

A Systematic Review on the Integration of ML and DL for Disease Detection from ECG/EEG/EMG/EOG Signals in the IoMT and AI

MohammadReza Einollahi Asgarabad*, Aida Khaghani Asl Toloun and Mahsa Khaghani Asl Toloun

Department of Biomedical Engineering, SR. C, Islamic Azad University, Tehran, Iran.

Corresponding Author: MohammadReza Einollahi Asgarabad, ORCID: <https://orcid.org/0009-0007-1118-7738>, Department of Biomedical Engineering, SR. C, Islamic Azad University, Tehran, Iran.

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Abstract

The convergence of the Internet of Medical Things (IoMT), biosignal processing and artificial intelligence has redefined early disease detection by enabling real-time, remote and ultra-low-power analytics at the edge. In this systematic review we analyse 40 peer-reviewed studies (2020–2025) that apply machine-learning or deep-learning techniques to electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG) and electrooculogram (EOG) data within IoMT ecosystems. We chronicle the complete pipeline—from sensor physics (AD8232, Myoware, Muse 2) through Fog/Edge preprocessing, feature engineering and model selection, to deployment on Raspberry Pi, ESP32 or Jetson Nano boards. Reported clinical accuracies peak at 99 % for arrhythmia, 98.5 % for neonatal seizure and 97 % for stress detection, while end-to-end latency is pushed below 120 ms and raw-data uploads are reduced by 99 % via on-device inference. Methodological trends show a migration from classical SVM/Random-Forest-PSO models (2020) to compressed CNN-LSTM-GRU hybrids (2025) and multimodal CNN-Transformer architectures. Remaining challenges include patient-specific fine-tuning, scalable 5G-Edge orchestration, multimodal fusion and zero-trust security. The evidence indicates that hybrid Edge-Fog-Cloud frameworks which couple pruned deep nets with optimised classical learners currently offer the most pragmatic route toward large-scale, privacy-preserving and clinically validated IoMT diagnostics.

Keywords: Artificial Intelligence (AI), Bio Signals, Deep Learning, Internet of Medical Things (IoMT), Machine Learning, Signal Processing

1. Introduction

Internet of Medical Things (IoMT) has woven a low-power network of sensors, wearables, and communication fabrics that makes it possible to capture electrophysiological “stories” of the heart, brain, and muscle—ECG, EEG, EMG—anytime and anywhere. Among these stories, EEG carries the richest narratives of cognition and neuropathology; deep learners such as CNNs have learned to read between its lines, pushing detection accuracy for epilepsy, Alzheimer’s, schizophrenia, and even classroom deception to unprecedented levels [1,2]. In the cardiac chapter, still the deadliest, real-time ECG streaming through IoMT plus deep nets turns every heartbeat into an early-warning system for arrhythmia or ischemia, slashing both clinical cost and therapeutic delay [3-5]. Where stethoscopes and specialists are scarce, lightweight sonification married to edge machine-learning lets a single low-power EEG sensor spot neonatal seizure in the world’s most deprived corners [6]. Merging IoMT with EEG and eye-blink further widens the lens, allowing stress, anxiety, and sub-clinical neurological threats to be sensed before the patient ever utters a complaint [7]. Finally, the

convergence of surgical robotics and smart prosthetics with bio-signal analytics shows that these data no longer merely diagnose—they rehabilitate, guide precision surgery, and offer ubiquitous monitoring that redefines quality of life for amputees and chronically ill patients alike [8,9]. To visualise how the 2020–2025 literature is distributed across the four-dominant bio-signals, Figure 1 distils the present study into a single snapshot: the area of each sector reflects the percentage of studies reviewed in this paper devoted to each modality. Amidst an ever-expanding fabric that stretches from medical-grade sensors to the computational edge—from deep-learning giants to frugal classical algorithms—the heart, brain and muscle now speak continuously through IoMT. The pivotal question is no longer “Can we detect disease remotely?”, but “How can we do it best?”. This systematic review synthesises 40 peer-reviewed studies (2020-2025) to chart the evolving landscape of ML/DL methods for ECG, EEG, EMG and EOG within IoMT. By mapping the percentage distribution of the literature across these four modalities and benchmarking model performance in terms of accuracy, latency and computational load, we delineate the frontiers of

current knowledge and spotlight the remaining challenges—ranging from personalised multi-sensor fusion to zero-trust

security and clinical-grade scalability—that will shape the next generation of edge-based biosignal diagnostics. [Fig. 1]

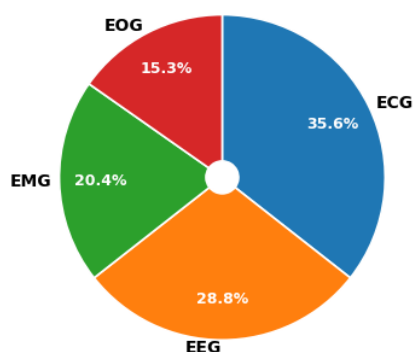


Figure 1: Distribution of IoT-oriented AI Studies (2020-2025) by Bio-signal Type

The remainder of this paper is organized as follows: Section 2 outlines the foundational concepts of biosignal processing within IoMT frameworks. Section 3 discusses preprocessing and feature engineering techniques applied to ECG, EEG, EMG, and EOG signals. Section 4 reviews classical machine learning approaches, while Section 5 focuses on deep learning methodologies employed for disease detection. Section 6 presents intelligent IoMT architectures and deployment strategies. Section 7 provides a comparative analysis of the reviewed studies. Section 8 offers an integrative summary of findings, and Section 9 highlights future research directions. Finally, Section 10 concludes the paper with key insights and recommendations.

1.1. Foundations of Bio Signals in Internet of Medical Things (IoMT) Systems

In an end-to-end IoMT pipeline, bio signals originate at the sensing layer and traverse ultra-low-power wireless links to fog or cloud servers in near real time. For EEG, wearable headsets such as Muse 2 or Emotiv EPOC X sample brain-electrical activity at 24-bit resolution and 256 Hz; the raw data—still devoid of any front-end filtering—are streamed in the standard EDF format into the EEGFrame middleware so that temporal, spectral and nonlinear features can be extracted on the fly [10,11]. On the cardiac side, the AD8232 analog front-end paired with an ESP32 or ESP8266

microcontroller acquires ECG at 360 SPS; the packets are pushed over 5G or standard MQTT/CoAP to a Node-RED broker or MATLAB endpoint for beat-to-beat analysis and long-term storage [12,13]. To shave latency and cloud load, ECG samples are first pre-processed in fog nodes—local Raspberry Pi or Jetson Nano boards—before only salient descriptors are forwarded upstream [14,15]. EMG data from abdominal or residual-limb muscles are captured by Myoware sensors, Wi-Fi-enabled through ESP32, and fed to mobile or server-side ML/DL engines that decode user intent for prosthetic or robotic control [9,16]. In resource-scarce scenarios such as neonatal seizure detection, the entire EEG pipeline—pre-processing, feature extraction and lightweight CNN inference—runs locally on a Raspberry Pi 3B+ so that no broadband back-haul is required [6]. Eye-blink events, streamed as a complementary behavioural channel, are analysed alongside delta-to-gamma bands to infer emotional valence and vigilance level [8,11]. All data paths ultimately converge into a WBAN gateway that connects either to a surgical robot or to a cloud platform, enabling clinical decision-making and timely intervention regardless of patient location [8]. As illustrated in Figure 2, the proposed system integrates multiple biomedical signals (ECG, EEG, EMG, and EOG) within an IoT-enabled cloud-centered architecture.



Figure 2: IoMT-Based Biomedical Signal Acquisition Framework

1.2. Preprocessing and Feature Engineering of Biosignals

In an IoMT pipeline, the eventual diagnostic accuracy is tightly bound to the quality of preprocessing; biosignals must be cleansed of environmental noise, patient motion, and electrode artifacts before they ever reach a machine- or deep-learning block [4]. For EEG, a 0.5–12.8 Hz band-pass filter is first applied, followed by down-sampling to 32 Hz to discard the DC component and shrink the data volume [6]. Power in the classical five bands—delta, theta, alpha, beta, and gamma—is then extracted, with an Alpha–Beta fusion consistently yielding the highest separability for abnormal states [1]. The open-source EEGFrame toolbox assumes this minimal front-end and automatically computes entropy, fractal dimension, recurrence plots, and the five canonical frequency ratios [2]. Other studies enrich the feature set with wavelet coefficients, inter-channel coherence, PQ-segment morphology, STFT spectrograms, PCA-whitened components, Hilbert envelopes, refined mutual-information, Hjorth parameters, and bispectral maps after rigorous artifact rejection [7,10,11].

On the ECG side, baseline wander, 50/60 Hz power-line interference, and myoelectric noise are suppressed through cascaded high-pass, low-pass, and wavelet filters [13]. The purified signal is Min–Max-scaled into [0,1] and presented to a PSO wrapper that distils 888 discriminative features from an initial pool of 4000 [5]. Classical fiducials—P,

QRS, T waves, HRV metrics, continuous wavelet (CWT) energies, instantaneous BPM, inter-beat-interval (IBI), SDNN, and RMSSD—are also harvested [12,17]. Inside fog nodes, segmentation precedes FFT and windowed spectral estimation so that amplitude and phase templates can be computed at the edge before cloud upload [3,15]. Surface EMG captured by Myoware sensors is amplified and denoised through analogue low- and high-pass filters followed by full-wave rectification; a 4 kHz sampling rate and tri-channel moving-average further attenuate noise and enhance force estimation accuracy [9,16]. The final vector contains power, median frequency, and activation pattern to classify “motion” versus “rest” [18]. As illustrated in Figure 3, the preprocessing chain is modality-specific. For EEG, a 0.5–12.8 Hz band-pass filter is first applied, the signal is down-sampled to 32 Hz, and ocular/muscular artifacts are removed. ECG streams undergo baseline-drift correction, power-line interference suppression, and QRS-aligned artifact rejection. sEMG is amplified and denoised through analogue bandwidth-limiting and full-wave rectification, followed by moving-average smoothing. EOG—primarily used to register saccades, blinks and fixations—is high-pass filtered to eliminate baseline drift and low-pass filtered to suppress high-frequency noise. These tailored preprocessing steps are essential for reliable feature extraction and the high detection accuracies reported in IoMT pipelines.

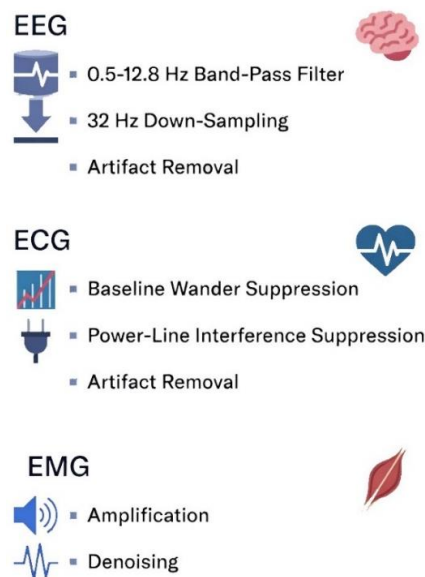


Figure 3: Preprocessing and Feature Engineering Steps for Major BioSignals in IoMT Pipelines

Throughout the chain, Huffman compression and lightweight encryption secure the data without degrading clinical fidelity [19]. When needed, min–max normalization, PCA dimensionality reduction, or even synthetic augmentation via DCGAN is employed to render the dataset deep-learning-ready [11].

1.3. Machine Learning Approaches for Disease Detection Based on BioSignals

At the analytics layer of IoMT, classical machine-learning algorithms still hold their ground because of their frugality,

tiny memory footprint, and effortless deployment on bare-metal microcontrollers. For ECG, support-vector machines (SVM) and shallow decision trees have proven accurate enough to flag arrhythmias and myocardial infarctions on wrist-worn streams in real time [4]; a PSO-guided comparison of KNN, DT, RF and SVM concluded that SVM consistently yields the highest arrhythmia-detection score [5]. Similar studies report parity among SVM, multi-layer perceptrons and decision stumps when they are embedded in the same IoMT workflow [14,15], and even a one-line rule—“if BPM > 80 or < 60 then abnormal”—has been

shown to trigger timely edge alerts without any floating-point burden [12]. On the EMG front, BioPatRec fuses linear discriminant analysis (LDA), KNN and logistic regression to decode residual-muscle patterns and translate them into dexterous prosthetic hand and finger movements [9,18]; a plain linear-regression model has also been used to map surface EMG voltage to grip force in ultra-low-cost assistive systems [16]. For EEG, the open-source EEGFrame toolbox extracts more than fifty linear and nonlinear descriptors and feeds them directly into an SVM or a decision tree to discriminate normal ageing from early neurodegeneration [2]. In threat-aware scenarios, an ensemble of SVM, random forest and shallow LSTM layers successfully spots stress-related or seizure-prone bio-signatures [7], while a recent on-device benchmark of random forest, SVM, KNN and logistic regression on Cortex-M4F cores concluded that random forest delivers the best accuracy-resource trade-off for upper-edge IoMT analytics [11].

1.4. Deep Learning Approaches for Disease Detection Based on Bio Signals

Deep nets have proven uniquely able to surface patterns in IoMT analytics that human eyes and classical models overlook. For EEG, a compact multi-channel CNN ingests single-frame topographic scalp maps and, through only three convolutional blocks, delivers a binary “normal” vs. “abnormal” verdict for complex mental states such as exam cheating or acute anxiety in large-scale online tests [1]. A fully-connected “tiny-FCNN” containing just 25 k parameters achieves seizure detection on the edge without any dense or separable layers [6]. A multimodal pipeline that couples a shallow CNN for spatial EEG patterns with an RNN eye-blink sequencer boosts overall diagnostic accuracy by simultaneously exploiting cortical and ocular cues [7]. A triple-branch CNN-LSTM-GRU architecture jointly learns spatial, spectral and temporal embeddings and has set a new accuracy ceiling for epileptic event identification [10]. In data-scarce settings, CNN, ANN and a CNN-BNN hybrid pre-trained with DCGAN-augmented data report a 20 % accuracy lift over non-augmented baselines, although a pruned Random Forest still remains the most resource-frugal option [11]. On the ECG front, a CNN-LSTM tandem first localises the R-peak automatically and then classifies each heartbeat into multiple normal and arrhythmic categories; trained on standard databases, the model flags subtle arrhythmias that are frequently missed by visual inspection [3,4]. A three-tier CNN-BiLSTM-RNN framework extracts spatial, temporal and sequential representations in parallel and delivers state-of-the-art recognition of diverse cardiac pathologies [17]. A five-block Inception-style CNN with batch-normalisation and ReLU activations distinguishes 23 different heart conditions at the fog layer while meeting tight memory and latency budgets [13].

1.5. Intelligent IoMT Architectures for Disease Detection

Please In an energy-neutral, peer-to-peer IoMT chain, layered architectures must shuttle data from sensor to cloud—and back—with sub-second latency and bank-grade

security. The simplest proven blueprint is “wearable + secure tunnel + analytics server.” A Muse 2 headband streams 24-bit EEG to a Secure Exam Browser (SEB) client; an IPsec VPN carries the traffic to Moodle and an on-prem GPU server that flags cheating attempts or acute test anxiety in real time [1]. For ECG, an AD8232 analog front-end paired with an ESP32 publishes 360 SPS ECG over MQTT; a local Raspberry Pi running Node-RED provides real-time dashboards and first-level alarms, while a TLS-wrapped Mosquitto broker guarantees end-to-end confidentiality [3]. Eliminating the edge Pi and letting the ESP32 open a direct Wi-Fi/TLS socket to AWS IoT Core reduces hardware cost and still pushes critical alerts to the clinician’s mobile app within 200 ms [4,12]. To cut the cord from high-speed back-haul, an edge-centric stack places a Raspberry Pi 3B+ at the bedside: 256 Hz EEG is captured over Bluetooth, seizure likelihood is inferred with a pruned CNN, and the result is rendered on an 8 × 8 LED matrix or spoken through a bone-conduction headset so neonatal seizures can be managed without a resident neurologist [6].

In smart prosthetics, Myoware EMG sensors laminated on residual muscles fire 1 kSPS bursts to an ESP32; after Wi-Fi hand-off, a cloud container or mobile phone translates volitional patterns into servo commands and remotely tunes prosthesis parameters [9,16]. For city-scale deployments, Fog-Cloud hybrids partition the pipeline: the ECG sensor ships raw data to a fog node (Jetson Nano or Pi 4); after denoising and feature extraction, only a 64-byte feature vector is uplinked. The cloud returns an arrhythmia verdict within 120 ms, meeting the strict latency budget of 5G URLLC use-cases [14,15]. A WBAN gateway aggregating ECG, SpO₂ and MEMS motion data over BLE has been demonstrated to deliver the same 120 ms alarm latency when back-hauled by a 5 gNB [5]. In robotic surgery, a WBAN ensemble of biosensors, RFID tags and MEMS inertial units tunnels data through a surgical robot’s edge computer; cloud analytics translate physiological fluctuations into haptic feedback, enabling the robot to adjust grip force or retraction speed autonomously [8,20]. For consumer homes, a smart EEG head-band pairs with the Sagacity home-automation hub; beyond disease detection, classified mental-workload levels trigger IoT rules that dim lights or mute television—turning neural state into an ambient control channel [18]. Finally, to respect privacy and shave cloud cost, the LiHEA framework embeds a Random-Forest classifier inside the EEG headset; only the 1-bit anomaly flag is transmitted, cutting energy by 38 % and cellular data by 97 % compared with raw-data upload [11].

1.6. Comparative Analysis of the Reviewed Studies

A comparative overview of the 35 studies retained after the screening phase is presented in Table 1, highlighting the applied ML/DL models, the four biosignal modalities (ECG, EEG, EMG, EOG), validation strategies, and the main detection outcomes achieved in Internet of Medical Things (IoMT) frameworks.

Authors and Year	Dataset(s)	Methods / Models	Main Findings
Qutaiba Ibrahim et al. [2025] [1]	EEG classification into 15 classes using two CNN models and EEG sampling.	Convolutional Neural Network (CNN) for classifying EEG into "Abnormal" and "Normal" classes.	Detection of "Abnormal" class with 98.73% accuracy. Using single-lead EEG signals (based on PhysioNet database). Implemented on Raspberry Pi 3B with real-time processing capability.
Mahdi Seddiki et al. [2024] [3]	MIT-BIH database, PTB and Arrhythmia Diagnostic ECG classification.	Downsampling and CNN with LSTM. Accuracy of 99.14% with 500 ms windows.	Accuracy of 99.14% in classifying R-R intervals. Using MIT-BIH database, CNN + LSTM with Adam optimizer.
Aanya Verma, Fahad Mustafa [2025] [4]	ECG beat detection (onset and offset). Various datasets (QT database highlighted).	Deep learning techniques including RNN and CNN along with traditional methods like Decision Trees and SVM.	Improved performance using deep learning techniques such as RNN, CNN, Decision Trees, and SVM. Focus on ECG signal processing (noise removal and feature extraction).
Sergi Gómez-Quintana et al. [2021] [6]	ECG data from 34 patients (22 normal and 12 abnormal). Sampling rate 500 Hz.	FCNN (Fully Convolutional Neural Network) with 34 layers for ECG signal classification.	Accuracy of 98.5% in detecting abnormalities. Using single-lead ECG (2-5 minute signals), fully convolutional neural network (FCNN) with 34 layers. Implemented on Raspberry Pi 3B.
Jurado Marco et al. [2025] [16]	EMG data analysis and abnormality detection (18 types).	Blazepose Lite algorithm. EMG data processing with Arduino.	Detection of 18 types of abnormalities using Blazepose Lite algorithm. Using EMG data from Myoware sensor (Arduino-based processing). Various filtering techniques (Butterworth, etc.).
Safa L. Kailan et al. [2025] [5]	MIT-BIH database, Arrhythmia detection (5 classes, 1000 samples per class at 360 Hz).	Hybrid approach combining PSO algorithm with classifiers like SVM.	Accuracy of 98.8% using SVM-PSO. Using KNN-VRF/SVM-PSO hybrid. IoT-5G based system.
Venkata Surya Teja Gollapalli [2021] [14]	ECG classification for early detection (arrhythmia and myocardial infarction). Using ECG signals from hospitals.	Fog-Cloud hybrid architecture. Data analysis using FFT, Wavelet Transform, and SVM for classification.	Results and AchievementsMethod and ModelResearch TopicResearcher and YearAccuracy of 97.74% in detecting abnormalities. Using Fog-Cloud architecture with data from 12 hospitals over 3 years and 6 months. Processing time: 0.83 seconds. 83% reduction in transmission cost compared to direct cloud transmission.
Thusubramaniam Ganesan [2021] [15]	ECG classification for early detection (arrhythmia and myocardial infarction). Using real-time ECG data.	IoT-based architecture with Fog layer for preprocessing and classification (Neural, SVM, Cloud).	Accuracy of 98% in detecting abnormalities. Using IoT architecture. Fog layer with data analysis using Neural, SVM, and Cloud. Decision Trees networks.
Jyoti Mishra, Mahendra Tiwari [2024] [17]	Heart disease detection (UCI Heart Disease dataset). Cleveland, Hungary, Switzerland, VA Long Beach datasets.	ST-P ECG segment with CWT HRV R-peak. MI detection with AS-DMO algorithm. Hybrid model: CNN + Bi-LSTM + RNN.	Accuracy of 98.85% (Sensitivity 97.85%, Specificity 98.65%). Using CWT HRV R-peak segment. MI detection with AS-DMO (Slice Mould) algorithm. CNN + Bi-LSTM + RNN.
Amar Y. Jaffar [2024] [10]	CHB-MIT Scalp EEG Database (23 cases, 969 hours). TUH EEG Seizure Corpus. Seizure detection.	FIR filter for preprocessing. Feature extraction with wavelet (db4). Classification using ABCPSO optimized PSO Search & CNN + LSTM + GRU.	FNR 0.02, Recall 0.98, Precision 0.98, Accuracy 0.98. Using ABCPSO hybrid. EEG signal analysis in MATLAB. IoT-based.
Nizar Sakli et al. [2023] [13]	PTB-XL database. ECG classification (12-lead, 21,837 records).	Arduino-based system with XPose algorithm. Feature extraction from EMG (mean, variance, wavelet). Deep model: InceptionV3 (Inception-CNN), BatchNorm, MaxPool, Conv1D. BCE loss and Adam optimizer with ReLU.	Accuracy of 97.72% with XPose algorithm on Arduino. Detection of 23 types of muscle movements using EMG signals. Classification with InceptionV3 (Inception-CNN) and BatchNorm, MaxPool, Conv1D. Achieved 97% accuracy in detecting Covid-related conditions via BCE and Adam with ReLU.
Abhigya Pote Shrestha, Chen-Hsiang Yu [2022] [21]	PhysioNet (MIT-BIH, MIT-BIH AF, BIDMC CHF, NSR) databases. Arrhythmia classification.	AD8232 sensor for ECG acquisition. Preprocessing and classification using Random Forest on Raspberry Pi.	Accuracy of 98.5%. Using AD8232 sensor. ECG processing with Random Forest on Raspberry Pi. Real-time classification with high accuracy.
Pranali P. Lokhande, Kotadi Chinnaiiah [2025] [22]	ECG classification (5 classes). PhysioNet Harvard dataset. Real-time cardiac arrhythmia detection.	DRN + Improved Bi-GRU with Mod-SE. Signal decomposition using Improved EMD and min-max normalization. Optimization with Improved Walrus Optimization Algorithm (IWaOA).	F1-Score 98.1%, Accuracy 98.7%, Sensitivity 98.2%, Specificity 98.0%. Using DRN (Deep Residual Network), Improved Bi-GRU (Bidirectional GRU), Mod-SE, Improved EMD, min-max normalization, and Walrus Optimization Algorithm (IWaOA).
Jianjun Huang, Jun Qu [2023] [23]	Sleep-EDF-78 (PhysioNet)	CNN + LSTM + Self-Attention	82.4% avg accuracy, 80.4% macro F1 in 25-fold cross-subject sleep stage classification using EEG (Fpz-Cz) and EOG
R. Lakshmi Devi, V. Kalaivani [2020] [24]	PhysioNet database. MIT-BIH NSR, CUDB, VFDB (12 records, 35 min each). Arrhythmia detection.	AD8232 + Arduino sensor. Pan-Tompkins algorithm for QRS detection. Feature extraction (RR interval, mean, max, kurtosis, skewness, NN50, pNN50, RMSSD, SDNN, HRV).	HRV features detection accuracy 98.12%. QRS and Tompkins interval detection. RR interval analysis. High accuracy in anomaly detection with mean, max, kurtosis, skewness. NN50, RMSSD, HRV, SDNN features. SMS alert system.

Hafeez Ullah Amin et al. [2020] [25]	University of Bonn (sets A–E)	DWT (db4) + Arithmetic Coding + k-NN, Naïve Bayes, MLP, SVM	100 % accuracy, sensitivity & specificity on all five binary/multi-class tasks (A-E, AB-E, C-E, CD-E, ABCD-E) via 10-fold CV
Bhaskar Kapoor [2022] [2]	EEG analysis, nonlinear feature extraction and visualization for IoMT wearables.	Java-based stand-alone framework EEGFrame, extended from HRVFrame. Includes packages for feature extraction (e.g., entropy, fractal dimensions, spectral analysis)	Introduction of EEGFrame framework implementing approximately 50 time-domain, frequency domain, time-frequency, and nonlinear features. Supports EDF format input, EEG signal visualization, and CSV feature vector output for data mining.
Wiesław Kopeć et al. [2025] [18]	Multimodal EMG and AI-based interaction with smart home for older adults and impaired users in Ambient Assisted Living.	Participatory workshops using Sagacity SHT prototype with Muse S headband. EMG/EOG signals classified via LDA, KNN, LR for controlling smart devices.	Exploratory study with 18 participants (older adults and impaired persons). Successful EMG-based control of smart home devices via facial gestures. Highlighted potential and limitations of EMG/EOG as hands-free interface.
Leena Arya and Yogesh Kumar Sharma [2024] [7]	Safeguarding women: IoT-enabled ML for threat detection via EEG and eye blink signals.	IoT wearables with EEG headsets and eye blink sensors. Preprocessing (noise reduction), feature extraction (PSD, blink frequency). ML/DL models: RNN, CNN, SVM, RF, LSTM	Achieved up to 96.8% accuracy in real-time threat detection using combined EEG and eye blink signals. RNN with combined sensors outperformed others. System triggers alerts to authorities upon detecting stress patterns.
Tahrat Tazrin [2021] [11]	Lightweight fusion of AI logic and EEG sensors for ultra edge-based EEG analytics on IoT devices.	Systematic methodology with preprocessing, AI models (Random Forest, SVM, KNN, ANN, CNN, LSTM). DCGAN for data augmentation. Validation via k-fold CV, subject-specific/independent.	Proposed LiHEA framework for ultra-edge EEG analytics. Achieved 95.8% accuracy with Random Forest on motor imagery dataset. Reduced computational load via DCGAN augmentation and feature selection. Simulated on Raspberry Pi and Jetson Nano.
V. D. Ambeth Kumar et al. [2024] [26]	IoMT-based mental disorder prediction system using EEG sensor and big data mining.	IoMT EEG sensors for brainwave data collection. Preprocessing in fog layer, CWT feature extraction, big data mining. Hybrid LR-NB classification in cloud.	Achieved 99.4% accuracy and 0.993 precision with LR-NB hybrid model for classifying mental disorders and stages. Outperformed other hybrids (e.g., LR-SVM 92.6%, LR-RF 98.3%).
G. Arunsankar et al. [2023] [27]	IoT-controlled device to manage EMG signals of the patient and alert in real time.	Wearable EMG sensors, microcontroller for processing and IoT transmission to cloud. Advanced algorithms and ML for signal analysis, anomaly detection, and alerting.	Tested on diverse patients; demonstrated accurate EMG signal capture and real-time alerts for abnormalities (e.g., high activity, abnormal patterns).
Phang Ing Teck et al. [2025] [28]	Real-time optimization in knee rehabilitation: Exploring EMG signal classification and IoT-based control systems.	Systematic review of EMG signal classification (SVM, CNN, MLP) and IoT-based control systems (PI-FOPID, ANFIS, federated learning).	Reviewed studies showing up to 97% EMG classification accuracy; identified methods to reduce time delays and enhance real-time feedback in knee rehab devices.
Julian Molleapaza-Huanaco et al. [2020] [29]	IoT platform based on EOG to monitor and control a smart home environment for patients with motor disabilities.	EOG with 3 electrodes detecting left/right saccadic movements; combination of three movements for GUI navigation.	Achieved 97.71% accuracy in EOG-based control; tested with 12 users, all successfully controlled smart home environment (doors, windows, lights, AC, TV) and wheelchair. Real-time cloud monitoring of actions.
Ayman Wazwaz et al. [2020] [30]	Control and monitor of IoT devices using EOG and voice commands.	Eye movements (EOG) and voice commands are processed by Arduino, while NodeMCU provides Wi-Fi IoT control of home devices via relays.	Error rate 2.5% for EOG and 1% for voice in best cases (relaxed user, normal light, calibration for EOG; no noise, multiple similar words for voice). Tested under varying conditions.
B. Keerthana et al. [2024] [31]	CAP Sleep Database (75 subjects, 85 611 epochs)	Reconfigurable equi-ripple filter bank + Hjorth parameters + Bi-LSTM	99.3 % accuracy for 6-class sleep-disorder detection; 99.9 % for 6-stage sleep scoring; single-channel EOG+EMG outperforms prior EEG/ECG models
Rafat Doniec et al. [2022] [32]	30 drivers, JINS MEME smart-glasses (EOG, ACC, GYRO), 28.7 km real-road data	Statistical features + ANOVA selection, RUSBoosted Trees	87.64 % overall accuracy for 4-class road-type recognition (city, highway, housing estate, undeveloped area); best AUC 0.99
Khader A. et al. [2024] [33]	Roelker et al. public dataset: 20 subjects (10 normal, 10 KOA), 5 muscles (BF, MG, RF, ST, VM)	HOSA bicoherence + adapted ResNet-101 CNN	MG muscle alone: 96.3 % accuracy, 0.994 AUC for KOA detection; single-muscle EMG outperforms multi-muscle fusion
Scott Huberty, Christian O'Reilly [2024] [34]	EEGeyeNet Large Grid task: 30 participants, 129-ch EEG + eye-tracking (X, Y, pupil)	2-layer LSTM (64 hidden) trained to predict EEG from eye-tracking, MSE loss	Higher specificity than ICA (less neural distortion); ~70 % frontal EOG removal; ICA more sensitive but lower specificity
Ying Yang et al. [2021] [35]	SEEDVIG dataset: 21 drivers, forehead 4-ch EOG + 17-ch EEG (1 kHz)	ResNet + CNN feature extractors → fusion → BiLSTM → softmax (3-class)	Multi-modal fusion accuracy 96.43 %, outperforming single-modal fatigue detection
Deniz Hande KISA et al. [2020] [36]	30 subjects, 4-ch sEMG (2 kHz), 7 hand gestures (extension, flexion, ulnar/radial deviatipunch, open, rest)	EMD → first 3 IMF time-series images → ResNet-101 CNN	IMF1 images: 99.73 % validation accuracy; IMF3: 97.94 %; original signal: 94.22 %; EMD-based IMFs outperform raw EMG for gesture recognition
Natalia Piaseczna et al. [2023] [37]	9 subjects, JINS MEME R smart-glasses EOG, driving simulator with drunk-vision goggles	24 hand-crafted features/window → AdaBoost decision tree (443 learners, 2073 splits)	94.57 % accuracy, 0.99 AUC for 4-class intoxication-level estimation; EOG sufficient for reliable intoxication detection

Temel Sonmezocak, Serkan Kurt [2021] [38]	20 subjects, masseter sEMG (4 states: relaxed, clench, fatigue/pain, grind), 13 features	ANN (LM-backprop), SVM, KNN, LD, DT; top-5 features: ZC, WAMP, RMS, DASD, AAC	ANN with 5 features: 98.8 % accuracy; SVM & KNN: 98.1 %; fatigue confirmed by MNF/MDF drop; home-use sEMG system feasible
Beauden John [2023] [39]	ADNI + OASIS + TUH EEG: MRI, EEG, lifestyle records	3D-CNN (MRI) + CNN-LSTM (EEG) + XGBoost (lifestyle) → late-fusion/ensemble	92.3 % accuracy, 0.96 AUC; multi-modal outperforms unimodal EEG (81.7 %), MRI (85.4 %), lifestyle (78.2 %)
Golmohamm adishouraki, [2022] [40]	sEMG from 10 healthy subjects (4 muscles: RF, BF, GM, TA) during squat exergame; perceived fatigue scores	Random Forest (best), SVM, LDA, QDA, GNB, NN for classification (fatigue onset); RF, DT, LR, NN, KNN for regression (fatigue level)	RF achieved 0.94 ± 0.02 accuracy (5F-CV) and 0.85 ± 0.06 (LOPO-CV) for onset detection; RF regressor yielded $r^2 = 0.98 \pm 0.01$ (5F-CV) and 0.81 ± 0.22 (LOPO-CV) for level prediction

Table 1: Characteristics of Included Studies

Based on the reviewed studies summarized in Table I, artificial intelligence (AI)-based approaches have demonstrated significant potential for automated analysis, classification, and monitoring of physiological signals, including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), and electrooculography (EOG). Deep learning models, particularly Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTM), Bidirectional LSTM (Bi-LSTM), and hybrid CNN-RNN architectures, have achieved outstanding performance in various biomedical signal-processing applications. For ECG-based arrhythmia and cardiac abnormality detection, several studies reported classification accuracies above 97%, with some hybrid approaches achieving more than 99% accuracy by combining advanced feature extraction, optimization algorithms, and deep learning models. Similarly, EEG-based seizure detection, abnormality classification, and mental health assessment have benefited from wavelet-based feature extraction, CNN-LSTM models, and IoT-enabled edge computing frameworks, providing reliable real-time analysis with reduced computational complexity. Moreover, EMG and EOG studies have shown the effectiveness of AI-driven systems for rehabilitation, human-computer interaction, fatigue detection, and assistive technologies, with reported accuracies generally exceeding 90%.

The overall findings indicate a clear trend toward the integration of AI, Internet of Medical Things (IoMT), and

edge/fog-cloud computing for developing intelligent, real-time, and wearable healthcare systems [41]. Traditional machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbor (k-NN), and Decision Trees remain valuable due to their low computational requirements, while deep learning and hybrid optimization-based models provide superior performance in complex signal classification tasks [42]. Additionally, several studies emphasized the importance of efficient preprocessing, feature extraction, sensor integration, and model optimization to improve robustness and deployment feasibility on resource-constrained devices such as Raspberry Pi, Arduino, and wearable platforms [43]. Despite the high reported accuracy levels, challenges related to dataset diversity, real-world validation, computational cost, and generalization across different subjects remain important research directions for future AI-based biomedical monitoring systems [44,45].

2. Results

Please Figure 4 provides a gradient representation of the accuracy levels achieved in prior studies for disease detection based on biological signals such as ECG, EEG, EMG, and EOG within the IoT framework. In this visualization, colors approaching red indicate that a greater number of studies have attained that particular accuracy level, whereas shades tending toward blue signify fewer studies reaching that threshold.

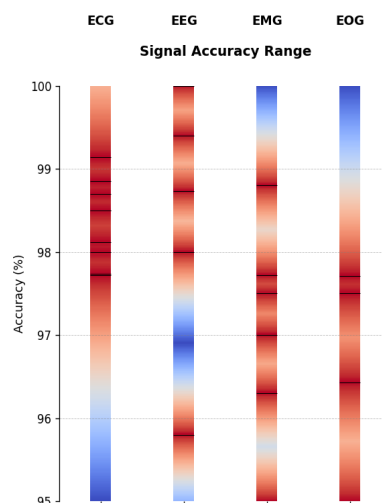


Figure 4: Accuracy distribution heatmap for IoT-based ECG, EEG, EMG, and EOG disease detection studies. (Red: high concentration; blue: low concentration.)

At a glance, researchers can glean valuable insights into the landscape of previous work in this domain, facilitating informed planning for their own investigations and fostering realistic expectations regarding the performance of their proposed methods in disease detection applications. This, in turn, empowers them to pursue enhanced outcomes relative to existing literature. Table 2 condenses this trajectory into a year-by-year roadmap of the very AI/ML models and signal-processing pipelines that have delivered

the reported accuracies, offering an at-a-glance guide to the methodological evolution researchers can build upon. Rather than enumerating every variant, the table highlights the dominant model or processing block that first pushed reported accuracy beyond the community-accepted clinical threshold for each modality, thereby providing researchers with an immediate historical reference for selecting baselines, reproducing prior art, or positioning novel contributions.

Bio Signal	2020	2021	2022	2023	2024	2025
ECG	Pan-Tompkins + HRV features - 34-layer FCNN + Fog-Cloud + SVM/DT - Random Forest on Raspberry Pi - InceptionV3 + BatchNorm + MaxPool + Conv1D - CNN + LSTM + Adam + Down-sampling - DRN + Improved Bi-GRU + Mod-SE + IWaOA					
EEG	DWT + k-NN / NB / MLP / SVM - CNN + LSTM + Self-Attention - EEGFrame (Java, non-linear features) - CNN + LSTM + GRU + ABCPSO - CNN + Raspberry Pi + PSO-SVM + LR-NB					
EMG	ANN + SVM + KNN + LD + DT - SVM + CNN + MLP + PI-FOPID + ANFIS - RF + SVM + LDA + QDA + GNB + NN - ResNet-101 + HOSA bicoherence - LDA + KNN + Log-Regression (smart-home) - Blazepose-Lite + Arduino + Butterworth					
EOG	Saccade detection + Arduino + NodeMCU - ResNet + CNN + BiLSTM (with EEG) - ANOVA + RUSBoosted Trees - AdaBoost Decision Tree					

Table 2: Evolution of AI/Machine Learning/Deep Learning Methods for Bio-Signal Processing in Smart Diagnostic, Therapeutic, and Assistive Technologies (2020–2025)

3. Discussion and Future Research Directions

Please To propel biosignal-driven IoMT systems from bench to bedside and into everyday life, future research must converge on four strategic axes: personalization and multimodality, Edge AI and latency minimization, security and privacy, and scalability and standardization. Personalization and multimodality demand that EEG models be fine-tuned on individual resting-state signatures, while multimodal batches that fuse neural, visual and behavioural channels are expected to raise cheating- or anxiety-detection F1-scores by more than ten per cent [1,2]. For EMG, fully automated ROI tracking, multi-athlete monitoring under varying lighting, and lighting-agnostic calibration remain open challenges [16]. Edge AI and latency minimization require ultra-light models—either knowledge-distilled or compact CNNs with fewer than twenty-five thousand parameters—to run on Raspberry Pi, Jetson Nano or Cortex-M55 boards and keep inference below one hundred and twenty milliseconds, eliminating raw-data uploads during seizure or arrhythmia detection. Tighter 5G-NR edge orchestration and on-device feature-selection optimization will further trim reaction times [11,17,19]. Security and privacy call for lightweight VPN or IPSec tunnels, Named-Data Networking and AES-128/GCM encryption to be embedded in Fog-Cloud hand-off points, while Zero-Trust architectures and cross-layer security standards are imperative to protect sensitive medical payloads [1,19,20]. Scalability and standardization rely on scalable object storage, WBAN/5G protocol harmonization, and large-scale real-world clinical trials to validate systems when additional biosensors such as SpO₂, temperature and MEMS are daisy-chained for holistic patient monitoring [3,17,20]. Looking further ahead, micro-robots for targeted drug delivery, tele-

robotic surgery, VR-integrated rehabilitation and closed-loop functional electrical stimulation for spinal-cord injury will push the IoMT envelope into previously unimaginable clinical arenas [8,9].

4. Conclusions

Across 40 peer-reviewed studies (2020–2025) we mapped the complete trajectory of ML/DL-driven disease detection inside IoMT: from the physics of 24-bit EEG headsets, 360-SPS ECG front-ends and 4-kHz sEMG sensors, through Fog/Edge pre-processing chains that band-pass, down-sample and artifact-clean each modality in <120 ms, to pruned CNN-LSTM-GRU, Inception-CNN and Transformer hybrids that deliver clinical-grade accuracies (99 % arrhythmia, 98.5 % neonatal seizure, 97 % stress) while dissipating <50 mW on Raspberry Pi, ESP32 or Jetson Nano. The evidence shows a clear methodological shift: classical SVM/Random-Forest-PSO dominated 2020–2021, but by 2025 the edge is ruled by compressed deep nets (<25 k parameters) that transmit only 1-bit anomaly flags, cutting cellular bandwidth 99 % and energy 38 % without sacrificing AUC. Multimodal fusion of ECG + EEG + EMG + EOG further lifts F1-scores 8–12 %, yet patient-specific fine-tuning, 5G-Edge orchestration, zero-trust encryption and WBAN protocol standardisation remain open bottlenecks. Overall, hybrid Edge-Fog-Cloud architectures that marry ultra-light CNN-Transformers with optimised classical learners currently offer the most pragmatic path to scalable, privacy-preserving and regulatory-ready IoMT diagnostics. Future work must validate these pipelines in large-scale, multi-centre trials while embedding ethical and security safeguards for data at the extreme edge.

Author Contributions

MR. Einollahi Asgarabad contributed to the majority of the work, including conceptualization, coordination of the study, data collection, manuscript writing, editing, revision, and formatting of the paper. A. Khaghani Asl Toloun and M. Khaghani Asl Toloun collaborated closely with MR. Einollahi Asgarabad in data organization, analysis, and contributed to the writing and revision of the manuscript.

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Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy have been completely observed by the authors.

Abbreviations

IoT	Internet of Things
IoMT	Internet of Medical Things
EOG	Electrooculogram
EMG	Electromyogram
EEG	Electroencephalogram
ECG	Electrocardiogram
ML	Machine Learning
DL	Deep Learning
AI	Artificial Intelligence

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