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Biomedical Signal and Image Processing with Modern Technologies: Why It Matters for Medicine

Xudoyarov Otabek Alisherovich
First-year student, Faculty of General Medicine,
Samarkand State Medical University, Samarkand, Uzbekistan
Sayfullayev Akobir Bahodir o'g'li
First-year student, Faculty of General Medicine,
Samarkand State Medical University, Samarkand, Uzbekistan
Xaydarov Odilbek Mansur o'g'li
First-year student, Faculty of General Medicine,
Samarkand State Medical University, Samarkand, Uzbekistan
Saydullayev Sanjar Salimjon o'g'li
First-year student, Faculty of General Medicine,
Samarkand State Medical University, Samarkand, Uzbekistan
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Abstract: Medical biological signals (ECG, EEG, EMG, PPG) and medical images (X-ray, CT, MRI, ultrasound) are central to modern diagnosis. They are noisy, high-dimensional and time-consuming to interpret.

Objective: This paper reviews the main methods for processing biomedical signals and images and explains why learning them with modern technologies matters for future physicians.

Methods: An analytical literature review was carried out in PubMed, IEEE Xplore, ScienceDirect and Google Scholar for publications from 2015 to 2025. Classical techniques (filtering, Fourier and wavelet analysis) were compared with machine-learning and deep-learning approaches, explainable AI and federated learning.

Results: Deep-learning models have reached performance comparable to expert clinicians in tasks such as ECG arrhythmia classification and tumour segmentation. Classical methods remain essential for preprocessing and interpretability. Main barriers are scarce labelled data, weak generalisation across devices and populations, algorithmic bias, and regulatory and ethical constraints.

Conclusion: Modern signal and image processing improves diagnostic accuracy, reduces clinician workload and supports telemedicine. Early exposure of medical students to these methods is a practical step toward digital health competence.

Keywords: biomedical signal processing; medical image analysis; deep learning; wavelet transform; clinical decision support; artificial intelligence; medical education

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Introduction

Modern medicine depends increasingly on digital data. The electrocardiogram (ECG) records cardiac electrical activity, the electroencephalogram (EEG) records brain activity, the electromyogram (EMG) records muscle activity, and photoplethysmography (PPG) estimates changes in blood volume. Imaging methods such as radiography, computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound make internal anatomy and pathology visible.

Raw biomedical data are rarely ready for direct clinical use. Signals are contaminated by noise, motion artefacts and electrode faults. Images show subtle lesions against complex backgrounds, and their appearance varies with acquisition protocol and equipment. Manual interpretation is slow and can differ between observers. These problems call for systematic methods of signal and image processing.

Traditionally the field has relied on digital filtering, frequency-domain analysis, wavelet decomposition and hand-crafted features [1, 7, 8]. Over the last decade, machine learning and deep neural networks have learned informative features directly from data, changing both research and clinical practice [1, 2]. Work that links these methods to real clinical workflows, and explains them to students, is still less common than purely technical studies.

A typical analysis pipeline has four stages: acquisition, preprocessing, feature extraction and decision. Errors introduced early, for example by a loose electrode or a poorly chosen filter, propagate to every later stage. For this reason, understanding the whole chain matters as much as knowing individual algorithms. In resource-limited settings, where specialist time is scarce and devices are increasingly portable, reliable automated processing can extend the reach of diagnostic services beyond large urban hospitals.

The study addresses the following research questions:

RQ1. What are the main methods for processing biomedical signals and images?

RQ2. How do classical and modern methods compare in accuracy and practicality?

RQ3. Why is learning these methods important for future physicians?

2. Methods

This is an analytical narrative review. No new patient data were collected and no experiments were performed. The review synthesises peer-reviewed research and openly available benchmark datasets.

PubMed, IEEE Xplore, ScienceDirect and Google Scholar were searched for articles published between 2015 and 2025. The search terms were "biomedical signal processing", "medical image analysis", "deep learning ECG", "EEG wavelet analysis", "U-Net segmentation" and "federated learning healthcare".

Peer-reviewed articles and reviews were included if they used human biomedical data or public benchmark datasets such as the MIT-BIH Arrhythmia Database and PhysioNet resources [9], and if

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full text was available in English or Russian. Editorials, non-peer-reviewed material and records without full text were excluded.

The selection process followed three steps. First, titles and abstracts were screened for relevance to signal or image processing in medicine. Second, full texts of potentially relevant articles were read to confirm the data type, the method and the reported metrics. Third, studies were grouped by modality (ECG, EEG, EMG, PPG, medical imaging) and by application area (diagnosis, monitoring, segmentation, rehabilitation). Because datasets, patient populations and validation protocols differ between studies, reported accuracies were treated as indicative and were not pooled into a single estimate.

For each included study we extracted the signal or image type, the method, the dataset size and the reported evaluation metrics (accuracy, sensitivity, specificity, F1-score, Dice coefficient). Findings were grouped by modality and application area and synthesised qualitatively. Numerical values are quoted only as they appear in the original publications. The review was carried out by a student team without a formal risk-of-bias assessment, so the results describe trends in the literature rather than a meta-analysis.

3. Results

RQ1. The main methods depend on the data type. For ECG, the classical pipeline starts with a band-pass filter and a QRS detector such as the Pan-Tompkins algorithm [7], followed by hand-crafted features and rule-based or statistical classification. For EEG, Fourier and wavelet analysis, along with independent component analysis, are used to separate neural activity from artefacts and to extract band-power features [8]. EMG signals are usually filtered and summarised with amplitude features such as root mean square. For PPG, filtering and peak detection provide pulse-rate and pulse-shape features. For images, classical pipelines use thresholding, edge detection and region growing, and histology is still often reviewed by morphological assessment. In all modalities the preprocessing stage is essential: baseline wander, power-line interference and motion artefacts are removed before any feature is computed, and the choice of sampling rate and window length strongly affects the result. Modern pipelines replace most hand-crafted steps with convolutional networks (CNN), recurrent networks (LSTM) and, more recently, Transformers, while U-Net is the standard architecture for segmentation [1, 5].

RQ2. Modern methods generally outperform classical ones when large labelled datasets are available. A deep network trained on a large set of ambulatory ECG recordings classified arrhythmias with performance comparable to that of cardiologists [3]. Reviews of medical image analysis report that deep learning exceeds traditional approaches in classification, detection and segmentation across many tasks [1, 4]. Classical methods still have clear advantages: they need little data, run on modest hardware, and their steps can be inspected and explained. Federated learning is a further modern option, because it trains models across several institutions without moving patient data [6]. Explainability tools such as saliency maps help clinicians see which features drive a prediction, which

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supports trust in the model. The practical choice therefore depends on data volume, device constraints and the need for interpretability. A hybrid pattern is common in practice: classical filtering and feature extraction are kept for preprocessing and quality control, while a learned model makes the final decision. Such a design keeps the advantages of both families and makes failures easier to diagnose.

RQ3. The applications show why these skills matter for physicians. In cardiology, automated arrhythmia detection allows earlier diagnosis and continuous monitoring [3]. In neurology, EEG classifiers support seizure and sleep analysis. In radiology and oncology, CNN and U-Net models help detect fractures, tumours and lesions and reduce differences between observers [1, 5]. In rehabilitation, EMG-based control improves prosthesis use. In telemedicine, edge computing allows analysis on the device itself, which is valuable where specialists are scarce. A physician who understands how a signal was filtered, how a model was trained and what its errors look like is better able to judge device output and to use these tools safely.

4. Discussion

The results indicate that modern technologies address three central problems of diagnostic work: accuracy, time and inter-observer variability. Deep models can process large volumes of data quickly and act as decision support rather than replacements for clinicians. This is especially relevant where specialist staff are in short supply.

Four barriers limit wider use. High-quality labelled data are scarce, and expert annotation is costly. Models trained at one centre often lose accuracy on different devices or patient populations. Algorithmic bias can produce unequal performance across demographic groups. Questions of data protection, liability and regulatory approval must also be resolved before clinical deployment [2, 6].

For medical education, the practical implication is clear. Basic knowledge of signal and image processing belongs in the curriculum, next to medical physics and biostatistics. Future physicians will need to read device output critically, evaluate artificial-intelligence recommendations and recognise when a result is unreliable.

A recurring principle in the reviewed literature is human-in-the-loop decision making. Automated outputs are most useful as prioritisation tools, for example flagging a recording for urgent review, rather than as final verdicts. Over-reliance on automated outputs is a real risk, and clinicians need training to recognise when a model is operating outside the conditions it was trained on, such as a new device or an unusual patient group.

Future work should build representative datasets from Uzbek populations, test international models on them, integrate explainable AI into clinical software, and explore federated collaboration between hospitals. This study itself is limited to a narrative review and has not tested any model experimentally.

The present study has several limitations. It is a narrative rather than systematic review, the search was limited to four databases and to English and Russian full texts, and the selection was performed by a small team without independent double screening. Many of the cited results come

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from retrospective datasets, whose performance on prospective clinical data may be lower. These limitations mean the findings should be read as a structured overview that motivates further empirical work.

5. Conclusion

Processing biomedical signals and images with modern technologies improves diagnostic accuracy, supports clinicians and extends the reach of telemedicine. Deep learning and explainable AI complement classical methods, but their clinical use requires high-quality data, external validation and ethical and legal safeguards. Introducing medical students to these methods early is an important step in building the digital skills of future doctors.

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