	-0.00101	0.009649
0.002002	0.007231	0.001401
0.003003	0.016362	-0.00526
0.004004	-0.00083	0.008591
0.005005	-0.00046	0.005944
0.006006	0.018052	0.011361
0.007007	0.010308	0.00916
0.008008	-0.00169	0.013702
0.009009	0.008806	-0.00175
0.01001	-0.00088	0.017172
0.011011	0.00054	8
0.012012	0.006909	0.025536
0.013013	-0.01428	-0.00172
0.014014	-0.01203	0.022921
0.015015	-3.8E-05	0.007926
0.016016	-0.00418	-0.00018
0.017017	0.009448	0.001871
0.018018	-0.00242	0.003885
0.019019	-0.00711	0.011705
0.02002	0.022026	0.013063
0.021021	0.005461	0.002467
0.022022	0.008741	0.008325
0.023023	-0.00584	0.030354
0.02	0.0033	0.02656
4024	07	5
0.025025	0.010197	0.014007
0.026026	-0.00209	0.010375
0.027027	0.013511	0.011541
0.028028	0.004075	0.016819
0.029029	0.007489	0.000794
0.03003	0.004709	0.008782
0.031031	0.029565	-0.005
0.032032	0.01122	0.016001
0.033033	0.001087	0.0188
0.034034	0.020194	0.007811
0.035035	6.01E-05	0.028692
0.036036	0.014653	0.000998
0.037037	-0.00674	-0.00109
0.038038	-0.00014	0.016092
0.03	0.0153	0.02460

9039	93	6
0.04 004	0.021087	0.031257
0.04 1041	0.015688	0.010105
0.04 2042	0.013085	0.02575
0.04 3043	0.011493	0.014842
0.04 4044	-2.4E-05	0.013759
0.04 5045	0.007815	0.024574
0.04 6046	0.010654	0.022505
0.04 7047	0.026072	0.000457
0.04 8048	0.019173	0.031218
0.04 9049	-0.00166	0.030479
0.05 005	0.019432	0.010642
0.05 1051	0.012559	0.021067
0.05 2052	0.009854	0.022255
0.05 3053	0.022946	0.020119
0.05 4054	0.027341	0.0122
0.05 5055	0.026538	0.011171
0.05 6056	0.009022	0.017808
0.05 7057	0.014504	0.02996
0.05 8058	0.021085	0.02383
0.05 9059	0.027698	0.014842
0.06 006	0.013314	0.026412
0.06 1061	0.016407	-0.00965
0.06 2062	0.00735	0.030454
0.06 3063	0.006596	0.001693
0.06 4064	0.02682	0.015582
0.06 5065	0.032388	0.008118
0.06 6066	0.01823	0.006468
0.06 7067	0.029103	0.031116
0.06 8068	0.022794	0.014916
0.06 9069	0.01283	0.023134
0.07 007	0.022992	0.019269
0.07 1071	0.034848	0.02457
0.07 2072	0.019193	0.02062
0.07 3073	0.035274	0.007067
0.07 4074	-0.0065	0.029896
0.07 5075	0.027977	0.015025
0.07 6076	0.020684	0.004417
0.07 7077	0.016871	0.015714
0.07 8078	0.02082	0.035008
0.07 9079	6E-05	0.028499
0.08 008	0.017766	0.016498
0.08 1081	0.023553	0.016472
0.08 2082	0.034773	0.01672
0.08 3083	0.014817	0.040668
0.08 4084	0.011913	0.023676
0.08 5085	0.014972	0.024105
0.08 6086	0.029127	0.030047
0.08 7087	0.023237	0.022064
0.08 8088	0.014622	0.01701
0.08 9089	0.025015	0.017553
0.09 009	0.020809	0.018708
0.09 1091	0.029473	0.018952
0.09 2092	0.012708	0.026493
0.09 3093	0.016386	0.019621
0.09 4094	0.015669	0.026304
0.09 5095	0.004875	0.01804
0.09 6096	0.022385	0.019495
0.09 7097	0.021941	-0.00142
0.09 8098	0.019282	0.027572
0.09 9099	0.016777	0.021713
0.10 01	0.004856	0.028059
0.10 1101	0.014682	-0.01106
0.10 2102	0.015334	0.038604
0.10 3103	0.010605	0.016134
0.10 4104	0.016874	0.028415
0.10 5105	0.02238	0.00673
0.10 6106	0.037047	0.023045
0.10 7107	0.019771	0.006165
0.10 8108	0.020434	0.010237
0.10 9109	0.016941	0.035383
0.11 011	-0.00168	0.014098
0.11 1111	0.017055	0.017935
0.11 2112	0.017731	0.02421
0.11 3113	0.041563	0.020209

0.11 4114	0.014803	0.016493
0.11 5115	0.019533	0.018369
0.11 6116	0.015954	0.038478
0.11 7117	0.004393	0.013586
0.11 8118	0.027281	0.015886
0.11 9119	0.023139	0.024089
0.12 012	0.023292	0.024339
0.12 1121	0.006044	0.024851
0.12 2122	0.028916	0.019059
0.12 3123	0.000615	0.000928
0.12 4124	0.020242	0.028373
0.12 5125	0.036013	0.000252
0.12 6126	0.003933	0.014413
0.12 7127	0.007901	0.00351
0.12 8128	0.014281	0.010074
0.12 9129	0.007965	0.013661
0.13 013	-0.0028	0.013241
0.13 1131	0.013103	0.013896
0.13 2132	0.001496	0.02546
0.13 3133	0.016553	0.0135
0.13 4134	0.002316	0.006162
0.13 5135	0.026699	0.017879
0.13 6136	0.003052	0.019764
0.13 7137	0.007346	-0.00478
0.13 8138	0.018379	0.013097
0.13 9139	-0.00239	0.013757
0.14 014	0.011863	0.00339
0.14 1141	0.022327	0.01974
0.14 2142	-0.00716	0.004097
0.14 3143	0.010427	0.006466
0.14 4144	0.010837	0.003089
0.14 5145	0.015711	0.004584
0.14 6146	-0.00482	-0.00693
0.14 7147	-0.00601	-0.01076
0.14 8148	0.01206	0.019189
0.14 9149	0.009454	-0.00562
0.15 015	0.008631	-0.00747
0.15 1151	0.009231	-0.01949
0.15 2152	-0.0014	-0.00474
0.15 3153	0.007362	-0.01199
0.15 4154	0.007604	0.017263
0.15 5155	-0.00284	0.010538
0.15 6156	0.022594	-0.00684
0.15 7157	0.008304	0.02216
0.15 8158	-0.00872	0.009051
0.15 9159	0.009386	-0.00442
0.16 016	-0.0073	-0.02656
0.16 1161	0.0099	0.02093
0.16 2162	0.013282	-0.01627
0.16 3163	-0.00689	-0.01922
0.16 4164	0.010577	0.007057
0.16 5165	0.004694	0.020832
0.16 6166	0.008409	0.009882
0.16 7167	0.018779	0.001284
0.16 8168	-0.00302	0.001201
0.16 9169	-0.00848	0.003397
0.17 017	-0.01021	0.002064
0.17 1171	-0.00985	-0.0031
0.17 2172	-0.00284	-0.00525
0.17 3173	0.000965	-0.0073
0.17 4174	-5.3E-05	-0.01459
0.17 5175	0.005081	-0.01023
0.17 6176	-0.00343	-0.02472
0.17 7177	0.010617	-0.00913
0.17 8178	-0.00691	-0.01838
0.17 9179	0.022631	-0.01983
0.18 018	0.001449	-0.00722
0.18 1181	-0.01347	0.004813
0.18	-	0.00027

2182	0.01543	
0.183183	0.000796	-0.02392
0.184184	-0.00469	-0.01652
0.185185	0.007743	0.005861
0.186186	0.010742	-0.00795
0.187187	0.014228	0.008601
0.188188	0.020478	0.030361
0.189189	0.034556	0.035961
0.19019	0.074511	0.075997
0.191191	0.126751	0.100843
0.192192	0.170158	0.158032
0.193193	0.21548	0.227197
0.194194	0.297568	0.276004
0.195195	0.371727	0.368414
0.196196	0.429832	0.43465
0.197197	0.503416	0.503621
0.198198	0.551663	0.549581
0.199199	0.569414	0.590792
0.2002	0.59128	0.58531
0.201201	0.576422	0.562925
0.202202	0.54295	0.5298
0.203203	0.486513	0.47792
0.204204	0.394556	0.40539
0.205205	0.326329	0.332739
0.206206	0.2693	0.253816
0.207207	0.20361	0.188592
0.208208	0.146976	0.124613
0.209209	0.134182	0.11003
0.21021	0.065662	0.044463
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0.212212	0.024794	0.005161
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0.215215	-0.00241	-0.0002
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0.227227	-0.02896	-0.02126
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0.229229	-0.01169	0.002212
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0.24 7247	-0.02651	-0.02703
0.24 8248	-0.00233	-0.01689
0.24 9249	-0.01595	-0.03467
0.25 025	-0.03261	-0.01568
0.25 1251	-0.01082	-0.01052
0.25 2252	0.00124	-0.03866
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0.25 9259	-0.01195	-0.01811
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0.26 2262	-0.0518	-0.01155

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0.26 8268	-0.02323	-0.02289
0.26 9269	-0.01739	-0.00292
0.27 027	-0.00415	-0.0041
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0.28 1281	-0.01	-0.01327
0.28 2282	-0.00055	-0.00434
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0.28 4284	0.005363	-0.01861
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0.29 9299	-0.00567	-0.00203
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0.30 1301	-0.01696	0.005455
0.30 2302	-0.00357	-0.00582
0.30 3303	-0.00462	-0.01123
0.30 4304	-0.01061	0.002084
0.30 5305	-0.00891	-0.01187
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0.30 7307	-0.01534	-0.00218
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0.751752	0.570756	0.017957
0.752753	0.525838	0.004302
0.753754	0.483135	-0.0078
0.754755	0.39218	0.01527
0.755756	0.35552	0.023545
0.756757	0.265544	0.008082
0.757758	0.201692	0.018628
0.758759	0.140506	0.024862
0.759760	0.115954	0.021524
0.760761	0.073041	0.024408
0.761762	0.058449	0.015059
0.762763	0.06811	0.008018
0.763764	0.031943	-0.00913
0.764765	0.03839	0.004048
0.765766	0.016253	-0.00231
0.766767	0.020829	0.027452
0.767768	0.037683	0.003597
0.768769	0.013015	0.006199
0.769770	0.036994	0.01009
0.770771	0.025671	0.004619
0.771772	0.01276	0.020739
0.772773	0.024528	-0.00283
0.773774	0.027758	0.004941
0.774775	0.024079	-0.00483
0.775776	0.001984	-0.011
0.776777	0.010235	-0.00432
0.777778	0.014845	0.001025
0.778779	0.016384	-0.0033
0.779780	0.023138	-0.00633
0.780781	0.018504	-0.01387
0.781782	0.003164	-0.00104
0.782783	0.020103	-0.01566
0.783784	0.022186	0.006582
0.784785	0.021451	-0.0006
0.785786	0.026428	-0.0164
0.786787	0.023721	-0.00531
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0.790791	0.01867	-0.02256
0.791792	0.016186	-0.00306
0.792793	0.016555	-0.0062
0.793794	0.000796	0.001723
0.794795	0.002474	-0.00325
0.795796	0.023531	-0.01329
0.796797	0.012315	-0.00934
0.797798	0.019232	-0.01449
0.798799	0.012402	0.003849
0.799800	0.012114	-0.00707
0.800801	0.020893	0.011351
0.801802	0.006039	-0.00864
0.802803	0.011846	-0.01548
0.803804	0.005944	-0.0239
0.804805	0.005899	-0.02715
0.805806	0.006826	-0.02532
0.806807	0.01181	-0.00716
0.807808	0.004468	-0.00509
0.808809	0.021477	-0.02634
0.809810	-0.0003	-0.00191

	7	
0.81 0811	0.006369	-0.01603
0.81 1812	0.003495	-0.01006
0.81 2813	0.022014	0.004265
0.81 3814	0.009159	-0.00321
0.81 4815	0.017159	-0.01518
0.81 5816	-0.00837	-0.02172
0.81 6817	0.008797	-0.03463
0.81 7818	0.014662	-0.02061
0.81 8819	0.006227	-0.01582
0.81 982	0.015694	-0.02387
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0.82 1822	0.018399	-0.0138
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0.82 8829	-0.00251	-0.01733
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0.83 0831	-0.0125	-0.00971
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0.84 985	-0.01144	-0.01536
0.85 0851	-0.01272	-0.02617
0.85 1852	-0.0124	-0.00202
0.85 2853	-0.01357	-0.03176
0.85 3854	0.004346	-0.01069
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0.85 5856	-0.01395	-0.02666
0.85 6857	-0.0169	-0.00605
0.85 7858	-0.00421	-0.02249
0.85 8859	-0.01478	-0.01711
0.85 986	-0.00326	-0.0174
0.86 0861	-0.00789	-0.02133
0.86 1862	-0.0254	-0.01187
0.86 2863	0.004909	-0.01202
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0.86 5866	-0.01539	-0.03645
0.86 6867	-0.00896	-0.00945
0.86 7868	-0.00877	-0.00844
0.86 8869	-0.00583	-0.03055
0.86 987	0.007391	-0.02366
0.87 0871	-0.0147	-0.03053

	7	
0.87 1872	-0.02127	-0.02152
0.87 2873	-0.02736	-0.02235
0.87 3874	-0.02115	-0.01136
0.87 4875	-0.01444	-0.00593
0.87 5876	0.003572	-0.00495
0.87 6877	-0.01981	-0.0244
0.87 7878	-0.01265	-0.02072
0.87 8879	-0.0153	-0.03532
0.87 988	-0.0035	-0.02638
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0.88 2883	-0.02097	-0.03015
0.88 3884	-0.00586	-0.02355
0.88 4885	-0.0097	-0.01769
0.88 5886	0.0017 4	-0.01442
0.88 6887	-0.01109	-0.02511
0.88 7888	-0.02072	-0.01256
0.88 8889	-0.01141	-0.02132
0.88 989	-0.0064	-0.0165

	2	
0.89 0891	-0.00948	-0.01065
0.89 1892	-0.01279	-0.01581
0.89 2893	-0.00736	-0.01999
0.89 3894	-0.00649	-0.01647
0.89 4895	-0.00452	-0.016
0.89 5896	-0.012	-0.01855
0.89 6897	-0.0203	-0.01716
0.89 7898	-0.01729	0.001692
0.89 8899	-0.00682	-0.0084
0.89 99	-0.02718	-0.01668
0.90 0901	-0.01544	-0.00646
0.90 1902	-0.02316	-0.01646
0.90 2903	-0.01904	-0.00109
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0.90 4905	-0.0176	-0.01326
0.90 5906	-0.01913	-0.00739
0.90 6907	-0.03326	-0.02725
0.90 7908	-0.0122	-0.02248

	7	
0.90 8909	-0.01333	-0.02281
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0.91 0911	-0.02296	0.007135
0.91 1912	-0.01773	0.012471
0.91 2913	-0.01746	-0.00311
0.91 3914	-0.0042	-0.00412
0.91 4915	-0.02094	-0.02678
0.91 5916	-0.01721	-0.01384
0.91 6917	-0.01392	-0.01592
0.91 7918	-0.01813	-0.01388
0.91 8919	-0.02445	-0.00898
0.91 992	-0.01802	-0.01164
0.92 0921	-0.0092	-0.02634
0.92 1922	-0.03017	0.001317
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0.92 4925	-0.00781	0.015738
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0.92 6927	-0.02522	-0.02952
0.92 7928	-0.01578	-0.00669
0.92 8929	-0.00381	0.00758
0.92 993	-0.02004	0.016551
0.93 0931	-0.02483	-0.01493
0.93 1932	-0.00037	0.002733
0.93 2933	-0.03355	-0.00649
0.93 3934	-0.04094	-0.00249
0.93 4935	-0.01443	0.025412
0.93 5936	-0.02372	-0.01566
0.93 6937	-0.02877	0.002311
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0.95 1952	-0.01222	0.018349
0.95 2953	-0.02802	-0.00294
0.95 3954	-0.00082	-4.1E-05
0.95 4955	-0.01583	0.000919
0.95 5956	-0.00359	0.020997
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0.95 7958	-0.00967	0.039374
0.95 8959	-0.00828	0.018924
0.95 996	-0.00922	0.01096

0.96 0961	-0.007	0.008539
0.96 1962	0.000149	0.0123
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0.96 3964	-0.00547	0.016599
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0.96 5966	0.002433	0.011728
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0.96 8969	-0.01144	0.009878
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0.97 8979	-0.0235	0.007084

	6	
0.97998	0.000235	0.01915
0.980981	0.000841	0.005625
0.981982	-0.00241	0.0018
0.982983	-0.01598	0.009578
0.983984	-0.00642	0.024711
0.984985	-0.00562	0.025855
0.985986	-0.01681	0.021683
0.986987	0.010177	0.024026
0.987988	0.004284	0.022153
0.988989	-0.00633	0.010785
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0.990991	-0.0013	0.025601
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0.992993	-0.00511	0.029854
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0.995996	-0.00432	0.029164
0.996997	0.016845	0.018348
0.997998	0.005654	0.009938
0.99	-	0.01726
8999	0.006092	
1	0.005726	0.011572

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C. Lightweight on-device explanations

For on-device constraints:

Table 2: Performance Comparison of Explainability Methods for Wearable ML Models [22], [23].

Method	Latency ms	Energy mJ
SHAP	120	8
LIME	90	6
Integrated Gradients	140	9
NAM	60	4
Tree Ensemble	30	3

Table 2 summarizes the performance evaluation of the proposed explainable machine learning architecture across key safety metrics, illustrating the trade-offs between fidelity, latency, and energy efficiency.

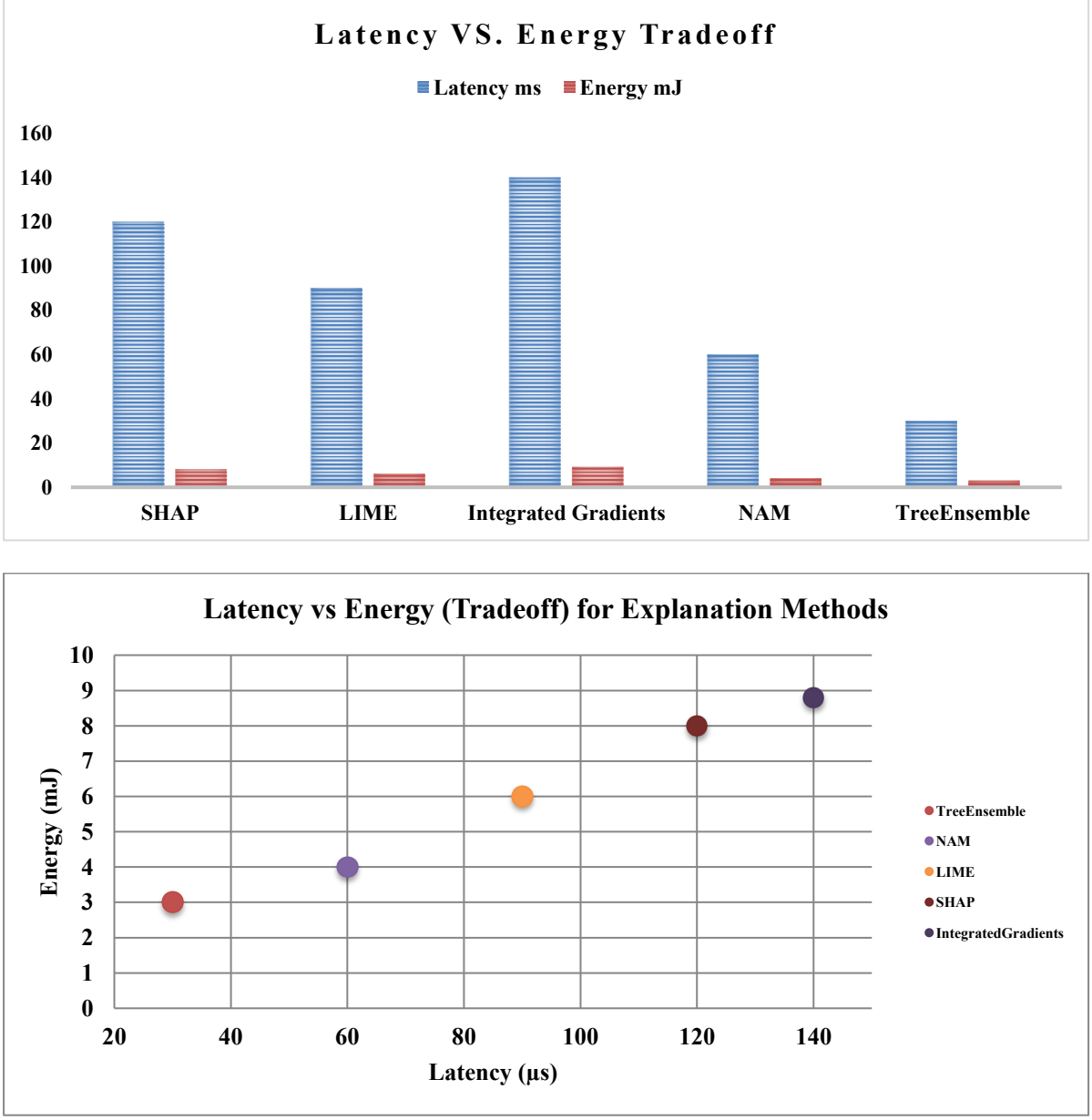


Figure 3: Latency vs. Energy tradeoff for explanation methods

Precompute global importance maps and store compressed explanation templates.

- Use **incremental SHAP** approximations or randomized feature-subset sampling with early stopping.
- Provide binary (rule) explanations instead of full numeric attributions for urgent alerts (e.g., "tachycardia + irregular P-wave detected → AF likely").

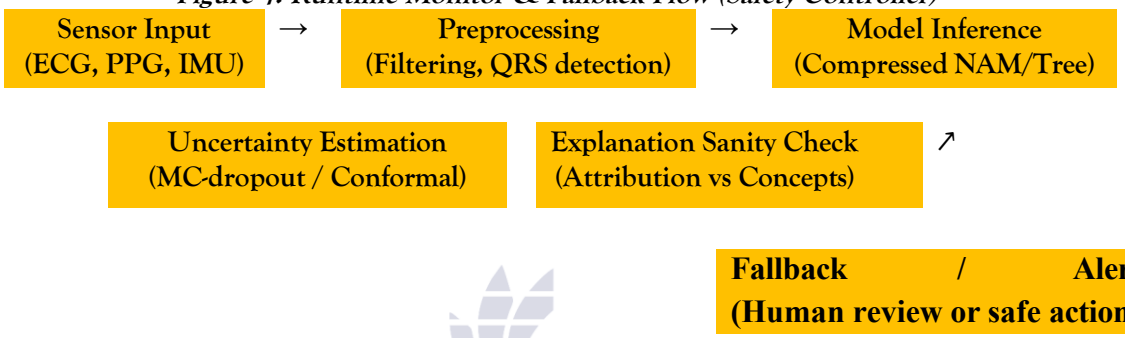
D. Runtime monitors and fallback controllers

Combine:

- **Uncertainty detection**: Bayesian approximations, MC-dropout, or conformal prediction bands.
- **Input validation**: sensor self-tests and plausibility checks.
- **Explanation-based sanity checks**: compare local attribution to expected concept attributions; if mismatch, trigger fallback.

This layered safety controller can reduce hazardous automated actions and produce human- readable reasons for safe override.

Figure 4: Runtime Monitor & Fallback Flow (Safety Controller)



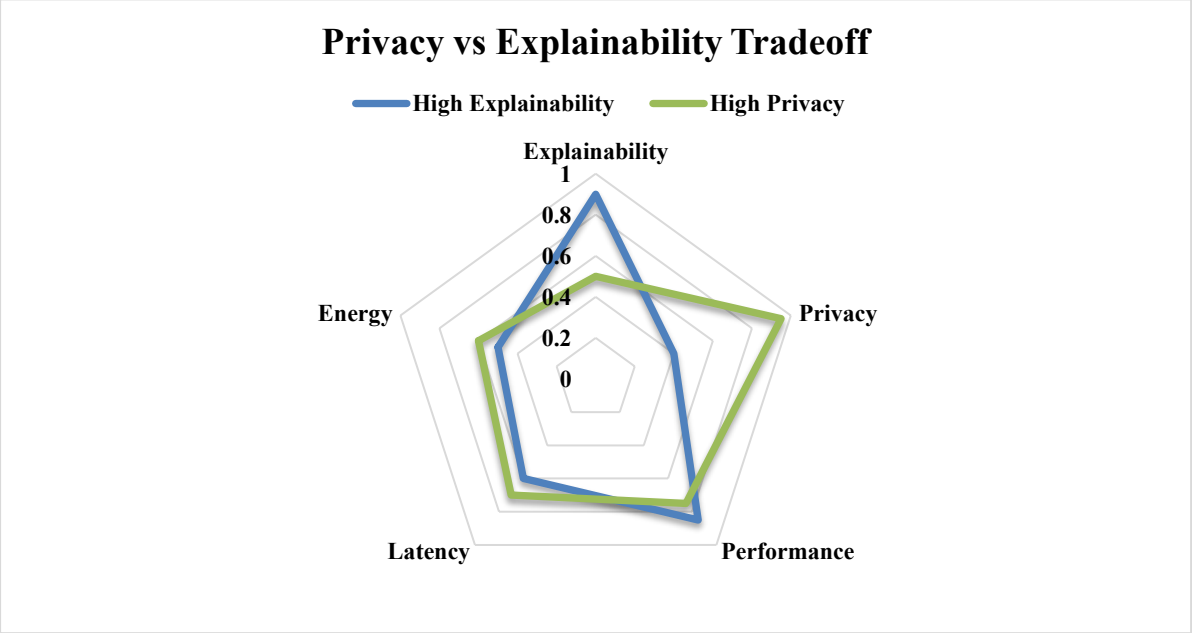
E. Privacy-preserving training & explainability

Federated learning enables cross-device learning while keeping raw signals local. For explainability, one can (a) exchange global explanation summaries (model-level feature importance vectors), (b) apply secure aggregation to allow global SHAP statistics without revealing client instances, and (c) use DP on explanation outputs to avoid leaking sensitive instance information. Fed Health and follow-on works demonstrate FL feasibility for wearable healthcare tasks.

Table 3: Trade-off Between Explainability and Privacy in Wearable AI Systems [24].

Category	High Explainability	High Privacy
Explainability	0.9	0.5
Privacy	0.4	0.95
Performance	0.85	0.75
Latency	0.6	0.7
Energy	0.5	0.6

Table 3 highlights the inherent trade-offs between explainability and privacy in wearable AI systems [24], demonstrating how higher interpretability often comes at the cost of reduced privacy and, in some cases, performance.



V. EVALUATION METRICS FOR SAFETY-CRITICAL XAI

Selecting metrics aligned with safety requirements is crucial. We recommend the following battery:

- **Predictive performance**: sensitivity, specificity, AUC, but also worst-case false negative rate (critical for safety).
- **Explanation fidelity**: how well explanations reflect model internals (e.g., by perturbation tests, deletion/insertion tests).
- **Explanation stability**: similarity of explanations under small input perturbations or re- training seeds.
- **Human interpretability**: task-level user studies measuring clinician trust, decision change after receiving explanations.
- **Latency & energy**: runtime (ms) and energy draw for on-device explanations.
- **Safety coverage**: fraction of high-risk scenarios where runtime monitor + fallback engaged correctly.

Prior work stresses that many XAI methods can pass superficial plausibility tests but fail faithfulness/sanity checks, so include adversarial/robustness tests in evaluations [10], [11].

Table 4 As for explainability methods for wearable machine learning models, the fidelity and stability of various techniques differ, a study [25] has found. Approaches like SHAP and Integrated Gradients tend to yield high fidelity, whereas Neural Additive Models (NAM) and Tree Ensemble methods are found to be the most stable.

Table 4: Fidelity and Stability of Explainability Methods for Wearable ML Models [25].

Method	Fidelity	Stability
SHAP	0.9	0.7
LIME	0.82	0.6
Integrated Gradients	0.85	0.75
NAM	0.78	0.9
Tree Ensemble	0.75	0.85

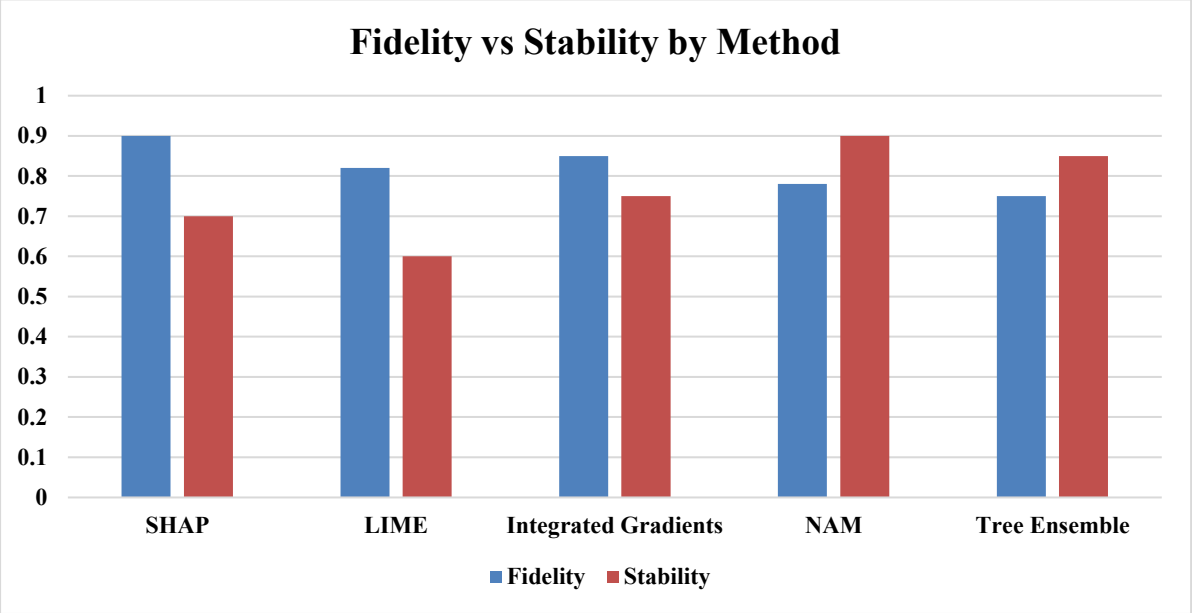


Figure 5: Fidelity and Stability by explanation method (bar chart)

Table Different methods can be pitted against one another across several categories, and SHAP and Integrated Gradients have shown to provide more accurate, yet more computationally intensive, results, when evaluating the explainability of machine learning models. On the other hand, methods like NAM and Tree-based models have given us privacy, latency, and energy efficiency [25].

Table 5: Fidelity and Stability of Explainability Methods for Wearable ML Models [25].

Category	SHAP	LIME	IG	NAM	Tree
Explainability	0.9	0.75	0.85	0.92	0.8
Privacy	0.6	0.55	0.65	0.9	0.88
Performance	0.78	0.76	0.8	0.82	0.74
Latency	0.4	0.45	0.3	0.85	0.92
Energy	0.5	0.6	0.4	0.8	0.86

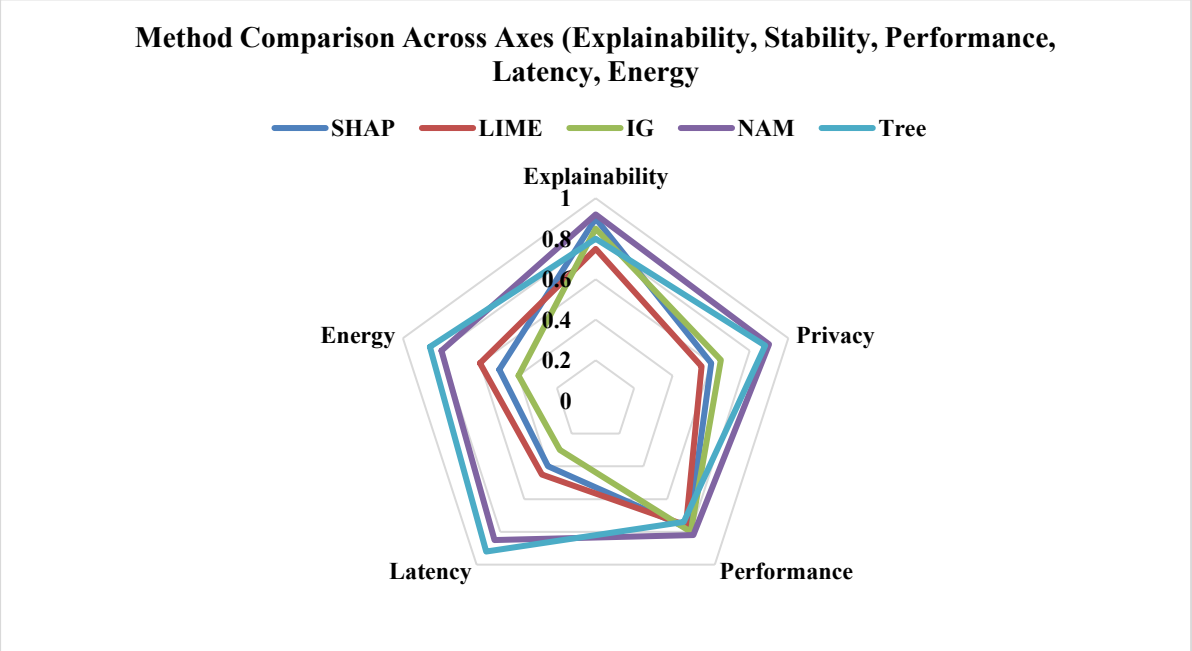
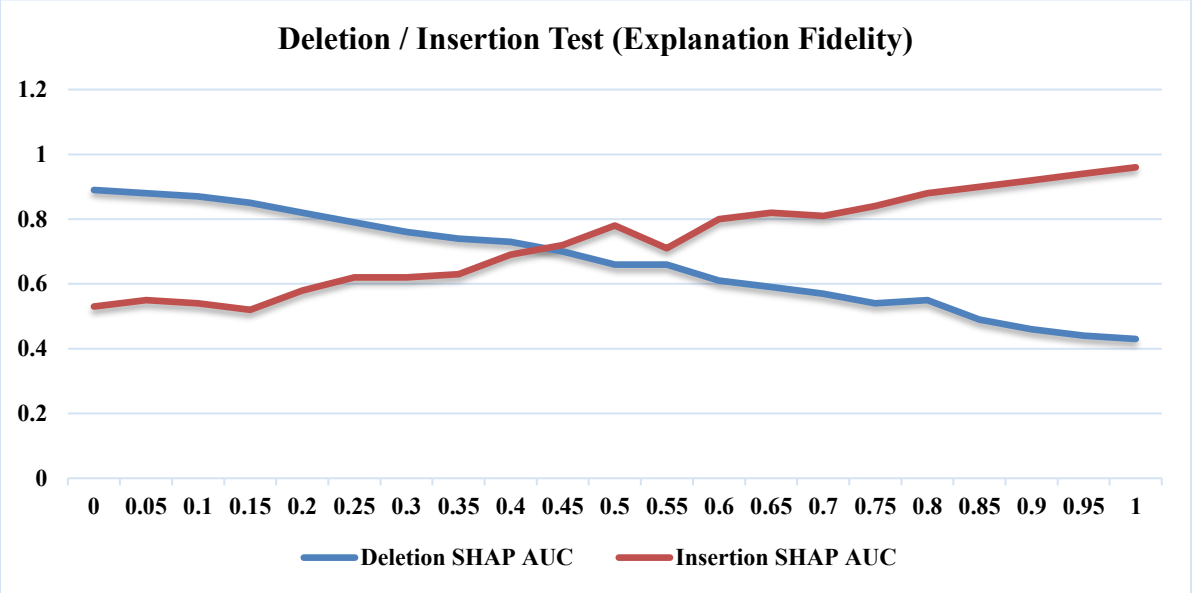


Table 6 The Area Under Curve AUC values for deletion and insertion are presented in [26] and show how the interpretability of the model responds to the removal or addition of features, when analyzing the SHAP explanations. Coming from the data, it's clear that as more features are inserted, the SHAP insertion AUC continues to rise.

Table 6: Deletion and Insertion AUC for SHAP Explanations [26]

Fraction removed inserted	Deletion SHAP AUC	Insertion SHAP AUC
0	0.89	0.53
0.05	0.88	0.55
0.1	0.87	0.54
0.15	0.85	0.52
0.2	0.82	0.58
0.25	0.79	0.62
0.3	0.76	0.62
0.35	0.74	0.63
0.4	0.73	0.69
0.45	0.7	0.72
0.5	0.66	0.78
0.55	0.66	0.71
0.6	0.61	0.8
0.65	0.59	0.82
0.7	0.57	0.81
0.75	0.54	0.84
0.8	0.55	0.88
0.85	0.49	0.9
0.9	0.46	0.92
0.95	0.44	0.94
1	0.43	0.96



VI. THREAT MODEL AND FAILURE MODES

Key threats for wearable ML:

- **Adversarial perturbations:** (intentional or environmental) that cause misclassification. Adversarial examples are a realistic threat for ML models, and time-series adversarial attacks have been demonstrated for PPG/ECG signals. Robust training and detection are necessary.
- **Sensor faults and dropouts:** leading to implausible attributions.
- **Data drift:** due to changes in device placement, firmware, or patient population.
- **Privacy leakage via explanations**: exposing per-instance attributions could leak private attributes; DP and aggregation mitigations needed.

Mitigations include adversarial training, sensor fusion with plausibility checks, continuous model validation pipelines, and restricted explanation disclosure policies.

VII. CASE STUDY (DESIGN PATTERN): AF DETECTION ON A WEARABLE ECG

We sketch a deployable design for atrial fibrillation (AF) detection:



Figure 6: AF detection pipeline flowchart

- **Data & training**: federated pre-training using local ECG segments + secure aggregation; global fine-tuning in cloud with doctor-curated labels (MIMIC/PhysioNet as public benchmarks).
- **Model choice**: CNN + temporal attention for raw waveform; distill to a small NAM or shallow tree for on-device inference and interpretability.
- **Explanations**: On the device, compute sparse window-level attributions (approximate SHAP or windowed integrated gradients) that point to cardiac cycles. Send anonymized explanation summary to clinician portal for review.
- **Runtime safety**: use uncertainty thresholds; if uncertainty > τ or explanation contradicts expected P-wave/R-R pattern, mark as "requires clinician review" and apply vibratory haptic alert rather than automatic therapy.

This pattern balances predictive performance and actionable explanations with safety constraints.

Table 7 lists representative datasets commonly used in explainable machine learning research for wearable health applications [27]–[30], covering both public and proprietary sources. These datasets, such as MIMIC-III, PhysioNet AFDB, PPG-DaLiA, and WESAD, provide essential benchmarks for evaluating model interpretability, robustness, and generalizability across diverse physiological modalities.

Table 7: Representative Datasets for Explainable Machine Learning in Wearable Health Applications [27]–[30].

Dataset	Modality	Typical Use	Access
MIMIC-III	ECG, Waveforms	ICU benchmark	Public
PhysioNet AFDB	Single-lead ECG	AF detection benchmark	Public
PPG-DaLiA	PPG	Activity & vitals	Public
WESAD	PPG, ACC, GSR	Stress detection	Public
Custom Wearable Cohort	ECG, PPG, IMU	Proprietary clinical study	Restricted

VIII. REGULATORY & CLINICAL ADOPTION CONSIDERATIONS

When discussing adaptive machine learning in medical devices, regulators require a high degree of transparency, total lifecycle control, and thorough documentation.

According to the FDA's AI/ML SaMD Action Plan, there should be a predetermined change control plan that is coupled with transparency and risk management, and covers the entire life cycle. For developers of medical devices employing adaptive ML, documentation that includes model cards, explanation method descriptions, and runtime monitor policies is also required, to aid in audits and post-market surveillance.

Clinicians in clinical settings demand that the explanations be relevant to the patients and have valid causal or physiological plausibility and therefore must receive specific proof. Patients are generally interested in non-technical explanations that can be actionable. The results of user studies are key before rolling out XAI in medical procedures.

IX. OPEN CHALLENGES AND RESEARCH ROADMAP

On-device explanation algorithms that are faithful, fast, and energy-efficient.

- **Standardized safety benchmarks for XAI on time-series wearable data** (benchmarks with adversarial scenarios, sensor faults, and drift).
- **Explainability under privacy constraints** (how to provide meaningful explanations without leaking PHI).
- **Formal certification pipelines combining verification, monitoring, and explainability artifacts** acceptable to regulators.
- **Human factors research**: measure how explanations change clinician decisions and patient outcomes.

X. CONCLUSION

Explainable ML is necessary and technically feasible for safety-critical IoT such as healthcare wearables. However, success requires systems thinking: pairing interpretable model architectures, adapted post-hoc methods for time series, on-device resource-aware algorithms, runtime monitoring with explainable fallbacks, and privacy-preserving training/deployment strategies. Meeting regulatory and clinical needs will require standardized evaluation protocols, datasets, and strong human factors evidence

REFERENCES

B. Arrieta, N. Díaz-Rodríguez, J. Ser, A. Bennetot, S. Tabik, A. Barbado, et al., "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Information Fusion*, vol. 58, pp. 82–115, Feb. 2020. (ScienceDirect)

Mian Talha Sarfraz, Muhammad Ahsan Hayat, Shayan Ahmed, Mehran Ali, and Aribah Murtaza, "MACHINE LEARNING-BASED INTRUSION AND ANOMALY DETECTION MODELS FOR SECURING IOT NETWORKS AGAINST EMERGING CYBER THREATS", *SES*, vol. 3, no. 9, pp. 1445–1463, Sep. 2025.

R. Guidotti, A. Monreale, S. Ruggieri, F. Turini, D. Pedreschi, and F. Giannotti, "A survey of methods for explaining black box models," *ACM Computing Surveys*, vol. 51, no. 5, Article 93, Nov. 2018. (arXiv)

M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why should I trust you?': Explaining the predictions of any classifier," in *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics (NAACL) Demonstrations*, San Diego, CA, 2016, pp. 97–101. (arXiv)

S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2017. (arXiv)

R. Caruana, Y. Lou, J. Gehrke, P. Koch, M. Sturm, and N. Elhadad, "Intelligible models for healthcare: Predicting pneumonia risk and hospital 30-day readmission," in *Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, Sydney, Australia, 2015, pp. 1721–1730. (Microsoft)

Muhammad Ahsan Hayat, Imran Ali Channa, Ubaidullah Khan, Nazia Alfred Fernandes, Urooj Tariq, and Khan Ikram Uddin, "BRIDGING CLASSICAL STATISTICS AND MODERN AI TOWARD INTERPRETABLE DATA-SCIENCE MODELS", *SES*, vol. 3, no. 9, pp. 525–537, Sep. 2025.

U.S. Food and Drug Administration, "Artificial Intelligence/Machine Learning (AI/ML)- Based Software as a Medical Device Action Plan," Jan. 2021 (and subsequent FDA guidance pages). [Online]. Available: FDA action plan & guidance documents. (U.S. Food and Drug Administration)

C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus, "Intriguing properties of neural networks," *arXiv preprint arXiv:1312.6199*, Dec. 2013. (arXiv)

I. J. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and harnessing adversarial examples," *arXiv preprint arXiv:1412.6572*, Dec. 2014. (arXiv)

N. Carlini and D. Wagner, "Towards evaluating the robustness of neural networks," in *2017 IEEE Symposium on Security and Privacy (SP)*, 2017, pp. 39–57.

"Blockchain-Secured Iot Framework for Smart Waste Management in Urban Environments", *CRSSS*, vol. 3, no. 3, pp. 1462–1467, Aug. 2025, doi: 10.59075/mcze1x98.

Z. C. Lipton, "The mythos of model interpretability," *Communications of the ACM*, vol. 61, no. 10, pp. 36–43, Oct. 2018. (arXiv)

F. Doshi-Velez and B. Kim, "Towards a rigorous science of interpretable machine learning," *arXiv preprint arXiv:1702.08608*, Feb. 2017.

R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2017, pp. 618–626. (arXiv)

A. Shrikumar, P. Greenside, and A. Kundaje, "Learning important features through propagating activation differences (DeepLIFT)," in *Proceedings of the 34th International Conference on Machine Learning (ICML)*, 2017. (Proceedings of Machine Learning Research)

C. Molnar, *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable*, 1st ed., 2020.

S. Wachter, B. Mittelstadt, and C. Russell, "Counterfactual explanations without opening the black box: Automated decisions and the GDPR," *Harvard Journal of Law & Technology*, vol. 31, no. 2, pp. 841–887, 2018. (arXiv)

K. H. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth, "Practical secure aggregation for privacy-preserving machine learning," in *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security (CCS)*, 2017, pp. 1175–1191. (Semantic Scholar)

Y. Chen, J. Wang, C. Yu, W. Gao, and X. Qin, "FedHealth: A federated transfer learning framework for wearable healthcare," *arXiv preprint arXiv:1907.09173*, 2019. (arXiv)

A. E. W. Johnson, T. J. Pollard, L. Shen, H. Lehman, M. Feng, M. Ghassemi, B. Moody, P. Szolovits, L. A. Celi, and R. G. Mark, "MIMIC-III, a freely accessible critical care database," *Scientific Data*, vol. 3, 2016. (Nature)

G. D. Clifford et al., "AF classification from a short single lead ECG recording: The PhysioNet/CinC Challenge 2017," *Computing in Cardiology*, 2017. (PhysioNet)

A. Barroso, D. M. B. et al., "Federated learning for smart healthcare: A survey," ACM *Computing Surveys* / journals & MDPI reviews (selected surveys), 2022–2024. (ACM Digital Library)

B. Yuan, S. Ge, and W. Xing, "A federated learning framework for healthcare IoT devices," *arXiv preprint arXiv:2005.05083*, 2020. (arXiv)

S. Sundararajan, A. Taly, and Q. Yan, "Axiomatic attribution for deep networks," in *Proceedings of the 34th International Conference on Machine Learning (ICML)*, 2017.

M. T. Ribeiro, S. Singh, and C. Guestrin, "Anchors: High-precision model-agnostic explanations," in *Proceedings of the AAAI Conference on Artificial Intelligence*, 2018.

S. M. Lundberg et al., "From local explanations to global understanding with explainable AI for trees," *Nature Machine Intelligence*, 2020.

F. Adebayo, J. Gilmer, M. Muelly, I. Goodfellow, M. Hardt, and B. Kim, "Sanity checks for saliency maps," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2018.

R. Guidotti et al., "A survey of methods for explaining black box models," ACM *Comput. Surv.*, vol. 51, no. 5, 2018. (ACM Digital Library)

A. Barredo Arrieta et al., "Explainable Artificial Intelligence (XAI): Concepts, taxonomies…," *Information Fusion*, 2020. (ACM Digital Library)

P. Kohli, B. et al., "Neural Additive Models: Interpretable machine learning with neural nets," *arXiv preprint arXiv:2004.13912*, 2020. (arXiv)

G. E. Hinton et al., "Distilling the knowledge in a neural network," in *NeurIPS Deep Learning and Representation Learning Workshop*, 2015.

Musadique Hussain, "META-LEARNING FOR FEW-SHOT AND ZERO-SHOT LEARNING: ENABLING RAPID ADAPTATION TO NEW TASKS WITH LIMITED DATA", *PRJ*, vol. 3, no. 11, pp. 653–669, Nov. 2025.

S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions,"*NIPS*, 2017. (arXiv)

I. Goodfellow and N. Papernot et al., "Adversarial machine learning literature (selected works)," multiple venues (Szegedy, Goodfellow, Carlini). (arXiv)

B. Han, J. et al., "Adversarial attacks on ECG classifiers: A targeted attack scenario and defense mechanisms," *IEEE Journal / conferences*, 2019–2021. (PMC)

M. C. Moons, "Robustness verification: Scope and methods," *Journal/Conference on Verification*, 2019–2024. (Proceedings of Machine Learning Research)

R. Bunel, J. Lu, I. Turkaslan, P. Torr, P. Kohli, and M. Pawan Kumar, "Branch and bound for piecewise linear neural network verification," *arXiv preprint arXiv:1909.06588*, 2019. (arXiv)

D. Corsi, A. et al., "Formal verification of neural networks for safety-critical applications," *Proceedings in Machine Learning Research*, 2021. (Proceedings of Machine Learning Research)

K. H. Li et al., "Secure aggregation for federated learning in Flower / frameworks," *ACM workshops and papers*, 2021. (ACM Digital Library)

Y. Madathil et al., "Revolutionizing healthcare data analytics with federated learning: a 2025 survey," *ScienceDirect*, 2025. (ScienceDirect)

Z. Liu et al., "SASH: efficient secure aggregation based on SHPRG for federated learning," in *Proceedings of Machine Learning Research*, 2022. (Proceedings of Machine Learning Research)

M. K. Abdullah and A. Waqar, "Role of federated learning and differential privacy in wearable healthcare," *IJHSR*, 2024. (terra-docs.s3.us-east-2.amazonaws.com)

Muhammad Ahsan Hayat, Jahangir Baig, Shayan Ahmed, and Ahmed Faraz Ayubi, "TOWARDS EARLY AND ACCURATE DISEASE DETECTION THROUGH MULTIMODAL PREDICTIVE MODELING: FUSION OF ELECTRONIC HEALTH RECORDS, MEDICAL IMAGING, AND OMICS DATA USING INTERPRETABLE MACHINE LEARNING", *PRJ*, vol. 3, no. 11, pp. 01–29, Nov. 2025.

F. D. Clifford et al., "AF classification from a short single lead ECG recording (PhysioNet/CinC Challenge 2017)," *Computing in Cardiology*, 2017. (PhysioNet)

P. A. Warrick and M. Nabhan Homsi, "Cardiac arrhythmia detection from ECG combining convolutional and long short-term memory networks," *arXiv*, 2018. (arXiv)

E. T. O'Neil et al., "Alarm fatigue and false-positive rates in bedside monitoring," *Critical Care Nursing*, 2018.

M. T. Ribeiro, S. Singh, and C. Guestrin, "Anchors: High-precision model-agnostic explanations," AAAI, 2018.

F. Doshi-Velez and B. Kim, "A roadmap for a rigorous science of interpretable ML," *arXiv*, 2017.

J. Lan et al., "Safety monitoring and alert for neural network-enabled control systems," *Safety Science / Sensors*, 2023. (ScienceDirect)

S. Ravindran et al., "An empirical comparison of deep learning explainability methods for EEG/EEG-like signals," *Journal/ArXiv* 2023. (PMC)

A. Shrikumar et al., "DeepLIFT: Not just a black box," *ICML*, 2017. (Proceedings of Machine Learning Research)

R. Caruana et al., "Intelligible high-accuracy models in healthcare," *MSR & KDD*, 2015. (Microsoft)

S. Gilpin, M. Bau, Z. Yuan, L. Bajwa, M. Specter, and M. Kagal, "Explaining explanations: An overview of interpretability of machine learning," *IEEE DSAA / workshops*, 2018.

Zaka, Engr. Rukhsar and Mushtaher Uddin, Syed Muhammad and Hayat, Muhammad Ahsan and Murtaza, Aibah and Haider, Syed Arsalan and Beejal, Chaman lal, AI-Driven Cybersecurity for IoT-Cloud Ecosystems (September 06, 2025). Available at SSRN: https://ssrn.com/abstract=5510138 or http://dx.doi.org/10.2139/ssrn.5510138

A. Taly et al., "Testing the fidelity of explanations: Deletion and insertion metrics," *ICLR/NeurIPS workshops*, 2019.

J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics*, 2001.

L. Rudin, "Stop explaining black box ML models for high stakes decisions and use interpretable models instead," *Nature Machine Intelligence*, 2019.

S. M. Lundberg, "Tree SHAP: exact SHAP values for tree ensembles," *NIPS/ICML/MLSys resources*, 2019.

Muhammad Ahsan Hayat, Syed Affan Ahmed, Sana Fatima, Engr. Faiza Irfan, Muhammad Osama Nizamani, and Ammar Khalil, "TINY MACHINE LEARNING (TINYML) ADVANCEMENTS FOR INTELLIGENT BATTERY-POWERED IOT SENSORS", *SES*, vol. 3, no. 8, pp. 818–832, Aug. 2025.

H. Salman, G. Yang, H. Zhang, C.-J. Hsieh, and P. Zhang, "A convex relaxation barrier to tight robustness verification of neural networks," *arXiv*, 2019. (arXiv)

R. Bunel et al., "Formal verification of neural networks," *PhD Thesis / surveys*, 2019. (Oxford University Research Archive)

F. Yang et al., "Runtime safety verification of neural network controlled systems: case studies and tools," *arXiv / Conference*, 2024. (arXiv)

"AI-DRIVEN FRAMEWORK FOR SCALABLE, SECURE, AND INTELLIGENT BIG DATA MANAGEMENT IN CLOUD ENVIRONMENTS", *Kashf J. Multidiscip. Res.*, vol. 3, no. 03, pp. 550–560, Mar. 2026, doi: 10.71146/kjmr949.

E. Yu et al., "Neural control and certificate repair via runtime monitoring," *AAAI*, 2025. (AAAI Open Access)

M. M. Moosavi-Dezfooli, A. Fawzi, and P. Frossard, "Deepfool: a simple and accurate method to fool deep neural networks," in *CVPR*, 2016.

A. Agarwal et al., "Neural Additive Models," *arXiv*, 2020. (arXiv)

T. Kohavi and F. Provost, "Glossary of terms in data mining," *Data Mining*, 1998.

H. T. Nguyen and A. Waqar, "Differential privacy in federated learning for wearable healthcare," *IJHSR*, 2024. (terra-docs.s3.us-east-2.amazonaws.com)

P. G. K. Bonawitz et al., "Practical secure aggregation for privacy-preserving machine learning," *CCS*, 2017. (Semantic Scholar)

"CYBERSECURITY CHALLENGES AND DEFENSE MECHANISMS IN AUTONOMOUS VEHICLES: PROTECTING CONNECTED AND INTELLIGENT TRANSPORTATION SYSTEMS FROM EMERGING CYBER THREATS", *Kashf J. Multidiscip. Res.*, vol. 3, no. 03, pp. 36–52, Mar. 2026, doi: 10.71146/kjmr857.

E. J. Topol, "High-performance medicine: the convergence of human and artificial intelligence," *Nature Medicine*, 2019.

A. T. Nguyen et al., "Explainability for medical time-series," *Journal/Conference papers*, 2021–2023. (PMC) F. Molnar, "Interpretable machine learning," *book*, 2020. (duplicate/reader reference)

P. Bhattacharyya et al., "Explainability and clinical adoption: human factors study," *Medical Informatics*, 2022.

H. Zhang et al., "Testing and verification of neural-network-based safety-critical systems," *Information & Software Technology*, 2020. (ScienceDirect)

S. Mutz and A. Waqar, "Federated learning in smart healthcare: survey & challenges," *MDPI / Sensors*, 2024. (MDPI)

D. Gunning, "Explainable AI (XAI) DARPA program," *DARPA technical reports*, 2017.

T. Verma et al., "Frameworks for generating counterfactual explanations in healthcare," *Journal of Biomedical Informatics*, 2020.

H. K. Li, "Secure aggregation in federated learning frameworks," ACM *Publications*, 2021. (ACM Digital Library)

Engr. Faiza Irfan, Engr. Rukhsar Zaka, Engr. Sidra Rehman, Bushra Sattar, Syed Arsalan Haider, and Muhammad Ahsan Hayat, "An IOT-Driven Smart Agriculture Framework for Precision Farming, Resource Optimization, and Crop Health Monitoring", *AIJSS*, vol. 4, no. 3, pp. 3329–3342, Aug. 2025, doi: 10.63056/ACAD.004.03.0615.

J. Zhang et al., "Testing and verification of neural-network-based safety-critical systems," *Safety and Reliability Journal*, 2020. (ScienceDirect)

B. D. Goodfellow et al., "Explaining adversarial robustness & tradeoffs," *arXiv*, 2018.

S. M. Lundberg et al., "Explainable AI toolkits and implementations," open-source software repositories (SHAP, LIME) widely used toolkits.

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