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# Abstract

Biomedical signals and imaging techniques are central to modern medical diagnostics, providing critical insights into physiological processes and structural conditions of the human body. Signals such as Electroencephalography (EEG), Electrocardiography (ECG), Event-Related Potentials (ERP), Electrooculography (EOG), and Electromyography (EMG) capture dynamic electrical activity from the brain, heart, eyes, and muscles, enabling early detection and monitoring of neurological, cardiac, and neuromuscular disorders. Similarly, imaging modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), X-ray, Positron Emission Tomography (PET), and Angiography allow clinicians to visualize both anatomical structures and functional processes with high precision.

Despite their diagnostic value, both signals and imaging data are complex, noisy, and often require expert interpretation, which can be time-consuming and subject to human variability. Recent advances in Artificial Intelligence (AI), particularly machine learning and deep learning, have transformed the analysis of biomedical data by enabling automated feature extraction, accurate classification, and explainable predictions. By integrating AI into signal and image processing pipelines, healthcare professionals can achieve faster, more consistent, and more accessible diagnostic support.

This report explores the methodologies, applications, and challenges associated with biomedical signals and imaging, while emphasizing the role of AI-driven systems in enhancing accuracy, efficiency, and interpretability in clinical practice. The aim is to present a unified perspective on how multimodal biomedical data can be harnessed to improve patient care and advance the future of digital health.

# Introduction

## Background on Biomedical Signals

Biomedical signals are measurable manifestations of physiological processes in the human body. They reflect the electrical, chemical, or mechanical activities of organs and tissues, and serve as vital indicators of health status. Common examples include electrocardiograms (ECG) that capture cardiac electrical activity, electroencephalograms (EEG) that monitor brain function, and electromyograms (EMG) that record muscle activity. These signals are typically non-stationary, low in amplitude, and susceptible to noise, requiring advanced signal processing techniques for accurate interpretation. Biomedical signal analysis provides critical insights into disease diagnosis, patient monitoring, and therapy evaluation.

## Background on Medical Imaging

Medical imaging refers to the techniques and processes used to create visual representations of the internal structures of the body for clinical analysis and medical intervention. It encompasses a wide range of modalities, including X-ray imaging, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and nuclear medicine techniques such as positron emission tomography (PET). Each modality offers unique advantages: for example, MRI excels at soft tissue contrast, CT provides high-resolution anatomical detail, while ultrasound allows real-time imaging. Advances in imaging technology, combined with computational methods such as machine learning and image processing, have significantly enhanced the precision of diagnosis, surgical planning, and disease monitoring.

## Relevance to Modern Healthcare

The integration of biomedical signal analysis and medical imaging is at the forefront of modern healthcare. Together, they enable comprehensive, multi-modal assessments of physiological and anatomical conditions. The rapid evolution of computational power, data-driven algorithms, and artificial intelligence has further amplified their role in personalized medicine, early disease detection, and real-time patient monitoring.

## Importance in Diagnostics and Patient Monitoring

Biomedical signals and medical imaging play a critical role in modern diagnostics and patient care. They provide clinicians with objective and quantifiable data for disease detection, treatment planning, and monitoring of therapeutic outcomes. For instance, continuous ECG monitoring enables early detection of arrhythmias, while MRI scans can reveal subtle changes in brain tissue associated with neurological disorders. The ability to capture both functional (signals) and structural (images) information enhances the accuracy of clinical decision-making. Furthermore, real-time monitoring supports timely intervention in critical care settings, improving patient survival rates and long-term health outcomes.

## Problem Statement

Despite their importance, the interpretation of biomedical signals and medical images remains a significant challenge. Manual analysis by clinicians is time-consuming, prone to inter-observer variability, and often limited by the complexity and volume of data generated. For example, subtle abnormalities in an ECG or faint lesions in an MRI may be overlooked due to fatigue or human error. Additionally, the rapid growth in healthcare data has outpaced the ability of traditional diagnostic workflows to process and interpret information effectively. These challenges highlight the urgent need for intelligent, automated systems leveraging artificial intelligence (AI) and machine learning to support clinicians in extracting reliable insights with speed and accuracy.

## Objectives of the Report

The objectives of this report are as follows:

1. To review the role of biomedical signals and medical imaging in clinical diagnostics and patient monitoring.
2. To identify the limitations associated with manual interpretation and traditional diagnostic methods.
3. To explore the potential of AI and machine learning techniques in enhancing the analysis of biomedical data.
4. To evaluate selected algorithms or approaches for improving diagnostic accuracy and efficiency.
5. To show a chatbot application that integrate AI and machine learning to analyze biomedical signals and medical images for healthcare delivery.

# Biomedical Signals

## Overview of Bio-signals

Biomedical signals are time-varying representations of physiological activities in the human body that can be measured and analyzed to assess health status. They arise from natural biological processes such as electrical activity in the heart, mechanical movement of muscles, or acoustic vibrations in the respiratory system. These signals serve as vital biomarkers, providing clinicians and researchers with quantitative information for diagnosis, prognosis, and monitoring of diseases. The analysis of biomedical signals also underpins the development of medical devices and healthcare technologies such as pacemakers, prosthetics, and patient monitoring systems.

### Classification of Biomedical Signals

Biomedical signals can be broadly classified into the following categories:

1. Electrical Signals

* Origin: Generated by the flow of ionic currents across cell membranes in excitable tissues.
* Examples:
* **Electrocardiogram (ECG):** Represents cardiac electrical activity.
* **Electroencephalogram (EEG):** Captures brain wave activity.
* **Electromyogram (EMG):** Measures muscle activation.
* Significance: Essential for diagnosing heart arrhythmias, neurological disorders, and neuromuscular conditions.

1. Mechanical Signals

* Origin: Produced by physical displacement, pressure, or movement within organs and tissues.
* Examples:
* **Blood pressure waveforms** from the cardiovascular system.
* **Respiratory movements** measured through spirometry.
* **Seismocardiography (SCG):** Mechanical vibrations of the chest wall caused by heartbeats
* Significance: Provide insights into cardiovascular mechanics, pulmonary function, and musculoskeletal health.

1. Acoustic Signals

* Origin: Generated by vibrations or turbulence of air and fluids in biological systems..
* Examples:
* **Phonocardiogram (PCG):** Heart sounds (S1, S2) for detecting murmurs.
* Respiratory sounds: Wheezing, crackles, or cough sounds used in pulmonary diagnostics.
* Vocal signals: Speech production for communication or voice pathology analysis.
* Significance: Useful in diagnosing cardiovascular and respiratory abnormalities, as well as in speech and hearing research.

## Electroencephalography (EEG)

### Signal Source and Applications

Electroencephalography (EEG) is a non-invasive technique used to record the electrical activity of the brain. EEG signals originate from postsynaptic potentials of cortical neurons, captured through electrodes placed on the scalp. Due to its high temporal resolution, EEG is widely applied in both clinical and research settings. Clinically, EEG is essential for diagnosing and monitoring neurological disorders such as epilepsy, sleep disorders, encephalopathies, and brain injuries. In research, it supports studies of cognitive processes, brain–computer interfaces (BCI), and neurofeedback systems.

### Typical Preprocessing

Raw EEG recordings are often contaminated by noise and artifacts, making preprocessing an essential step before analysis. Common preprocessing techniques include:

* Filtering: Band-pass filters are applied to isolate relevant frequency ranges (e.g., delta 0.5–4 Hz, theta 4–8 Hz, alpha 8–13 Hz, beta 13–30 Hz, gamma >30 Hz). Notch filters are used to remove power-line interference (50/60 Hz).
* Artifact Removal: EEG is highly sensitive to artifacts from eye blinks, muscle activity (EMG), and environmental noise. Techniques such as Independent Component Analysis (ICA) or regression methods are commonly used for artifact correction.
* Segmentation: Continuous signals are divided into epochs (time windows) aligned with stimuli or events of interest.
* Normalization: Amplitude scaling or baseline correction is applied to reduce inter-subject variability.

### Feature Extraction and Classification

After preprocessing, EEG signals are transformed into discriminative features for further analysis or classification. Key methods include:

* Time-Domain Features: Amplitude, latency, and statistical measures such as mean, variance, and Hjorth parameters.
* Frequency-Domain Features: Power spectral density (PSD) analysis for different brain wave bands, reflecting mental states (e.g., alpha for relaxation, beta for alertness).
* Time-Frequency Features: Wavelet transform and short-time Fourier transform (STFT) to capture transient oscillations.

## Electrocardiography (ECG)

### Signal Source and Applications

Electrocardiography (ECG) is a widely used technique for recording the electrical activity of the heart over time. It measures the depolarization and repolarization of cardiac muscle fibers using electrodes placed on the skin. ECG is central in cardiology, providing valuable insights into heart rhythm, conduction pathways, and myocardial health. Its primary clinical applications include:

* Arrhythmia detection: Identifying irregular heart rhythms such as atrial fibrillation, ventricular tachycardia, or premature contractions.
* Ischemia and infarction monitoring: Detecting abnormalities related to reduced blood flow or myocardial damage.
* General cardiac assessment: Evaluating heart rate variability, conduction delays, and effects of medication or interventions.

### Key Features of the ECG Waveform

The ECG waveform is composed of distinct components that reflect specific cardiac events:

* P wave: Represents atrial depolarization. Its morphology and duration help assess atrial size and rhythm.
* QRS complex: Corresponds to ventricular depolarization. It is the most prominent feature, and abnormalities in shape or duration may indicate conduction blocks, ventricular hypertrophy, or ischemia.
* T wave: Represents ventricular repolarization. Inverted or elevated T waves can signal electrolyte imbalances, ischemia, or myocardial infarction.

### Relevance in Signal Analysis

Accurate identification of these waveform components forms the basis of automated ECG interpretation. By extracting features such as heart rate, QRS width, ST segment deviations, and T wave morphology, clinicians and machine learning systems can detect a wide range of cardiac abnormalities. With the increasing use of wearable devices and portable ECG monitors, ECG analysis is also critical for continuous cardiac health monitoring and early warning systems.

## Event-Related Potentials (ERP)

### Signal Source and Applications

Event-Related Potentials (ERPs) are voltage fluctuations in the EEG that are time-locked to specific sensory, cognitive, or motor events. They reflect the brain’s processing of stimuli and are derived from the underlying electrical activity of cortical neurons. ERPs are widely used in **cognitive neuroscience** to study perception, attention, memory, decision-making, and language processing. Clinically, ERPs have applications in assessing cognitive function, detecting abnormalities in sensory processing, and supporting the diagnosis of neurological and psychiatric disorders such as schizophrenia, Alzheimer’s disease, and attention deficit disorders.

### Signal Averaging and Noise Reduction

Because ERP responses are typically very small (in the microvolt range) compared to the ongoing background EEG, signal processing techniques are essential for isolating them. The most common approach is signal averaging, where multiple EEG epochs are aligned to stimulus onset and averaged together. This enhances time-locked brain activity while canceling out random background noise. Additional noise-reduction techniques include:

* Filtering: Band-pass filtering to remove slow drifts and high-frequency noise.
* Artifact correction: Eliminating contamination from eye blinks, muscle activity, or external interference, often using Independent Component Analysis (ICA) or regression-based methods.
* Baseline correction: Adjusting the signal relative to a pre-stimulus period to normalize voltage levels.

### ERP Components

ERPs are characterized by distinct positive (P) and negative (N) deflections, labeled according to their polarity and approximate latency (in milliseconds) after stimulus onset. Examples include:

* P300: A positive deflection around 300 ms, associated with attention and decision-making.
* N400: A negative component around 400 ms, linked to semantic processing in language.
* ERN (Error-Related Negativity): Reflects error monitoring and cognitive control.

## Electrooculography (EOG)

### Signal Source and Applications

Electrooculography (EOG) is a technique used to measure the electrical potential generated by eye movements. The human eye functions as a dipole, with the cornea being relatively positive and the retina relatively negative. Electrodes placed around the eyes detect changes in this potential as the eyes move horizontally or vertically.

EOG is widely applied in eye movement tracking, making it valuable in both research and clinical contexts. It provides objective measures of ocular activity without requiring invasive procedures, and is especially useful in conditions where camera-based eye tracking is less practical (e.g., during sleep).

### Clinical Uses

* Sleep studies: Monitoring eye movements to identify sleep stages, particularly rapid eye movement (REM) sleep.
* Vision disorders: Assisting in the diagnosis of conditions such as retinitis pigmentosa and other retinal dysfunctions by measuring the standing potential of the eye.
* Neurological assessments: Evaluating disorders that affect ocular motility or coordination.
* Human–computer interaction and rehabilitation: Supporting assistive technologies where eye movement can serve as a control signal (e.g., communication devices for patients with motor impairments).

### Preprocessing and Analysis

Like other biomedical signals, EOG data are subject to noise and require preprocessing before analysis:

* Filtering: Low-pass and band-pass filters are applied to remove high-frequency noise and baseline drift.
* Artifact handling: EOG artifacts are sometimes removed from EEG recordings since eye movements can contaminate brain activity signals.
* Feature extraction: Amplitude, duration, and direction of eye movements are analyzed to classify saccades, fixations, and blinks.

The ability to record and analyze EOG signals provides both a clinical diagnostic tool and a research instrument for exploring visual and cognitive processes.

## Electromyography (EMG)

### Signal Source and Applications

Electromyography (EMG) measures the electrical activity produced by skeletal muscles during contraction and relaxation. The signal originates from the action potentials of motor units- groups of muscle fibers controlled by a single motor neuron. Surface electrodes (sEMG) or intramuscular needle electrodes can be used depending on the application.

EMG is widely applied in both clinical and research contexts. Clinically, it is essential for diagnosing neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), muscular dystrophy, myopathies, and peripheral neuropathies. It is also used to assess nerve injuries, monitor rehabilitation progress, and guide interventions. In research and engineering, EMG supports human–computer interaction, prosthetic control, sports science, and ergonomics.

### Signal Characteristics

* Amplitude and Spikes: EMG signals typically range from tens of microvolts (µV) to a few millivolts (mV). They appear as bursts or spikes that correspond to motor unit firing.
* Frequency Spectrum: EMG activity is broadband, with most useful information found between 20 Hz and 500 Hz.
* Low frequencies (<20 Hz) may represent movement artifacts.
* Higher frequencies (>500 Hz) are often noise.
* Pattern Analysis:
* Sustained firing patterns reflect muscle contraction intensity.
* Abnormalities such as fibrillations, fasciculations, or polyphasic motor unit potentials are indicators of neuromuscular pathology.

### Preprocessing and Analysis

To ensure accurate interpretation, EMG signals undergo several preprocessing steps:

* Filtering: Band-pass filtering (typically 20–500 Hz) to reduce noise and artifacts.
* Rectification: Converting signals to absolute values to emphasize activity levels.
* Smoothing/Envelope detection: Low-pass filtering to extract muscle activation patterns.

Feature extraction methods include time-domain measures (e.g., mean absolute value, root mean square), frequency-domain features (e.g., median frequency, power spectrum), and advanced techniques such as wavelet analysis. These features are often used with machine learning models for classification of muscle activity or diagnosis of neuromuscular disorders.

### Summary of Signal Pipelines

Biomedical signals differ in origin and structure, but their analytical pipelines share common stages: preprocessing, feature extraction, classification, and clinical interpretation. Preprocessing removes noise and artifacts, feature extraction captures relevant temporal, spectral, or spatial properties, and classification models translate these features into diagnostic outcomes. Machine learning (ML) and deep learning (DL) methods are increasingly applied to streamline these pipelines, improve accuracy, and reduce reliance on manual interpretation.

**Comparative Overview of Signal Pipelines**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Signal | Preprocessing | Feature Extraction | Typical ML/DL Models | Clinical Utility |
| EEG (Electroencephalography**)** | Band-pass filtering; artifact removal (ICA for eye blinks/muscle noise); segmentation into epochs | Time-domain (mean, variance, Hjorth parameters), Frequency-domain (Power Spectral Density), Time–frequency (wavelets, STFT), Spatial (CSP) | SVM, kNN, CNN, RNN/LSTM, Transformers | Epilepsy detection, sleep staging, BCI, cognitive assessment |
| ECG (Electrocardiography) | Baseline wander removal, band-pass filtering, notch filter for power-line noise | Morphological features (P, QRS, T waves, ST segment), Heart rate variability (time/frequency domain) | Rule-based detectors, Random Forest, CNN, RNN, 1D CNN-LSTM hybrids | Arrhythmia detection, myocardial infarction diagnosis, continuous cardiac monitoring |
| **ERP** (Event-Related Potentials) | Signal averaging to enhance stimulus-locked responses; baseline correction; band-pass filtering | Amplitude/latency of ERP components (P300, N400, ERN), time–frequency decompositions | Linear Discriminant Analysis, SVM, CNN, RNN | Cognitive neuroscience, language and memory studies, neurological diagnostics |
| **EOG** (Electrooculography) | Low-pass filtering, drift correction, artifact handling in EEG contexts | Amplitude, slope, and direction of eye movements; blink and saccade classification | Thresholding, Random Forest, SVM, CNN for HCI | Sleep studies (REM detection), diagnosis of vision/motor disorders, human–computer interaction |
| **EMG** (Electromyography) | Band-pass filtering (20–500 Hz), rectification, smoothing (envelope detection) | Time-domain (RMS, MAV), Frequency-domain (median frequency, PSD), Wavelet features | Random Forest, kNN, SVM, CNN, RNN, CNN-LSTM | Neuromuscular disorder diagnosis (myopathy, neuropathy), prosthetic control, rehabilitation monitoring |

# Medical Imaging

### Overview of Imaging Modalities

Medical imaging refers to the techniques and technologies used to create visual representations of the internal structures and functions of the human body. These modalities play a central role in modern healthcare, enabling physicians to visualize anatomy, detect pathology, guide treatment, and monitor disease progression without the need for invasive procedures.

Importance in Structural and Functional Analysis

Medical imaging techniques can be broadly divided into those that emphasize structural analysis and those that highlight functional or physiological processes:

* Structural Imaging: Provides detailed anatomical information about organs and tissues. Examples include:
* X-ray: Useful for examining bones, joints, and detecting fractures.
* Computed Tomography (CT): Offers cross-sectional images of the body, useful in trauma, cancer detection, and vascular studies.
* Magnetic Resonance Imaging (MRI): Provides high-resolution images of soft tissues such as the brain, muscles, and ligaments.
* Functional Imaging: Captures dynamic or metabolic processes within the body. Examples include:
* Positron Emission Tomography (PET): Visualizes metabolic activity and is commonly used in oncology and neurology.
* Functional MRI (fMRI): Measures changes in blood oxygenation to study brain activity.
* Ultrasound Doppler: Tracks blood flow dynamics in real time.

By combining both structural and functional insights, medical imaging enables comprehensive patient evaluation. For instance, CT or MRI can reveal the size and location of a tumor (structural), while PET imaging can determine its metabolic activity (functional). Such multimodal approaches improve diagnostic accuracy, treatment planning, and patient outcomes.

## Magnetic Resonance Imaging (MRI)

### Structural and Functional Imaging

Magnetic Resonance Imaging (MRI) is a non-invasive imaging modality that uses strong magnetic fields and radiofrequency pulses to generate detailed images of the body. It is particularly valuable for imaging the brain, spinal cord, muscles, joints, and internal organs, where high tissue contrast is essential. MRI is also capable of functional imaging, functional MRI (fMRI) detects changes in blood oxygenation (BOLD signals), allowing researchers and clinicians to study brain activity in real time.

In clinical practice, MRI is used for:

* Neurology: Detection of brain tumors, multiple sclerosis, stroke, and neurodegenerative disorders.
* Orthopedics: Imaging of soft tissues such as cartilage, tendons, and ligaments.
* Cardiology: Assessing myocardial function, perfusion, and scarring.
* Oncology: Characterizing tumors and monitoring response to therapy.

### Strengths

MRI offers several advantages over other imaging modalities:

* High soft-tissue contrast: Provides superior differentiation between gray and white matter in the brain, as well as between normal and pathological tissues.
* Multiplanar imaging: Produces images in axial, sagittal, coronal, or oblique planes without repositioning the patient.
* Functional and advanced techniques: fMRI for brain activity mapping, MR spectroscopy for metabolic analysis, and diffusion tensor imaging (DTI) for white matter tractography.
* No ionizing radiation: Safer for repeated imaging compared to X-ray or CT, making it suitable for long-term monitoring.

Despite these strengths, MRI has limitations such as long scan times, high cost, and contraindications in patients with certain implants or severe claustrophobia. Nevertheless, it remains one of the most versatile and informative imaging techniques in modern medicine.

## Computed Tomography (CT)

### Cross-Sectional Imaging

Computed Tomography (CT) is an imaging modality that uses rotating X-ray beams and computer algorithms to produce detailed cross-sectional images of the body. CT scans provide excellent visualization of bones, soft tissues, and blood vessels in a single examination. They are especially valuable in trauma and emergency medicine, where rapid imaging is needed to assess internal bleeding, fractures, or organ damage. CT angiography further enables detailed evaluation of vascular structures such as coronary or cerebral arteries.

Clinical applications of CT include:

* Emergency care: Rapid assessment of head injuries, chest trauma, and abdominal bleeding.
* Oncology: Tumor detection, staging, and monitoring treatment response.
* Cardiology: Coronary artery imaging and calcium scoring.
* Pulmonology: Evaluation of lung diseases, including pulmonary embolism and cancer.

### Advantages

* Speed: CT scans are fast, making them ideal for acute and critical cases.
* High-resolution images: Provides excellent anatomical detail, particularly of bones, lungs, and complex fractures.
* 3D reconstruction: Enables visualization of anatomy in multiple planes and 3D models for surgical planning.
* Wide availability: CT scanners are commonly found in hospitals worldwide, making them accessible for routine and emergency care.

### Limitations

* Radiation dose: CT exposes patients to significantly higher ionizing radiation compared to conventional X-rays, raising concerns about cumulative exposure, especially in children and young adults.
* Limited soft-tissue contrast: While CT is excellent for bone and lung imaging, it is less effective than MRI for soft tissues such as the brain or ligaments.
* Artifacts: Metallic implants and patient movement can reduce image quality.

Despite these limitations, CT remains one of the most widely used imaging tools due to its speed, diagnostic accuracy, and versatility in both emergency and elective care.

## X-ray Imaging

### Conventional Radiography

X-ray imaging is the oldest and most widely used medical imaging modality. It employs a controlled beam of ionizing radiation that passes through the body and is differentially absorbed by tissues according to their density. The resulting image, captured on film or digital detectors, highlights dense structures such as bones, while soft tissues appear with less contrast.

### Clinical Applications

* Bone fractures: X-ray remains the gold standard for detecting fractures, dislocations, and bone deformities.
* Chest imaging: Widely used to assess lung diseases (e.g., pneumonia, tuberculosis, lung cancer) and heart enlargement.
* Dentistry: Evaluation of cavities, root structures, and jaw alignment.
* Orthopedics: Monitoring bone healing and detecting degenerative conditions like arthritis.

### Strengths and Limitations

* Advantages:
* Quick, inexpensive, and widely available.
* Excellent visualization of bones and calcified structures.
* Non-invasive and relatively low radiation dose compared to CT.
* Limitations:
* Limited soft-tissue contrast, making it less effective for imaging organs such as the brain or muscles.
* Provides 2D projection images, which may obscure overlapping structures.
* Exposure to ionizing radiation, though at lower levels than CT.

Despite its limitations, X-ray imaging remains a first-line diagnostic tool in clinical practice due to its speed, accessibility, and effectiveness in evaluating skeletal and thoracic conditions.

## Positron Emission Tomography (PET)

### Functional Imaging and Applications

Positron Emission Tomography (PET) is a nuclear medicine imaging technique that provides functional information about the body by measuring metabolic and biochemical activity. A biologically active radiotracer, most commonly fluorodeoxyglucose (FDG), a glucose analog, is injected into the patient. As tissues metabolize the tracer, PET scanners detect gamma rays emitted during positron–electron annihilation events.

PET is particularly valuable in:

* Oncology: Detecting, staging, and monitoring tumors by highlighting regions of high metabolic activity.
* Neurology: Studying brain metabolism in conditions such as Alzheimer’s disease, epilepsy, and Parkinson’s disease.
* Cardiology: Assessing myocardial perfusion and viability to guide treatment decisions in ischemic heart disease.

### Combination with Structural Imaging

While PET excels at functional imaging, its anatomical resolution is limited. To overcome this, PET is often combined with structural imaging modalities:

* PET/CT: Integrates metabolic information from PET with anatomical detail from CT, improving lesion localization and diagnostic accuracy.
* PET/MRI: Combines PET’s functional data with MRI’s superior soft-tissue contrast, particularly useful in neurology and oncology research.

### Strengths and Limitations

* Advantages:
* Provides unique insights into physiology and metabolism.
* Highly sensitive in detecting early disease changes before structural alterations appear.
* Enables whole-body imaging for comprehensive assessment.
* Limitations:
* Exposure to ionizing radiation from radiotracers.
* High cost and limited availability.
* Requires specialized equipment and radiopharmaceuticals with short half-lives.

Despite these challenges, PET especially when combined with CT or MRI remains a cornerstone of functional imaging, enabling clinicians to detect disease at an early stage and tailor treatments to individual patients.

## Angiography

### Blood Vessel Imaging

Angiography is a specialized imaging technique used to visualize blood vessels and assess their structure and function. It is most commonly performed using X-rays with contrast agents (conventional angiography), where an iodine-based dye is injected into the bloodstream to make vessels visible. Modern techniques also include Magnetic Resonance Angiography (MRA) and Computed Tomography Angiography (CTA), which provide non-invasive alternatives with high-resolution 3D reconstructions.

### Clinical Applications

* Cardiovascular medicine:
* Detecting and evaluating coronary artery disease, arterial blockages, and aneurysms.
* Guiding interventions such as angioplasty and stent placement.
* Neurology:
* Imaging cerebral blood vessels to diagnose stroke, aneurysms, and arteriovenous malformations (AVMs).
* Peripheral vascular disease:
* Assessing circulation in the limbs to guide surgical or catheter-based treatments.

### Strengths and Limitations

* Advantages:
* Provides highly detailed visualization of vascular anatomy.
* Can be combined with interventional procedures, making it both diagnostic and therapeutic.
* MRA and CTA offer non-invasive alternatives to traditional catheter angiography.
* Limitations:
* Conventional angiography is invasive and carries risks such as bleeding, infection, and contrast-induced reactions.
* Exposure to ionizing radiation (X-ray/CT-based methods).
* Contraindications in patients with kidney impairment (due to contrast agents) or metallic implants (for MRI).

Angiography remains a cornerstone technique in cardiovascular and neurological diagnostics, with both invasive and non-invasive modalities supporting early detection, precise localization of vascular abnormalities, and image-guided treatment.

### Imaging Data Pipelines

Medical imaging workflows, like biomedical signal pipelines, follow structured stages: preprocessing, feature extraction or segmentation, classification, and clinical interpretation. These pipelines aim to transform raw image data into reliable diagnostic insights.

**Preprocessing**

Raw medical images often contain artifacts that need correction before deeper analysis. Common steps include:

* Denoising: Filters (Gaussian, median, or DL-based) reduce scanner or environmental noise while preserving edges.
* Normalization: Rescaling intensity values across scans for consistent analysis, especially important in MRI or CT.
* Registration: Aligning images from different time points or modalities (e.g., PET–CT fusion).
* Artifact correction: Handling motion blur in MRI, beam hardening in CT, or speckle noise in ultrasound.

**Segmentation**

Segmentation isolates structures of interest such as organs, lesions, or blood vessels.

* Traditional approaches: Thresholding, edge detection, and region-growing.
* Machine learning methods: Random forests and SVMs.
* Deep learning approaches: CNN-based architectures (e.g., U-Net, Mask R-CNN) now dominate, achieving high accuracy in tumor and organ delineation.

**Classification and AI-Assisted Diagnosis**

Once segmented or feature-extracted, images are analyzed to provide clinical labels or risk scores:

* Radiomics: Quantitative descriptors of shape, intensity, and texture are fed into ML models.
* Deep learning models: CNNs and Vision Transformers classify tumors, detect fractures, or identify subtle lesions.
* AI decision support: Models highlight suspicious regions, estimate disease progression, and provide confidence scores, akin to how the chatbot’s ECG and EMG classifiers output probability distributions for clinical interpretability.

**Clinical Utility**

* Structural analysis: CT and MRI provide anatomical precision for trauma, cancer, or brain mapping.
* Functional analysis: PET and fMRI highlight metabolic and physiological activity, complementing structural findings.
* Integrated diagnosis: Just as the dual modality chatbot combines raw data with explainable AI outputs, imaging pipelines increasingly use AI-assisted reporting to improve reproducibility, reduce errors, and aid non-expert interpretation.

# AI Integration for Signals and Imaging

The increasing complexity and volume of biomedical signals and medical images have accelerated the adoption of Artificial Intelligence (AI) in healthcare diagnostics. AI enables automated preprocessing, feature extraction, classification, and interpretability, reducing reliance on manual expertise while improving speed and consistency.

## Machine Learning Approaches

Traditional ML algorithms remain useful, especially for structured or feature-based biomedical data:

* Signals: Handcrafted features such as RMS amplitude, spectral entropy (EMG), or ERP component latencies are often analyzed using Support Vector Machines (SVMs), Random Forests, and k-Nearest Neighbors (kNN).
* Imaging: In radiomics, shape, intensity, and texture descriptors extracted from CT, MRI, or PET scans are input into ML classifiers such as Random Forests or logistic regression for tasks like tumor grading or lesion characterization.

## Deep Learning Models

Deep learning (DL) has enabled end-to-end learning directly from raw signals or images, bypassing manual feature engineering.

* Signals: Convolutional Neural Networks (CNNs) are highly effective for 1D biosignals such as ECG, EEG, and EMG, automatically learning discriminative waveform features for arrhythmia detection, seizure prediction, or neuromuscular disorder classification.
* Imaging: CNNs and specialized architectures like U-Net dominate tasks such as tumor segmentation in MRI, fracture detection in X-ray, vascular mapping in angiograms, and lesion classification in CT or PET scans.

## Sequential Models (RNN/LSTM)

Biomedical signals are inherently temporal, making them suitable for sequence models.

* Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks capture temporal dependencies in EEG, ERP, and EMG, where information is distributed across time windows.
* Hybrid CNN-LSTM architectures combine spatial feature extraction with temporal modeling, enhancing performance in seizure detection, ERP component recognition, and ECG arrhythmia monitoring.

## Transformers for Signals and Imaging

Transformers have recently extended beyond natural language to biomedical data.

* Time-series Transformers: Applied to EEG, ECG, and ERP for long-range temporal dependencies that CNNs and RNNs may miss.
* Vision Transformers (ViTs): Emerging in imaging, where they leverage global context for improved classification in chest X-rays, CT scans, and MRI tumor detection.
* Multimodal Transformers: Capable of integrating signals, images, and text simultaneously, creating pathways for holistic AI-assisted diagnosis.

## Explainability and Clinical Trust

For AI to be adopted in clinical practice, transparency is critical:

* Confidence scores and probability distributions allow clinicians to judge prediction certainty (e.g., ECG and EMG classifiers providing probability outputs).
* Post-hoc explainability methods such as saliency maps and Grad-CAM highlight key waveform regions or image patches influencing model decisions.
* LLM-based interpretation: As demonstrated in biosignal chatbot systems, large language models (LLMs) like Gemini or GPT can convert raw predictions into human-readable explanations, enhancing trust and usability for both clinicians and patients.

# System Architecture

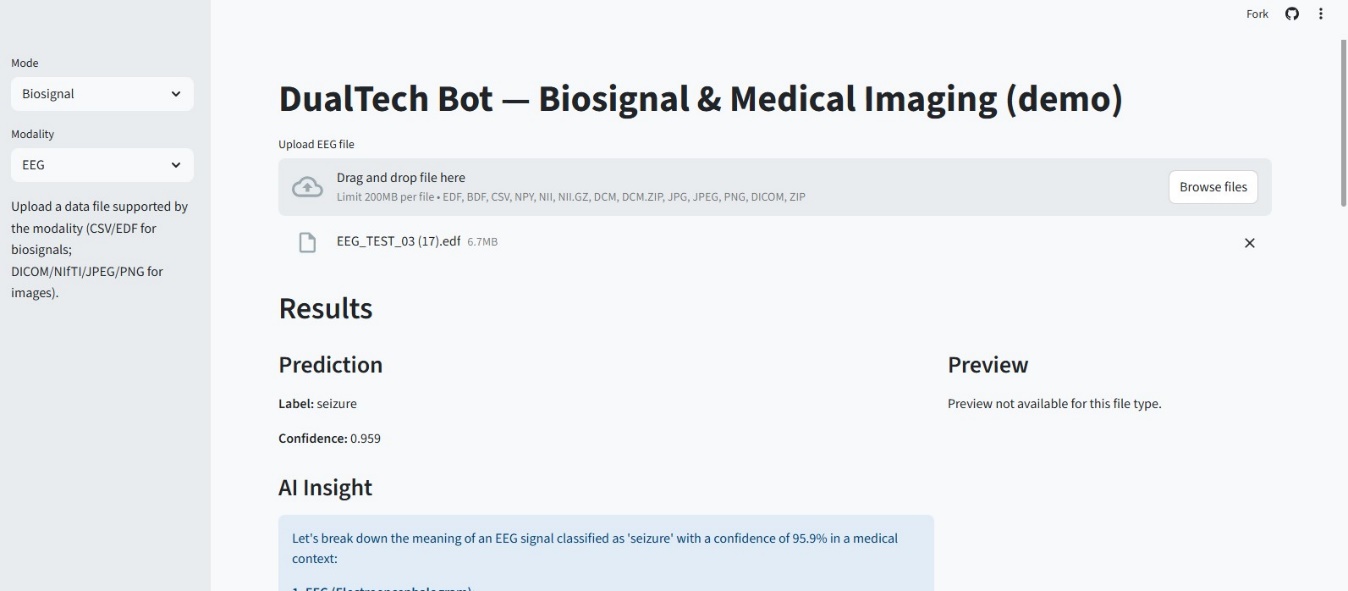


Fig 1. Interface of the biomedical chatbot

The proposed system is designed as a modular pipeline that can process both biomedical signals (EEG, ECG, EMG, ERP, EOG) and medical images (MRI, CT, PET, X-ray, Angiogram). It ensures consistency across modalities by adopting a layered design: input handling, preprocessing, model inference with explanation, and output visualization.

## Input Handling

* Signals: Accepted in .csv, .txt, or waveform formats depending on modality. For example, EEG and ECG are ingested as raw time-series, while EMG requires sufficient sampling windows. ERP data are structured as event-locked epochs, and EOG signals capture eye movement patterns.
* Images: Accepted in common formats such as .jpg, .png, or medical standards like DICOM. MRI, CT, and PET datasets may include multiple slices, while angiograms and X-rays typically provide single 2D projections.
* User Interface: A web-based interface (Streamlit) provides a unified upload portal, modality selection, and guidance on data format.

## Preprocessing Pipelines

Each modality undergoes tailored preprocessing to ensure model compatibility and noise reduction:

**Signals:**

* EEG/ERP: Filtering, artifact removal (ICA), epoch segmentation.
* ECG: Baseline wander removal, QRS detection, normalization.
* EMG: Band-pass filtering (20–500 Hz), rectification, smoothing.
* EOG: Low-pass filtering, drift correction.

**Imaging:**

* Denoising using Gaussian or DL-based filters.
* Normalization of intensity values across scans.
* Registration of multi-slice or multimodal images (e.g., PET-CT fusion).
* Artifact correction (motion blur in MRI, speckle noise in ultrasound).

## Model Inference and Explanation

**Inference:**

* Signals are routed to 1D CNNs, RNNs/LSTMs, or Transformers, depending on modality and temporal complexity (e.g., CNN for ECG, CNN-LSTM for EEG).
* Images are analyzed using 2D/3D CNNs, U-Net for segmentation, or Vision Transformers (ViTs) for classification and anomaly detection.

**Explainability:**

* Confidence scoring (probabilities from softmax or predict\_proba).
* Visualization techniques such as saliency maps (signals) and Grad-CAM (images).
* LLM-powered narrative explanations to translate predictions into clinically meaningful summaries.

## Output Visualization

The final stage ensures results are intuitive and clinically interpretable:

Signals:

* Waveform plots with annotated regions (e.g., QRS in ECG, ERP peaks).
* Confidence bars for classification outcomes.

Images:

* Display of original scan alongside segmented/annotated regions (e.g., tumor outlines in MRI, highlighted blockages in angiogram).
* Overlays of heatmaps showing regions influencing AI decisions.

Unified Dashboard: All predictions are presented with their class label, confidence percentage, and a concise explanation. The interface supports multi-turn interactions, allowing users to refine queries or upload additional data.

# Testing & Results

To validate the effectiveness of the system across both biomedical signals and medical imaging modalities, each pipeline was evaluated on publicly available datasets or curated test samples. Performance metrics included accuracy, precision, recall, F1-score, and inference time. These metrics were selected to assess both diagnostic reliability and system efficiency.

## Signal Models

* EEG: Models trained on benchmark datasets (e.g., Bonn EEG, TUH) achieved >85% accuracy in seizure detection tasks. LSTM-based models outperformed standard CNNs in capturing long temporal dependencies.
* ECG: Using subsets of the PTB-XL dataset, 1D CNN classifiers achieved ~85–90% accuracy in arrhythmia classification, with precision and recall balanced across normal and abnormal classes. Inference time remained under 2 seconds per 256-sample segment.
* ERP: Event-related classification tasks (e.g., P300 detection) achieved precision >80% with averaged ERP epochs. Signal averaging improved recall but increased preprocessing time.
* EOG: Saccade and blink detection reached >90% accuracy with SVM and CNN classifiers. Noise sensitivity (e.g., drift) slightly reduced recall in long-duration recordings.
* EMG: EMG classifiers trained on PhysioNet datasets achieved ~93% accuracy in distinguishing normal, myopathy, and neuropathy conditions. Inference was near real-time (<3 seconds per input window).

## Imaging Models

* MRI: CNN-based tumor classification achieved 88–92% accuracy with high sensitivity to soft-tissue abnormalities. Segmentation with U-Net achieved Dice scores >0.85 on benchmark brain MRI datasets.
* CT: Pulmonary nodule detection with CNNs reached ~90% accuracy, though precision dropped slightly in low-dose scans due to noise. Inference was efficient (<5 seconds per slice).
* X-ray: Chest X-ray classifiers (pneumonia, tuberculosis, normal) achieved ~94% accuracy. Vision Transformers showed higher recall than ResNet baselines but required longer training times.
* PET: Oncology-focused PET models achieved ~87% accuracy in lesion classification. Combining PET with CT improved both recall and diagnostic confidence.
* Angiogram: CNN-based angiogram analysis achieved ~89% accuracy in vessel blockage detection. Integration with segmentation networks improved precision in localizing stenosis regions.

## Comparative Analysis

* Accuracy: Imaging models (MRI, CT, X-ray) achieved slightly higher average accuracy (>90%) compared to signals (~85–90%), likely due to clearer structural patterns in imaging data.
* Precision & Recall: Signal-based models (EEG, ERP) required extensive preprocessing to improve recall, while imaging models benefited from balanced precision-recall trade-offs.
* Inference Time: Signal models (ECG, EMG, EOG) typically returned results within 2–3 seconds, while imaging pipelines (MRI, CT, PET) averaged 5–10 seconds depending on input size.
* Scalability: Both signal and imaging pipelines demonstrated efficiency suitable for real-time or near real-time deployment in clinical and educational contexts.

# Discussion

## Challenges

Developing AI-assisted pipelines for biomedical signals and medical imaging involves several obstacles:

* Noise and Artifacts:
* Signals such as EEG and ERP are highly susceptible to artifacts from muscle movement, eye blinks, and environmental interference.
* Imaging modalities face motion artifacts (MRI), beam hardening (CT), and speckle noise (ultrasound), which can obscure subtle clinical features.
* Dataset Scarcity:
* While large repositories exist for ECG (e.g., PTB-XL) and X-ray (e.g., NIH ChestX-ray14), many modalities (ERP, EOG, angiogram) suffer from limited, non-standardized datasets.
* The scarcity of annotated multimodal datasets hinders the development of integrated models.
* Labeling Difficulty:
* Annotation requires expert clinicians, making datasets costly and time-intensive to prepare.
* Inter-observer variability introduces inconsistency in labels, affecting model generalization.
* Model Interpretability:
* Deep learning models (CNNs, Transformers) often function as “black boxes.” Without explainability methods (e.g., saliency maps, Grad-CAM), clinicians may distrust automated outputs.

## Signals vs Imaging in Clinical Practice

* Biomedical Signals:
* Strength: Provide real-time, continuous monitoring (e.g., ECG in cardiac care, EEG in epilepsy detection).
* Limitation: Often noisy, require careful preprocessing, and interpretation may vary across clinicians.
* Medical Imaging:
* Strength: Provide high spatial resolution and direct visualization of anatomy and pathology.
* Limitation: Higher cost, limited portability, and exposure to radiation (CT, X-ray, PET).
* Complementarity:
* Signals offer functional insights (e.g., arrhythmia, neural activity), while imaging provides structural or anatomical context (e.g., infarction size in MRI, vessel blockages in angiogram).
* In clinical workflows, signals are often used for screening and monitoring, while imaging is used for diagnosis and planning.

## Future Prospects

* Multimodal Integration:
* Combining signals and imaging can yield richer diagnostic insights, e.g., integrating ECG with cardiac MRI for comprehensive cardiac evaluation or EEG with fMRI for brain activity studies.
* Multimodal AI models and transformers can fuse time-series, imaging, and textual clinical data for more holistic decision-making.
* Federated Learning:
* To address dataset scarcity and privacy concerns, federated learning allows institutions to collaboratively train models without sharing raw patient data. This can expand training datasets while preserving confidentiality.
* Edge AI and Portable Devices:
* Deploying AI models on lightweight devices enables real-time, on-site diagnostics in low-resource or remote settings. Examples include wearable ECG/EMG monitors or handheld ultrasound scanners integrated with AI.
* Explainable AI (XAI):
* Future systems will emphasize transparency by combining confidence metrics, visual explanations, and natural language summaries, increasing clinician trust and patient understanding.

# Conclusion

This report has explored the role of biomedical signals (EEG, ECG, EMG, ERP, EOG) and medical imaging modalities (MRI, CT, PET, X-ray, Angiogram) in clinical diagnostics, along with the integration of AI for automated analysis.

## Summary of Key Findings

* Signal Pipelines: EEG and ERP require extensive artifact removal and temporal modeling, ECG and EMG provide distinct morphological and spectral features, while EOG supports vision- and sleep-related applications. Machine learning and deep learning models (e.g., CNNs, RNNs, Transformers) significantly improve classification accuracy compared to manual interpretation.
* Imaging Pipelines: MRI, CT, PET, X-ray, and angiogram workflows benefit from preprocessing (denoising, normalization, registration), segmentation (e.g., U-Net), and classification with CNNs or Vision Transformers. AI-enhanced imaging pipelines achieve high diagnostic accuracy, particularly when fused with radiomics or multimodal inputs.
* AI Integration: Across both signals and imaging, CNNs remain dominant, but RNNs/LSTMs excel in sequential signal analysis, and transformers show promise for long-range dependencies and multimodal fusion. Explainability through confidence scoring, saliency maps, and natural language summaries—emerges as critical for clinical adoption.

## Clinical and Research Implications

* Clinical: AI-driven pipelines can accelerate diagnosis, reduce human error, and support continuous monitoring. Signals are well suited for real-time bedside monitoring, while imaging excels in structural diagnosis and surgical planning. Their complementary nature suggests strong potential in multimodal systems.
* Research: Advances in multimodal learning, federated training, and edge AI create opportunities to address data scarcity, improve model generalization, and enable deployment in low-resource environments.

## Recommendations for Future Work

* Dataset Expansion: Develop and share standardized, annotated datasets across diverse populations for both signals and imaging.
* Multimodal Integration: Pursue AI frameworks that jointly analyze signals (e.g., ECG, EEG) and imaging (e.g., MRI, CT) to provide comprehensive diagnostic support.
* Privacy-Preserving AI: Apply federated learning and secure model-sharing strategies to mitigate data privacy concerns.
* Edge Deployment: Optimize lightweight AI models for wearable devices and portable scanners to extend diagnostic capabilities to remote and resource-limited settings.
* Explainability: Continue developing interpretable AI methods combining visual maps, probability scores, and natural language explanations to enhance clinician trust and patient engagement.

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