
PhysioWave: A Multi-Scale Wavelet-Transformer for Physiological Signal Representation

Yanlong Chen

Integrated Systems Laboratory
ETH Zurich
yanlchen@student.ethz.ch

Mattia Orlandi

DEI
University of Bologna
mattia.orlandi@unibo.it

Pierangelo Maria Rapa

DEI
University of Bologna
pierangelomaria.rapa@unibo.it

Simone Benatti

DIEF
University of Modena and Reggio Emilia
simone.benatti@unibo.it

Luca Benini

Integrated Systems Laboratory
ETH Zurich
lbenini@iis.ee.ethz.ch

Yawei Li

Integrated Systems Laboratory
ETH Zurich
yawli@vision.ee.ethz.ch

Abstract

Physiological signals are often corrupted by motion artifacts, baseline drift, and other low-SNR disturbances, which pose significant challenges for analysis. Additionally, these signals exhibit strong non-stationarity, with sharp peaks and abrupt changes that evolve continuously, making them difficult to represent using traditional time-domain or filtering methods. To address these issues, a novel wavelet-based approach for physiological signal analysis is presented, aiming to capture multi-scale time-frequency features in various physiological signals. Leveraging this technique, two large-scale pretrained models specific to EMG and ECG are introduced for the first time, achieving superior performance and setting new baselines in downstream tasks. Additionally, a unified multi-modal framework is constructed by integrating pretrained EEG model, where each modality is guided through its dedicated branch and fused via learnable weighted fusion. This design effectively addresses challenges such as low signal-to-noise ratio, high inter-subject variability, and device mismatch, outperforming existing methods on multi-modal tasks. The proposed wavelet-based architecture lays a solid foundation for analysis of diverse physiological signals, while the multi-modal design points to next-generation physiological signal processing with potential impact on wearable health monitoring, clinical diagnostics, and broader biomedical applications.

1 Introduction

Physiological signals such as electroencephalography (EEG), electromyography (EMG), and electrocardiography (ECG) are essential for health monitoring, clinical diagnosis, and brain-computer interfacing [1]. Although large-scale foundation models for generic time-series data have recently shown remarkable success [2, 3], pretrained networks for biosignals remain scarce. While several EEG-specific encoders have been developed, such as LaBraM, which enables cross-dataset learning by segmenting signals into channel patches and training a vector-quantized neural spectrum tokenizer [4], and EEGPT, a pretrained Transformer designed for universal EEG feature extraction that

combines masked reconstruction with spatio-temporal representation alignment to mitigate issues of low SNR and inter-subject variability [5], similar models for other biosignals are still lacking. Biosignals differ fundamentally from images or language: they evolve continuously, exhibit strong non-stationarity, and are often corrupted by motion artifacts, baseline drift, and other low-SNR disturbances [6]. These challenges, compounded by high inter-subject variability, hinder the application of standard deep learning techniques [7]. As a result, there is an urgent need for modeling frameworks that can naturally accommodate the multi-scale, noisy, and heterogeneous nature of physiological time-series.

Traditional time-domain methods often overlook the rich spectral content of biosignals [8], while frequency-domain methods like fixed-window Fourier transforms assume stationarity, losing temporal resolution in rapidly changing signals [9]. In contrast, *wavelet-based* time-frequency methods can adaptively capture both fast transients and slower dynamics, making them ideal for nonstationary physiological data [10, 11]. However, modalities such as optical biosensing and EEG differ significantly in terms of dimension, sampling rate, and resolution, requiring modality-specific pre-processing. Existing segmentation and tokenization pipelines are not cross-modal, making them unsuitable for handling diverse signal types [12]. To address these issues, we propose a learnable wavelet decomposition pipeline that automatically selects and fuses multi-resolution filters based on signal content. Instead of relying on hand-engineered wavelet families, our method uses an Adaptive Wavelet Selector to assign optimal wavelet kernels for each channel, then aggregates approximate and detail components across multiple scales. This approach effectively captures both transient spikes (e.g., EMG bursts or ECG QRS complexes) and sustained low-frequency fluctuations, providing a robust front-end for downstream tasks [13, 14].

Although self-supervised learning has demonstrated success in time-series data, methods inspired by natural language processing often discard contiguous tokens in the time domain [2, 15]. Unlike words, raw biosignal segments do not neatly correspond to meaningful units, and randomly discarding them may remove key events or mask redundant portions, ultimately limiting model performance [16]. To overcome this, we introduce *Frequency-guided Masking (FgM)*, a mechanism that selectively occludes the most informative segments. Inspired by SpecAugment’s frequency masking and the masked acoustic modeling in HuBERT [17, 18], FgM measures the spectral energy of each patch to identify high-information regions. By masking high-energy patches more frequently, FgM forces the model to infer crucial details from context, thereby tightening the information bottleneck. A mix of energy-driven and random masking ensures training variability, preventing overfitting to fixed patterns and improving task generalization.

The wavelet-based decomposition and frequency-guided masking (FgM) work in tandem: adaptive wavelet filters separate the signal into multi-resolution bands, while FgM selectively masks bands with higher spectral energy, making them more likely to be occluded. This strategy of multiscale decomposition combined with energy-focused masking encourages the model to capture physiologically relevant patterns and reduce redundancy across frequencies. Empirically, masking high-energy bands yields richer, more discriminative features compared to random time-based masking, driving state-of-the-art performance in tasks such as arrhythmia detection (**66.7% F1 score** on PTB-XL [19]) and muscle activity classification (**94.5% accuracy** on EPN-612 [20], see Section 2.4).

Multi-modal biosignal learning faces two key challenges: first, extreme heterogeneity across modalities like EEG, EMG, and ECG, which operate at different sampling rates and temporal scales, leading to potential misalignment and spectral aliasing [21]; second, variability in signal quality due to motion artifacts or electrode drift [22]. To overcome these, we use modality-specific backbones: a pretrained encoder for EEG and newly pretrained PhysioWave encoders for EMG and ECG. These backbones remain frozen during downstream training, with only lightweight classification heads and fusion coefficients being learned. The fusion layer dynamically adjusts weights to prioritize reliable modalities, ensuring robust predictions. This linear-probing approach consistently outperforms single-modality baselines across multi-modal tasks (see Figures 5 and 6), including a **7.3% gain** in classification accuracy on DEAP [23], showcasing the effectiveness of dynamic, reliability-aware fusion for heterogeneous physiological data.

In summary, our work leverages wavelet-based decomposition and a FgM strategy to advance self-supervised learning in physiological signal processing. Specifically:

1. **PhysioWave: A versatile wavelet-driven architecture for physiological signals.** We propose PhysioWave, a versatile model framework applicable to diverse physiological

signals, and using this architecture which accommodates physiological signals with different sampling rates and dimensions through a learnable wavelet decomposition pipeline and a unified Transformer backbone, reducing the dependency on modality-specific preprocessing. A FgM mechanism is introduced to selectively occlude the most informative input segments, enhancing self-supervised learning.

2. **Enhanced representation learning.** Large-scale pre-trained models for EMG and ECG have been developed, trained on 823 GB of EMG data and 182 GB of ECG data, respectively, addressing the long-standing gap in foundational models for these modalities. Extensive evaluations across various tasks and datasets within each physiological modality demonstrate that PhysioWave consistently achieves state-of-the-art performance, underscoring its broad applicability and robustness (See Section 2.4).
3. **Unified multimodal framework.** By integrating our own pre-trained EMG and ECG models, which were developed using the PhysioWave architecture, with existing pre-trained EEG encoders, we build a unified framework that synergistically processes and fuses multimodal signals, producing superior performance compared to single-modal approaches.

2 Method

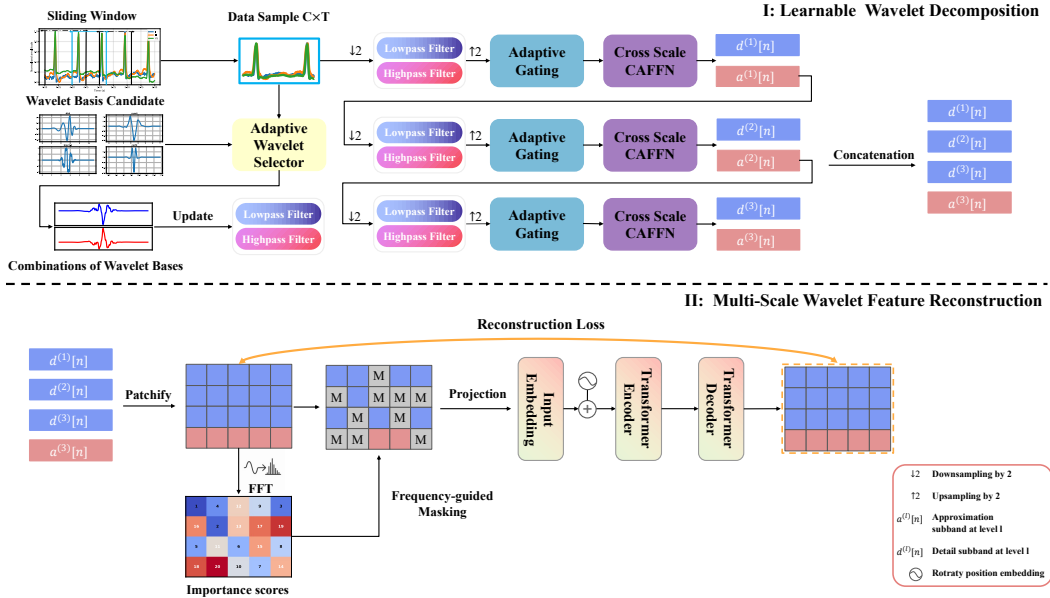


Figure 1: Model pretraining pipeline. The pipeline begins by initializing a set of standard wavelet functions (e.g., 'db6', 'sym4'), from which learnable low-pass and high-pass filters are generated. These filters are then used for wavelet decomposition to obtain multi-scale frequency-band representations. The decomposed features are processed into spatio-temporal patches, with importance scores computed using FFT-based spectral energy. High-scoring patches are masked and passed through Transformer layers, followed by a lightweight decoder for patch reconstruction.

Model Architecture: Figure 1 illustrates the end-to-end model pretraining pipeline. The raw multi-channel signal is first segmented into overlapping windows to form samples $x \in \mathbb{R}^{C \times T}$, where C denotes the number of channels and T the number of time steps. Each sample undergoes a learnable wavelet decomposition across L levels, yielding multi-scale frequency-band representations: detail subbands $d^{(l)}[n] \in \mathbb{R}^{C \times T}$ for $l = 1, \dots, L$ and a final approximation subband $a^{(L)}[n] \in \mathbb{R}^{C \times T}$. Concatenation of these $L + 1$ subband outputs along the channel axis produces a feature map $\text{Spec}(X) \in \mathbb{R}^{((L+1)C) \times T}$ (Section 2.1). Next, the feature map is partitioned into uniform spatio-temporal patches: for each patch we compute its FFT-based spectral energy, blend this value with random noise to produce an importance score, and mask the highest-scoring patches by replacing their embeddings with a learnable <MASK> token. The remaining patches are projected into token

embeddings and augmented with rotary positional embeddings (Section 2.2). Finally, the complete token sequence is passed through a stack of Transformer encoder layers, and a lightweight decoder reconstructs the masked patches (Section 2.3). In addition, end-to-end fine-tuning is performed downstream for single-modality tasks, while in multimodal settings modality-specific predictions are aggregated to yield the final output (Section 2.4).

2.1 Learnable Wavelet Decomposition

This module decomposes a multichannel time series $\{X_c(t)\}_{c=1}^C$ of length T into $L + 1$ subbands per channel by iterating Analysis, Adaptive Gating, and Feature Fusion.

Adaptive Wavelet Selector. Low-pass and high-pass filter taps $h^{\text{lo}}, h^{\text{hi}} \in \mathbb{R}^{K_0}$, where K_0 is the original wavelet filter length are extracted from a chosen discrete wavelet using PyWavelets [24]. These taps are then resampled to length K and normalized:

$$\tilde{h}^p(u) = \text{Interp}(h^p, K)[u], \quad \tilde{h}^p \leftarrow \tilde{h}^p \frac{\|h^p\|_1}{\|\tilde{h}^p\|_1}, \quad p \in \{\text{lo}, \text{hi}\} \quad (1)$$

Each channel's depthwise filters are then initialized by copying these taps:

$$k_c^{\text{low}}(u) := \tilde{h}^{\text{lo}}(u), \quad k_c^{\text{high}}(u) := \tilde{h}^{\text{hi}}(u), \quad \forall c = 1, \dots, C. \quad (2)$$

As depicted in the top-left corner of Figure 1, the model maintains M candidate wavelet bases $\{(k_w^{\text{low}}, k_w^{\text{high}})\}_{w=1}^M$ to accommodate diverse signal characteristics. For each input $x \in \mathbb{R}^{C \times T}$, temporal information is aggregated via average pooling and the resulting feature vector is passed through a compact MLP to produce unnormalized selection scores. Applying a softmax yields selection weights

$$\alpha = \text{Softmax}(\text{MLP}(\text{AvgPool}(x))) \in \mathbb{R}^M, \quad (3)$$

which are used to compute convex combinations of the candidate filters:

$$k^{\text{low}} = \sum_{w=1}^M \alpha_w k_w^{\text{low}}, \quad k^{\text{high}} = \sum_{w=1}^M \alpha_w k_w^{\text{high}}. \quad (4)$$

These aggregated filters serve as the effective low- and high-pass filters for all subsequent analysis and downsampling operations, and during training their weights continue to be updated to adapt to the actual signal distribution.

Analysis and Soft Gating. The learnable wavelet front-end performs a multi-resolution analysis in which each stage halves the temporal resolution while preserving both low- and high-frequency content. Let downsampling and nearest-neighbor upsampling by a factor of two be

$$\begin{aligned} (\downarrow_2 x)[n] &= x[2n], \quad n = 0, \dots, \lfloor \frac{T}{2} \rfloor - 1, \\ (\uparrow_2 x)[n] &= x[\lfloor \frac{n}{2} \rfloor], \quad n = 0, \dots, T - 1. \end{aligned} \quad (5)$$

At the first level ($\ell = 0$) every channel c is filtered and downsampled,

$$a_c^{(1)}[n] = \sum_{u=0}^{K-1} X_c(2n+u) k_c^{\text{low}}[u], \quad d_c^{(1)}[n] = \sum_{u=0}^{K-1} X_c(2n+u) k_c^{\text{high}}[u], \quad (6)$$

and the process recurses for $\ell = 1, \dots, L - 1$:

$$a_c^{(\ell+1)}[n] = \sum_{u=0}^{K-1} a_c^{(\ell)}(2n+u) k_c^{\text{low}}[u], \quad d_c^{(\ell+1)}[n] = \sum_{u=0}^{K-1} a_c^{(\ell)}(2n+u) k_c^{\text{high}}[u]. \quad (7)$$

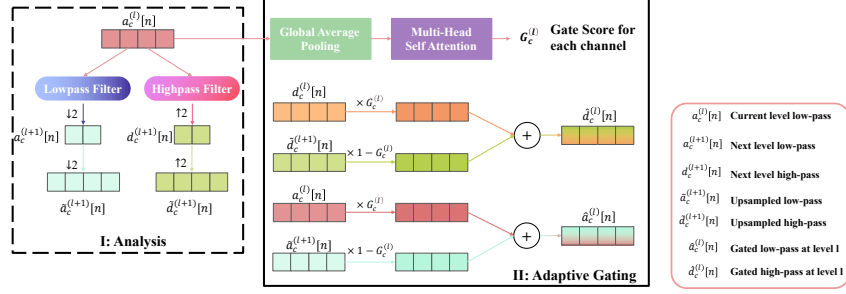


Figure 2: Analysis and soft gating process. The learnable wavelet front-end performs multi-resolution analysis by filtering and downsampling the input signal at each stage, preserving both low- and high-frequency components. At the first level ($\ell = 0$), the signal is decomposed into low-pass and high-pass components. This process recurses for $\ell = 1, \dots, L - 1$, applying downsampling at each level. After decomposition, the subbands are upsampled to the original resolution, and an adaptive gate $G_c^{(\ell)} \in [0, 1]$ is learned for each channel using multi-head attention. The gate dynamically combines the original and upsampled signals, facilitating fine-scale detail insertion.

After each decomposition, the new subbands are upsampled back to the original length

$$\tilde{a}_c^{(\ell+1)}[n] = (\uparrow_2 a_c^{(\ell+1)})[n], \quad \tilde{d}_c^{(\ell+1)}[n] = (\uparrow_2 d_c^{(\ell+1)})[n], \quad (8)$$

so that fine-scale details can be re-inserted into the current resolution. Rather than performing a hard skip connection—as is common in U-Net-style architectures [25]—an adaptive gate $G_c^{(\ell)} \in [0, 1]$ is estimated for every channel via multi-head attention pooling over $a_c^{(\ell)}$ (see Fig. 2). This gate weighs the contribution of the original and the upsampled signals,

$$\hat{a}_c^{(\ell)}[n] = G_c^{(\ell)}[n] a_c^{(\ell)}[n] + (1 - G_c^{(\ell)}[n]) \tilde{a}_c^{(\ell+1)}[n], \quad (9)$$

$$\hat{d}_c^{(\ell)}[n] = G_c^{(\ell)}[n] d_c^{(\ell)}[n] + (1 - G_c^{(\ell)}[n]) \tilde{d}_c^{(\ell+1)}[n]. \quad (10)$$

The soft-gating mechanism endows the model with three advantages: (i) it enables a learnable trade-off between current-level context and finer-scale detail, reducing aliasing and ringing artefacts that often arise from naive upsampling; (ii) the gate is estimated on a per-channel basis, allowing different physiological channels to emphasise frequency content most relevant to their noise characteristics; and (iii) by relying on attention rather than fixed skip connections, the model dynamically modulates information flow across levels, leading to more expressive multi-scale representations.

Feature Fusion. At each decomposition level $\ell = 1, \dots, L$, the gated approximation–detail pair $[\hat{a}_c^{(\ell)}[n], \hat{d}_c^{(\ell)}[n]]$ is concatenated along the channel axis and reshaped into a $\mathbb{R}^{2C \times 1 \times T}$ feature map. This map is fed to a *Cross-Scale Channel-Aggregation Feed-Forward Network* (CAFFN; see Fig. 3) [26]. CAFFN first applies a lightweight channel-aggregation block and then performs multi-head attention where the current features act as queries and the flattened feature maps from all shallower levels provide keys and values. Formally, let $\mathbf{U}^{(\ell)}$ be the CAFFN output before cross-scale fusion; the refined representation is obtained as

$$\mathbf{Y}^{(\ell)}[n] = \mathbf{U}^{(\ell)}[n] + \beta \text{Attention}(\mathbf{U}^{(\ell)}[n], \{\mathbf{Y}^{(i)}[n]\}_{i < \ell}), \quad (11)$$

where the learnable scalar β balances the current-level information with the context aggregated from coarser resolutions. This cross-scale fusion enables fine-grained subband features to be informed by long-range patterns captured at earlier levels, yielding scale-aware, frequency-aware representations for subsequent stages.

Finally, each refined map $\mathbf{Y}^{(\ell)}$ is split back into its approximation and detail halves, $\mathbf{Y}^{(\ell)} = [a^{(\ell)}, d^{(\ell)}]$, where $a^{(\ell)}, d^{(\ell)} \in \mathbb{R}^{C \times T}$. The multi-band representation is obtained by concatenating all detail subbands together with the final-level approximation:

$$\text{Spec}(X) = [d^{(1)}, d^{(2)}, \dots, d^{(L)}, a^{(L)}] \in \mathbb{R}^{(L+1)C \times T}. \quad (12)$$

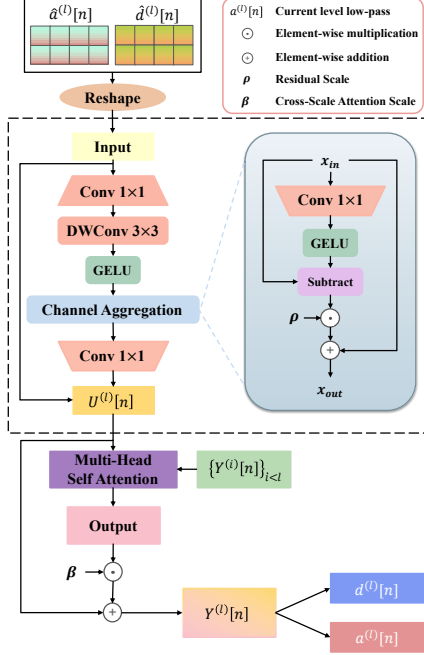


Figure 3: Cross-Scale CAFFN: This module refines multi-resolution features using convolution, channel aggregation, and self-attention.

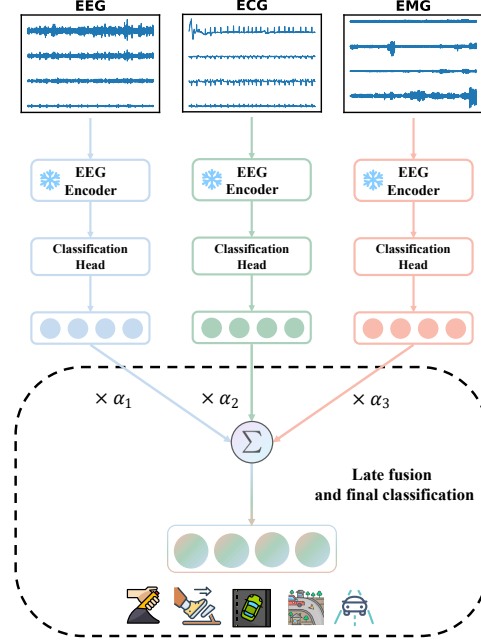


Figure 4: Multi-modal framework: Classification of driving behaviors in the MPDB dataset.

2.2 Frequency-guided Masking and Tokenisation

Frequency-guided masking. To address the challenge of selectively occluding informative segments, we introduce the frequency-guided masking process, as detailed in Algorithm 1. The multi-band feature map $\text{Spec}(X)$ from Eq. (12) is first sliced along the time axis into $N = \lfloor T/w \rfloor$ non-overlapping segments of length w , yielding a patch array of shape $\mathbb{R}^{N \times w}$ for each signal. In the next step, the FFT is applied to each patch to capture its frequency components. The energy of each patch in the frequency domain is then computed, which serves as an indicator of its importance. However, relying solely on frequency energy could lead to overfitting, especially in scenarios where certain high-energy patches are not necessarily the most informative. To mitigate this, random noise is introduced into the process. This randomness is controlled by the parameter α , which governs the trade-off between the energy and the random noise [16]. The mask ratio, ρ , determines the proportion of patches to be masked. Together, the combination of frequency-guided masking and random noise ensures that the model learns to focus on the most informative parts of the signal, while also being robust to variations and missing information.

Tokenisation. Each masked or unmasked patch is projected to a D -dimensional token through a shared linear layer, forming the matrix $E \in \mathbb{R}^{N \times D}$. Rotary positional embeddings $\{\varsigma_n\}_{n=1}^N \subset \mathbb{R}^D$ are then added,

$$\tilde{E}_n = E_n + \varsigma_n, \quad n = 1, \dots, N. \quad (13)$$

The resulting sequence $\tilde{E} \in \mathbb{R}^{N \times D}$, together with the mask M , is forwarded to the Transformer encoder, which must reconstruct the masked, information-rich patches from context, thereby encouraging robust and frequency-aware representation learning.

2.3 Reconstruction

Transformer encoder and lightweight decoder. The encoder comprises L standard *Transformer blocks* [27], where the only change is that the attention module uses *RoPE attention*. In RoPE attention the query and key sub-vectors of every head are rotated by deterministic sinusoidal factors that depend on their relative positions [28]. This rotation preserves dot-product magnitudes while

Algorithm 1 Frequency-guided masking

Require: Signal $x \in \mathbb{R}^{C \times T}$, patch width w , mask ratio ρ , importance weight α

- 1: $N \leftarrow \lfloor T/w \rfloor$ ▷ number of patches
- 2: Slice the time axis into N non-overlapping patches $p_1, \dots, p_N \in \mathbb{R}^w$

- 3: **for** $n = 1$ **to** N **do** ▷ score each patch
- 4: $F \leftarrow \text{FFT}(p_n)$ ▷ frequency spectrum
- 5: $e_n \leftarrow \sum_k |F_k|$ ▷ spectral energy
- 6: **end for**
- 7: Normalise $\mathbf{e} \leftarrow \frac{\mathbf{e} - \min(\mathbf{e})}{\max(\mathbf{e}) - \min(\mathbf{e})}$
- 8: Draw noise $z_n \sim \mathcal{U}(0, 1)$ for $n = 1, \dots, N$
- 9: $s_n \leftarrow \alpha e_n + (1 - \alpha) z_n$ ▷ blended score
- 10: $\mathbf{i} \leftarrow \text{argsort}(\mathbf{s})$ ▷ ascending: low score first
- 11: $L \leftarrow \lfloor (1 - \rho)N \rfloor$ ▷ patches to keep
- 12: **keep** $\leftarrow \mathbf{i}[1:L]$, **mask** $\leftarrow \mathbf{i}[L:N]$
- 13: Initialise $\mathbf{m} \leftarrow \mathbf{1}_N$; $\mathbf{m}[\text{mask}] \leftarrow 0$ ▷ binary mask
- 14: Replace each p_n with <MASK> if $m_n = 0$
- 15: Re-assemble the patched signal $\tilde{P} \in \mathbb{R}^{N \times w}$

- 16: **return** masked patches $\tilde{P}$, mask $\mathbf{m}$, sort indices $\mathbf{i}$

injecting position information, enabling each head to capture long-range temporal structure [29]. After the L blocks the encoder outputs a latent sequence in which the masked tokens already carry context-inferred estimates [30, 31].

A deliberately shallow decoder then projects the latent width to D_{dec} , refines it with L_{dec} vanilla Transformer blocks, and uses a final linear head to reconstruct every element of each patch, yielding $\hat{P} \in \mathbb{R}^{N \times w}$. Concentrating depth on the encoder while keeping the decoder light forces the model to store most semantic and spectral knowledge in the shared latent space [32].

Patch-level reconstruction loss. Let $\{\mathbf{p}_n\}_{n=1}^N$ and $\{\hat{\mathbf{p}}_n\}_{n=1}^N$ be the ground-truth and reconstructed frequency-band patches defined in Section 2.2, and let $\mathcal{M} = \{n \mid m_n = 1\}$ be the masked-patch index set. The model is trained to minimise the mean Smooth-L1 discrepancy over *only* the masked patches [33, 34]:

$$\mathcal{L} = \frac{1}{|\mathcal{M}|} \sum_{n \in \mathcal{M}} \text{SmoothL1}(\hat{\mathbf{p}}_n, \mathbf{p}_n) \quad (14)$$

This objective 14 compels the network to recover the multiscale, frequency-band information concealed by the mask.

2.4 Methods for downstream tasks

Single-modal setting. For tasks that involve a single modality (EMG or ECG), the pretrained encoder is fine-tuned end-to-end. All patch tokens produced by the final encoder block are aggregated through mean pooling to obtain a global representation, which is then fed to a lightweight two-layer MLP to yield the final classification prediction.

Multi-modal setting. As illustrated in Figure 4, every pretrained encoder is kept *frozen* and only its dedicated classification head—along with a set of fusion coefficients—is trained. This *linear-probing* strategy preserves the representations learned during pretraining while mitigating the risk of over-fitting that often arises when a large-parameter model is adapted to a small downstream dataset [5]. Let $\mathcal{M}$ denote the set of modalities present in a particular experiment. Each modality $m \in \mathcal{M}$ produces logits $\mathbf{z}_m$, and the learnable fusion weights $\alpha = \{\alpha_m\}_{m \in \mathcal{M}}$ are constrained by a softmax so that $\sum_{m \in \mathcal{M}} \alpha_m = 1$. The final prediction vector is obtained by

$$\mathbf{z}_{\text{fused}} = \sum_{m \in \mathcal{M}} \alpha_m \mathbf{z}_m \quad (15)$$

and $\mathbf{z}_{\text{fused}}$ is subsequently used to infer the task categories.

3 Experiments and Results

3.1 Datasets and Training Settings

Leveraging the **PhysioWave** architecture, two large-scale, modality-specific foundation models, **PhysioWave-ecg** and **PhysioWave-emg**, are pretrained on the most extensive open-access corpora currently available for their respective signal types (see Tables 7 and 8). PhysioWave-ecg is trained on approximately **182 GB** of twelve-lead ECG recordings, while PhysioWave-emg utilizes about **823 GB** of EMG data. For each modality, we provide three parameter configurations: *Small* (5M), *Base* (15M), and *Large* (37M). Both PhysioWave models share the same Transformer backbone; however, their learnable wavelet front-ends are *modality-aware* (see Tables 4 and 5 in Appendix B for full architectural and training details).

Signal Preprocessing. Each recording is denoised with a modality-specific band-pass filter followed by a 50 Hz notch. Traces with fewer than 12 ECG leads or 16 EMG electrodes are zero-padded and then resampled to 500 Hz (ECG) or 2 kHz (EMG). See Appendix C and D for full details.

Downstream Tasks and Evaluation Protocol The pretrained encoders are evaluated on the datasets listed in Table 9. All downstream experiments follow the single- and multi-modal procedures detailed in Section 2.4. Each benchmark is split *by subject* into **6:2:2** train/validation/test partitions to prevent subject leakage.

3.2 Downstream Experiment Results

ECG Multi-label Classification Results. Table 1 compares the proposed PhysioWave-ecg with recent large-scale pretrained ECG models. The *Small* model (5 M) already delivers competitive performance: on PTB-XL it raises F1 from 55.9 % (ECG-Chat [35], 13 B) to 65.8 % (+9.9 %), while attaining a comparable AUROC (92.7 % vs. 94.1%). Increasing capacity to *Base* and *Large* yields consistent gains; the 37 M variant sets new best scores on two of the three benchmarks, achieving **66.7 % / 94.6 %** (F1/AUROC) on PTB-XL and **54.8 % / 98.3 %** on Chapman–Shaoxing. On CPSC 2018 it surpasses the previous AUROC ceiling by +0.4 % (96.1 % vs. 95.7 %) and narrows the F1 gap to ECG-Chat from 80.1 % to 73.1 %.

Table 1: ECG rhythm classification.

Method (year)	Params	PTB-XL		CPSC 2018		Chapman–Shaoxing	
		F1	AUROC	F1	AUROC	F1	AUROC
ECG-Chat (2024)	13 B	55.9	94.1	80.1	95.7	—	—
MERL [36] (2024)	11 M	48.1	91.9	72.8	92.6	—	87.9
MaeFE (2023) [37]	9 M	64.7	88.6	71.6	94.5	—	—
OpenECG-SimCLR	11 M	46.9	91.5	73.1	92.4	52.3	95.1
OpenECG-BYOL	11 M	47.7	91.1	72.8	92.6	51.5	94.8
OpenECG-MAE	11 M	48.1	90.9	74.5	93.2	50.8	94.2
Ours–Small	5 M	65.8	92.7	71.6	95.5	52.1	96.4
Ours–Base	15 M	64.5	93.4	72.5	95.9	53.8	97.2
Ours–Large	37 M	66.7	94.6	73.1	96.1	54.8	98.3

Table 2: Surface-EMG gesture recognition.

Method (year)	Params	NinaPro DB5		EPN-612		UCI EMG	
		Acc.	F1	Acc.	F1	Acc.	F1
Moment (2024)	385 M	86.41	74.42	90.87	90.16	90.45	91.75
OTiS (2024)	45 M	85.31	72.61	87.55	88.03	90.62	89.28
Ours–Small	5 M	84.78	72.54	93.12	93.40	90.35	89.51
Ours–Base	15 M	86.02	73.78	93.68	93.91	91.92	92.77
Ours–Large	37 M	87.53	75.42	94.50	94.56	93.19	93.59

EMG Classification Results. Table 2 benchmarks the proposed *PhysioWave-EMG* against the only publicly released large-scale *generic* time-series models—*Moment* (385 M) and *OTiS* (45 M)—because no foundation model has yet been pretrained specifically for EMG signals [2, 38]. Even with just 5 M parameters, the *Small* variant already surpasses both baselines on the challenging EPN-612 dataset (93.1 % / 93.4 % versus 90.9 % / 90.2 % for *Moment*). Scaling up the encoder brings steady gains: the 37 M *Large* model achieves new state-of-the-art results on all three benchmarks—NinaPro DB5 (+1.1 % accuracy over *Moment*), EPN-612 (+3.6 %), and UCI EMG (+2.6 % over *OTiS*)—while still using less than 1/10 of *Moment*’s parameters.

Multi-modal Classification Results. The proposed multi-modal framework—built from the *Small* *PhysioWave-ecg* and *PhysioWave-emg* encoders together with an EEG branch (EEGPT for DEAP, LaBraM for MPDB)—achieves the best accuracy [23, 39].

On **DEAP**, fusing the EEGPT backbone with the *Small* *PhysioWave* ECG/EMG encoders lifts valence accuracy from 79.1% to 85.2% (+6.1%) and arousal accuracy from 81.3% to 88.6% (+7.3%), as shown in Figure 5. The multimodal system also surpasses TPRO-Net by 0.4 % and outperforms Bi-LSTM+attention and Bayesian pipelines by 7–22 % [40], underscoring the benefit of a multimodal framework over single-modality models.

On **MPDB**, the same multimodal architecture—obtained by replacing the EEG branch with LaBraM (5.8 M parameters)—improves accuracy from 70.4% (using LaBraM alone) to 74.9% (+4.5%), as shown in Figure 6. This outperforms generic sequence models such as MMPNet and EEGNet by 9% to 17% [39, 41].

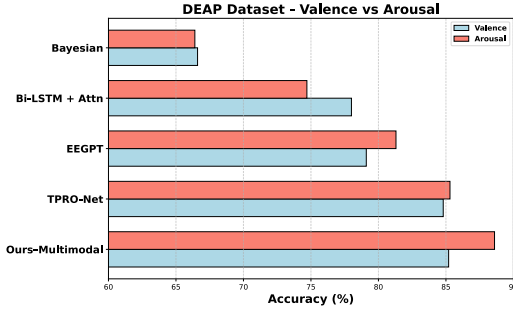


Figure 5: Results on the DEAP dataset.

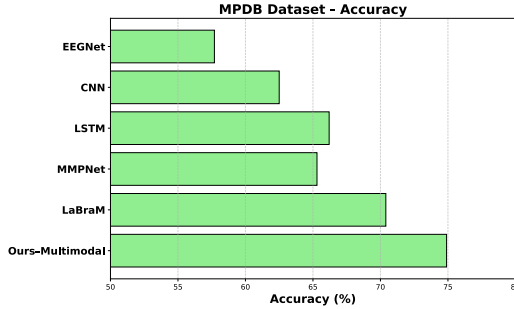


Figure 6: Results on the MPDB dataset.

3.3 Ablation Experiment Results

Table 3: Ablation on *PhysioWave-emg* for EPN-612 dataset.

Configuration	Train Loss	Accuracy (%)	F1 (%)
w/o Frequency-guided Masking	0.24	92.48	92.85
w/o pre-training	0.27	91.67	91.57
with all	0.22	93.12	93.67

As shown in Table 3, removing either design method degrades performance. Comparing to random masking with the same mask ratio of 0.7, discarding the frequency-guided masking strategy reduces F1 by 0.8%, while training the network from scratch (without pretraining) results in a 2.1% decrease in F1 and increases the training loss. The complete *PhysioWave* model thus benefits from *both* Frequency-guided Masking and large-scale self-supervised pretraining, achieving the highest accuracy and F1 score on EPN-612 dataset.

4 Conclusion

In conclusion, this work introduces PhysioWave, a novel wavelet-based architecture designed to enhance physiological signal processing by leveraging adaptive multi-scale decomposition and frequency-guided masking to advance self-supervised learning. The proposed model demonstrates state-of-the-art performance across both single-modality tasks, such as EMG and ECG classification, and in multi-modal settings that integrate EEG, EMG, and ECG signals. Our results underscore PhysioWave’s capacity to effectively capture the unique, time-varying characteristics of physiological signals, addressing key challenges such as non-stationarity, low signal-to-noise ratios, and high inter-subject variability. By combining wavelet decomposition with frequency-guided masking, PhysioWave improves feature extraction, making it particularly well-suited for real-world applications where these challenges are prominent.

Furthermore, the proposed framework sets new benchmarks for EMG and ECG analysis and establishes a strong foundation for future work in multi-modal biosignal processing. With its ability to adapt to heterogeneous and noisy physiological data, PhysioWave holds significant promise for a range of applications, including health monitoring, clinical diagnostics, and personalized medicine.

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A RELATED WORK

A.1 Self-supervised pre-training for Time Series

Self-supervised learning for time-series data has seen considerable advances with the development of models like MOMENT and OTIS, which are designed to handle the unique characteristics of time-series signals, such as non-stationarity, noise, and high variability across domains. Both models leverage large-scale pretraining to learn generalized representations for a wide range of tasks.

The MOMENT model, for instance, introduces a self-supervised learning framework for time-series data using masked representation learning. It captures both local and global temporal dynamics through its ability to reconstruct masked input sequences. MOMENT has been shown to perform well in tasks like classification, anomaly detection, and forecasting, even without task-specific supervision. Additionally, it applies contrastive learning to model dependencies and trends in the data, addressing challenges such as long-range dependencies in time series sequences [2].

OTiS, on the other hand, extends the idea of self-supervised learning to multi-domain time-series data. Its pre-training paradigm incorporates domain-specific tokenization and a dual masking strategy to handle the heterogeneity across time series from different domains, including EEG, audio, and financial data. By using a domain-specific tokeniser with learnable signatures, OTiS can capture domain-specific data characteristics while learning generalized features. This allows it to excel in various downstream tasks, such as classification, regression, and forecasting, across multiple domains [38].

Both models highlight the importance of large-scale pretraining on diverse datasets to unlock foundational model capabilities. MOMENT and OTiS aim to generalize across domains, mitigating issues caused by domain-specific differences like sampling frequencies and inter-variate relationships. These models represent significant strides in time-series analysis, particularly in scenarios where labeled data is scarce but large, diverse, and unlabeled datasets are available for pretraining.

This self-supervised approach provides a robust solution for time-series data, leveraging vast datasets for pretraining and fine-tuning these models on specialized tasks, thus achieving state-of-the-art performance in a range of applications from health monitoring to forecasting.

A.2 Self-supervised pre-training for EEG signal

Self-supervised learning has gained significant traction, particularly in natural language processing (NLP) and computer vision (CV), and has shown promising results in the domain of electroencephalography (EEG) [41]. In EEG, self-supervised learning models are leveraging the ability to pre-train models on large, unlabeled datasets, which can then be fine-tuned for specific downstream tasks. Two notable models in this domain are **EEGPT** and **LaBraM**, both of which advance self-supervised learning techniques for EEG signal analysis.

EEGPT (EEG Pretrained Transformer) employs a masked autoencoder-based self-supervised learning strategy specifically designed for EEG data. This model is trained to predict masked segments of the EEG signal, enabling it to learn robust representations of the signal’s spatio-temporal features. The dual self-supervised learning approach in EEGPT combines masked reconstruction and spatio-temporal alignment, effectively addressing the challenges posed by low signal-to-noise ratio (SNR) and inter-subject variability in EEG. This method allows EEGPT to perform well across a variety of EEG-based tasks, particularly in the context of brain-computer interface (BCI) applications where accurate feature extraction is critical [5].

LaBraM (Large Brain Model) is another significant model in self-supervised EEG pre-training. LaBraM focuses on learning universal EEG representations through unsupervised pre-training on large-scale EEG datasets from various domains. To address the challenge of cross-dataset learning, LaBraM segments EEG signals into channel patches and uses a vector-quantized neural spectrum prediction model to generate a compact neural tokenizer. This allows the model to learn generalized representations that can be fine-tuned on specific tasks, such as abnormality detection, emotion recognition, and gait prediction. The model’s ability to handle diverse EEG data with varying channel configurations and recording settings has been validated across multiple EEG-based tasks, demonstrating its robustness and scalability [4].

Both models underscore the importance of large-scale pretraining in the EEG domain. By learning from vast amounts of unlabeled data, these self-supervised models can capture the rich, multi-scale features of EEG signals, which are crucial for a wide range of applications in health monitoring and BCI systems. The ability of **EEGPT** and **LaBraM** to generalize across datasets and tasks highlights the potential of self-supervised learning to transform the analysis of EEG signals, making deep learning techniques more applicable and effective in the field of bio-signal processing.

A.3 Self-supervised Pre-training for ECG Signal

Self-supervised learning (SSL) has become a pivotal method in ECG foundation model development, addressing challenges such as the scarcity of labeled data and the need for robust generalization across diverse datasets. Recent advancements have introduced several effective SSL-based pre-training strategies for ECG data.

One such approach is OpenECG, which created a large ECG benchmark with over 1.2 million 12-lead ECG recordings from 9 centers. The study evaluated three prominent SSL methods—SimCLR, BYOL, and MAE—using ResNet-50 and Vision Transformer (ViT) architectures. The results showed that pre-training on diverse datasets significantly improved model generalization, with BYOL and MAE outperforming SimCLR. These methods demonstrated superior effectiveness in learning feature-consistency and generative representations compared to contrastive methods, which require large datasets to perform optimally [42].

Another notable model is ECG-Chat, a large ECG-language model designed for cross-modal cardiac diagnosis. It combines ECG waveform data with text reports using contrastive learning to align ECG features with medical text. The model was trained on a dataset that integrates both diagnosis and conversation tasks, achieving state-of-the-art results in ECG medical report generation. ECG-Chat also incorporates a novel method for mitigating hallucinations during report generation by integrating external cardiology knowledge via GraphRAG and DSPy components. This ensures that the generated ECG reports are grounded in clinical knowledge, enhancing accuracy and reliability [35].

These models highlight the potential of self-supervised learning for enhancing ECG analysis and improving diagnostic tools. By leveraging large-scale ECG data and pre-training strategies, both OpenECG and ECG-Chat advance the capabilities of ECG models, making them more robust and adaptable across a range of clinical and research applications. They represent a significant step toward improving the accessibility and accuracy of AI-driven cardiovascular diagnostics.

B HYPERPARAMETER SETTINGS

We employ **AdamW** with a weight decay of 0.01 and moment coefficients $\beta_1 = 0.9$ and $\beta_2 = 0.98$. The learning rate is linearly warmed up from 5×10^{-7} to 5×10^{-5} over the first ten epochs and then follows a cosine decay to a floor of 1×10^{-6} . Pretraining lasts for 50 epochs with a global batch size of 64 on 16 NVIDIA A100 GPUs, whereas all downstream experiments are carried out on 4 A100 GPUs. During downstream training, the same AdamW optimizer and the cosine scheduler is retained, but the learning rate is reduced to 1/10 of its pretraining value.

Table 4: Hyperparameters for masked ECG pre-training with **PhysioWave-ecg**.

Hyperparameter	PhysioWave-ecg-Small	PhysioWave-ecg-Base	PhysioWave-ecg-Large
Wavelet Front-End			
Input channels	12	12	12
Max decomposition level	4	4	4
Wavelet kernel size	24	24	24
Wavelet bases	{sym4, sym5, db6, coif3, bior4.4}		
Transformer Encoder			
Timesteps		1024	
Patch size ($H \times W$)		{1, 64}	
Embed dimension (= hidden size)	256	384	512
Encoder layers	6	8	12
Attention heads	8	12	16
MLP ratio		4.0	
MLP size	1 024	1 536	2 048
Drop-path		0.10	
Decoder			
Decoder embed dim		256	
Decoder depth / heads		8 / 8	
Pre-training Setup			
Batch size		64	
Peak / minimal learning rate		5×10^{-5} / 1×10^{-6}	
Optimizer (β_1, β_2)		AdamW (0.9, 0.98)	
LR scheduler		Cosine	
Weight decay		0.01	
Total / warm-up epochs		50 / 10	
Accumulated grad batches		64	
Gradient clipping		3	
Mask ratio / importance ratio		0.70 / 0.60	
Max sequence length		2 048	

Table 5: Hyperparameters for masked EMG pre-training with **PhysioWave-emg**.

Hyperparameter	PhysioWave-emg-Small	PhysioWave-emg-Base	PhysioWave-emg-Large
Wavelet Front-End			
Input channels	16	16	16
Max decomposition level	3	3	3
Wavelet kernel size	16	16	16
Wavelet bases	{db4, bior4.4, sym5, coif5}		
Transformer Encoder			
Timesteps		1024	
Patch size ($H \times W$)		{1, 64}	
Embed dimension (= hidden size)	256	384	512
Encoder layers	6	8	12
Attention heads	8	12	16
MLP ratio		4.0	
MLP size	1 024	1 536	2 048
Drop-path		0.10	
Decoder			
Decoder embed dim		256	
Decoder depth / heads		8 / 8	
Pre-training Setup			
Batch size		64	
Peak / minimal learning rate		5×10^{-5} / 1×10^{-6}	
Optimizer (β_1, β_2)		AdamW (0.9, 0.98)	
LR scheduler		Cosine	
Weight decay		0.01	
Total / warm-up epochs		50 / 10	
Accumulated grad batches		64	
Gradient clipping		3	
Mask ratio / importance ratio		0.70 / 0.60	
Max sequence length		2 048	

Table 6: Hyperparameters for downstream fine-tuning with **PhysioWave**.

Hyperparameter	Value
Batch size	32
Peak / minimal learning rate	5×10^{-4} / 1×10^{-5}
Learning rate scheduler	Cosine
Optimizer (β_1, β_2)	AdamW (0.9, 0.98)
Weight decay	0.01
Total epochs	Early stopping (max 50)
Warm-up epochs	5
Drop-path	0.10
Layer-wise learning rate decay	0.90
Label smoothing (multi-class classification)	0.10

C PRETRAINING DATASETS DESCRIPTION

C.1 Pretraining datasets for PhysioWave-ecg

In the pretraining of PhysioWave-ecg, we process ECG data to ensure it is suitable for model training. The process involves several key steps, including filtering, windowing, and handling different sampling rates.

First, we apply a bandpass filter (0.5–40 Hz) to remove unwanted low-frequency noise and high-frequency artifacts. Additionally, a 50 Hz notch filter is applied to eliminate power line interference. These filtering steps are crucial for improving the quality of the ECG signals.

To handle the data, we use a sliding window technique. The ECG signals, with 12 leads and a sampling rate of 500 Hz, are divided into overlapping windows of a fixed size (e.g., 1024 samples). If the signal length is insufficient for a full window, we apply zero-padding to maintain consistency across the dataset.

For ECG recordings with a sampling rate lower than 500 Hz, we upsample the signal to 500 Hz to ensure uniformity across the dataset. This is important for maintaining the integrity of the signal while ensuring that all data points are processed at the same sampling frequency.

Finally, the processed ECG data is saved in the HDF5 format, organized into a dataset with dimensions corresponding to the batch size, number of leads (12), and window size (1024 samples). This preprocessed data is then used to train the PhysioWave-ecg model.

Table 7: 12-lead ECG corpora used for pretraining.

Dataset	Subjects	Records	Dur. (s)	f_s (Hz)	Size
MIMIC-IV-ECG [43]	~160 000	~800 000	10	500	90.4 GB
MedalCare-XL [44]	13	16 900	10	500	26.2 GB
CODE-15% [45]	233 770	345 779	10	400	63.3 GB
Norwegian Athlete [46]	28	28	10	500	52.8 MB
Georgia Cohort [47]	10 344	10 344	10	500	1.2 GB

MIMIC-IV-ECG The MIMIC-IV-ECG module includes around 800,000 12-lead ECG recordings from nearly 160,000 patients, spanning from 2008 to 2019. Each ECG is 10 seconds long, sampled at 500 Hz, and matched with clinical data and cardiologist reports. The dataset provides not only the ECG waveforms but also machine-generated measurements such as RR intervals and QRS onset times, with all data de-identified to comply with HIPAA standards. The data is stored in the WFDB format for easy processing [43].

MedalCare-XL MedalCare-XL is a synthetic 12-lead ECG dataset containing 16,900 10-second ECGs across one healthy control and seven pathological classes. The dataset includes ECG signals

in three variations: raw, with noise, and filtered using highpass and lowpass Butterworth filters. Additionally, it provides parameter files detailing the electrophysiological model used for simulation. This dataset is valuable for training ECG analysis models, especially for personalized disease simulations [44].

CODE-15% The CODE-15 dataset is a stratified subset of the CODE dataset, containing 345,779 12-lead ECG records from 233,770 patients, collected between 2010 and 2016. It is widely used for ECG automatic diagnosis research and cardiovascular risk prediction. The scale and annotation quality make it a reliable resource for developing ECG AI algorithms [45].

Norwegian Athlete ECG Database The Norwegian Athlete ECG Database contains 12-lead ECG recordings from 28 elite athletes in Norway. Each ECG is 10 seconds long and recorded with a GE MAC VUE 360 electrocardiograph. The dataset includes both machine-generated interpretations and cardiologist reviews. The cohort consists of rowers, kayakers, and cyclists, with participants aged 20–43 years. The data helps address challenges in ECG interpretation for athletes, who often exhibit heart adaptations that can mimic pathological changes [46].

Georgia Cohort The Georgia Cohort dataset contains 10,344 12-lead ECGs from male (5,551) and female (4,793) patients, each 10 seconds long with a sampling rate of 500 Hz. The dataset is used for cardiovascular disease prediction and ECG classification tasks. The data offers a diverse set of ECG signals, providing an opportunity to study the effects of various cardiovascular conditions across different demographic groups [47].

C.2 Pretraining datasets for PhysioWave-emg

Table 8: Surface-EMG corpora used for pretraining.

Dataset	Subjects	Records	Dur. (s)	f_s (Hz)	Channels	Size
NinaPro DB6 [48]	10	~8.4 k	4	2 000	14	20.3 GB
NinaPro DB7 [49]	22	~5.4 k	5	2 000	12	30.9 GB
NinaPro DB8 [50]	12	~2.4 k	7.5	1 111	16	23.6 GB
EMG2Pose [51]	193	25 253	60	2 000	16	431 GB
EMG2Qwerty [52]	108	1 135	1 080	2 000	16	317 GB

For the pretraining of the PhysioWave-emg model, we process the raw EMG data through several critical preprocessing steps to ensure its suitability for training. First, a bandpass filter is applied to remove unwanted noise and artifacts, retaining frequencies between 20 Hz and 450 Hz, which are relevant for EMG analysis. A notch filter is then used to suppress 50 Hz power line interference, a common source of noise in EMG recordings. After filtering, we normalize the signals using z-score normalization, ensuring that each EMG channel has a mean of zero and a standard deviation of one, standardizing the input scale for machine learning models.

To prepare the data for training, we apply a sliding window approach, dividing the EMG signal into overlapping windows of 1024 samples with a step size of 512. If the sampling rate of the raw signal is below 2000 Hz, the data is upsampled to 2000 Hz to ensure consistency. Additionally, if the number of channels is less than 16, the data is padded with zeros to match the required dimensionality. Finally, the processed data is saved in an HDF5 format, allowing for efficient storage and incremental updates. This ensures easy access to the data and facilitates the addition of new data without overwriting existing information.

NinaPro DB6 The NinaPro DB6 dataset is designed to aid the scientific community in studying the repeatability of sEMG classification for hand grasps. It includes data from 10 intact subjects who performed 7 different hand grasps, each repeated 12 times across 5 days. The data was collected using 14 wireless Trigno EMG electrodes, with a sampling rate of 2 kHz. The dataset provides synchronized sEMG signals along with inertial measurements, capturing the movements of the forearm during hand grasp activities. The main goal is to develop models that can accurately recognize and classify these grasps for prosthetic control [48].

NinaPro DB7 The NinaPro DB7 dataset includes both myoelectric and inertial measurements from 20 intact subjects and 2 amputees. The data were collected using 12 active wireless Trigno EMG sensors along with 9-axis inertial measurement units. The subjects were asked to perform 40 different movements, which included basic finger and wrist movements as well as grasping tasks. The data were sampled at 2 kHz, with additional kinematic data collected from a 18-DOF Cyberglove worn on the contralateral hand. This dataset provides valuable insights for prosthetic hand control, enabling improved motion recognition through both myoelectric and inertial data [49].

NinaPro DB8 The NinaPro DB8 dataset is focused on the estimation and reconstruction of finger movements, rather than motion or grip classification. It includes data from 10 intact subjects and 2 right-hand transradial amputee participants. The dataset contains sEMG signals, accelerometer, gyroscope, and magnetometer data collected from 16 wireless Trigno EMG sensors, along with data from a Cyberglove worn on the contralateral hand. The subjects were asked to repeat 9 different movements, with each movement lasting between 6 to 9 seconds, followed by a 3-second rest period. This dataset is specifically designed to benchmark algorithms that decode finger position from contralateral EMG measurements using regression algorithms, making it a valuable resource for prosthetic hand control and rehabilitation studies [50].

EMG2Pose The EMG2Pose dataset consists of surface electromyography (sEMG) recordings paired with ground-truth motion-capture recordings of hand movements. It contains 25,253 HDF5 files, each representing time-aligned sEMG and joint angles for a single hand during a single stage. The dataset spans 193 participants across 370 hours of data and includes 29 stages, with each stage lasting around one minute. The dataset is structured with metadata that includes anonymized user IDs, session information, hand side (left or right), and whether the user was held out from the training set. This dataset is designed to advance the field of hand pose estimation from sEMG signals, offering a foundation for model training and evaluation in pose tracking and gesture recognition tasks [51].

EMG2Qwerty The EMG2Qwerty dataset consists of surface electromyography (sEMG) recordings obtained while users perform touch typing on a QWERTY keyboard. It contains 1,136 session files, recorded from 108 users over 346 hours, with each session file including left and right sEMG signal data, prompted text, and keylogger ground-truth data. The dataset is provided in an HDF5 format and offers a programmatic interface for easy access. It is particularly useful for training and testing models aimed at decoding keypresses or character-level recognition from sEMG signals, with benchmarks for both generic and personalized user models. This dataset is essential for research in sEMG-based text entry systems, focusing on enhancing accuracy in virtual keyboard applications and prosthetics [52].

D Downstream Datasets Description

PhysioWave-ecg is tested on the three ECG corpora (PTB-XL [19], Chapman-Shaoxing [53], and CPSC 2018 [54]), while PhysioWave-emg is assessed on the three EMG gesture datasets (Ninapro DB5 [55], EPN-612 [20], and UCI EMG-Gesture [56]). Multi-modal generalization is examined with DEAP [23] and MPDB [39].

Table 9: Public datasets used for downstream evaluation.

Dataset	Domain	Subjects	Channels	f_s (Hz)	Task
Ninapro DB5	EMG	10	16	200	Hand gestures
EPN-612	EMG	612	8	200	Hand gestures
UCI EMG-Gesture	EMG	36	8	200	Hand gestures
PTB-XL	ECG	18 869	12	500	Arrhythmia
Chapman-Shaoxing	ECG	45 152	12	500	Arrhythmia
CPSC 2018	ECG	10 330	12	500	Arrhythmia
DEAP	EEG/EMG	32	40	128	Emotion recognition
MPDB	EEG/ECG/EMG	35	64	1000	Driving behaviour

D.1 Downstream datasets for PhysioWave-ecg

PTB-XL The PTB-XL dataset is an extended version of the PTB database, containing 21,837 12-lead ECG recordings from 18,884 patients. The dataset includes a variety of cardiac conditions, with annotations for more than 60 different disease categories, including arrhythmias, myocardial infarction, and other heart diseases. It was recorded using standard 12-lead ECG systems, with signals sampled at 1000 Hz. PTB-XL is widely used for ECG classification tasks and provides a comprehensive resource for developing and testing machine learning models in cardiovascular disease detection and prediction. The dataset is publicly available and is often used as a benchmark for evaluating ECG classification algorithms [19].

Chapman-Shaoxing The Chapman-Shaoxing dataset is a large-scale ECG dataset containing 11,000 12-lead ECG recordings from over 5,000 subjects. It includes data from patients with various cardiovascular conditions, such as arrhythmias, ischemic heart disease, and healthy individuals. The recordings were collected using standard ECG machines, with a sampling rate of 500 Hz. This dataset is used in studies focused on ECG diagnosis and abnormality detection, offering a rich source of data for training and evaluating models that aim to predict cardiovascular diseases. The Chapman-Shaoxing dataset is particularly valuable for advancing research in automatic ECG analysis and arrhythmia classification [53].

CPSC 2018 The CPSC 2018 dataset, used in the China Physiological Signal Challenge, contains 15,000 12-lead ECG recordings from 5,000 patients, spanning a wide range of cardiovascular conditions. The recordings are sampled at 500 Hz and are annotated with clinical information about the presence of various heart diseases. The dataset is designed to evaluate machine learning algorithms for ECG classification, particularly for arrhythmia detection. The CPSC 2018 dataset provides a diverse and comprehensive set of ECG recordings, making it a critical resource for developing and benchmarking automatic ECG analysis systems. It has been widely used in ECG research and challenges to push forward the development of reliable and accurate diagnostic tools [54].

D.2 Downstream datasets for PhysioWave-emg

NinaPro DB5 The NinaPro DB5 dataset includes surface electromyography (sEMG) recordings for hand gesture recognition. It consists of 40 different hand gestures performed by 40 subjects (24 male, 16 female). Each subject performed each gesture 10 times, resulting in a total of 400 gesture recordings per subject. The dataset is recorded using 8 bipolar sEMG electrodes placed on the forearm, with a sampling rate of 2 kHz. The data is valuable for the development and evaluation of machine learning models for gesture recognition in prosthetics and human-computer interaction, providing a well-annotated set of hand gestures that can be used to train models for real-time sEMG-based gesture classification [55].

EPN-612 The EPN-612 dataset consists of surface electromyography (sEMG) data collected from 612 subjects using the Myo armband. It contains 5 different hand gestures (wave-in, wave-out, pinch, open, and fist) and a relaxed hand gesture, with 50 recordings per gesture from each subject. The dataset includes both raw sEMG signals and the corresponding labels for each gesture, making it suitable for gesture recognition tasks. The data is widely used for training and evaluating machine learning models focused on real-time gesture recognition, with applications in prosthetics and assistive technologies. The dataset is publicly available for research and benchmark purposes [20].

UCI EMG-Gesture The UCI EMG-Gesture dataset contains sEMG recordings for hand gesture recognition, collected from 10 subjects. Each subject performed 10 different gestures, with 3 repetitions for each gesture. The dataset was recorded using a 16-channel sEMG setup, with a sampling frequency of 2 kHz. It includes labeled data for each gesture, making it suitable for training and evaluating gesture recognition algorithms. This data set is valuable for researchers developing gesture models [56].

D.3 Downstream datasets for multi-modal tasks

DEAP The DEAP (Dataset for Emotion Analysis using Physiological Signals) dataset is a multi-modal dataset designed for emotion recognition research. It contains 32 participants, each providing

data across multiple physiological signals, including EEG, EMG, and GSR, while watching music videos designed to evoke different emotional states. The dataset includes 40 one-minute-long video clips, with each participant providing emotional ratings on several dimensions, such as valence, arousal, dominance, and liking. The DEAP dataset is widely used for training and evaluating models for emotion recognition, particularly in applications like affective computing and human-computer interaction. The dataset is available for research and provides an essential resource for studies combining physiological signals and emotion analysis [23].

MPDB The MPDB (Multimodal Physiological Dataset for Driving Behavior Analysis) is a comprehensive dataset designed to analyze driver behavior using multimodal physiological signals. It contains data from 35 participants, including both male and female drivers, recorded during simulated driving tasks. The dataset includes 59-channel EEG, single-channel ECG, 4-channel EMG, single-channel GSR, and eye-tracking data. These signals were collected during five distinct driving behaviors: smooth driving, acceleration, deceleration, lane changing, and turning. The data was synchronized with a six-degree-of-freedom driving simulator, providing a realistic driving experience. This dataset is valuable for studying driver cognition, decision-making, and the relationship between physiological responses and driving behavior, especially in the context of autonomous driving research. The dataset’s multimodal nature allows for the exploration of advanced models that integrate physiological signals for more accurate behavioral predictions and safety system designs [39].

E VISUALIZATION

E.1 Visualization of sEMG Pretraining

The following visualizations demonstrate the pretraining process for EMG signals, where the model learns to reconstruct the masked regions of the input signal, specifically focusing on the restoration of multi-scale wavelet decomposition features, $\text{Spec}(X)$. The images show different stages of the reconstruction task, including the target signal, the model’s prediction, the masked areas, and the final reconstructed signal. These visualizations illustrate the model’s ability to restore missing information from wavelet-decomposed features.

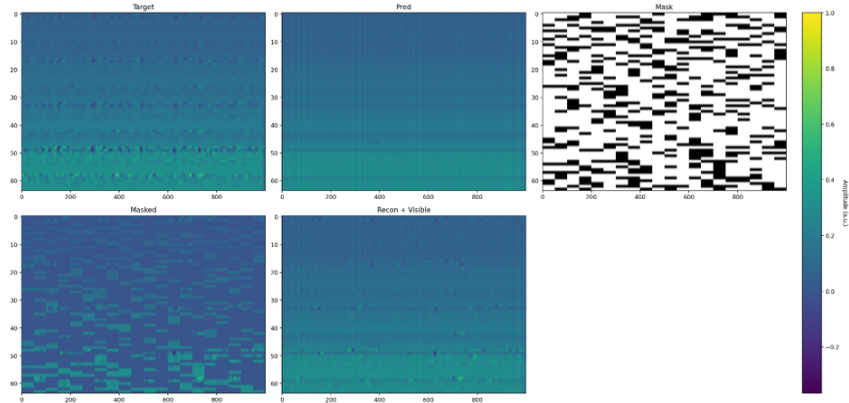


Figure 7: Reconstruction results for the 10th training epoch and the 1000th batch. The image illustrates the pretraining process where the model successfully restores masked regions of the signal during EMG pretraining. This represents the restoration of multi-scale wavelet-decomposed information at an earlier training stage.

Figure 7 shows the results for the 10th training epoch and the 1000th batch of the EMG pretraining process. As seen in the image, the model has learned to effectively restore the missing parts of the signal, showcasing its ability to handle the wavelet decomposition and its corresponding multi-scale features.

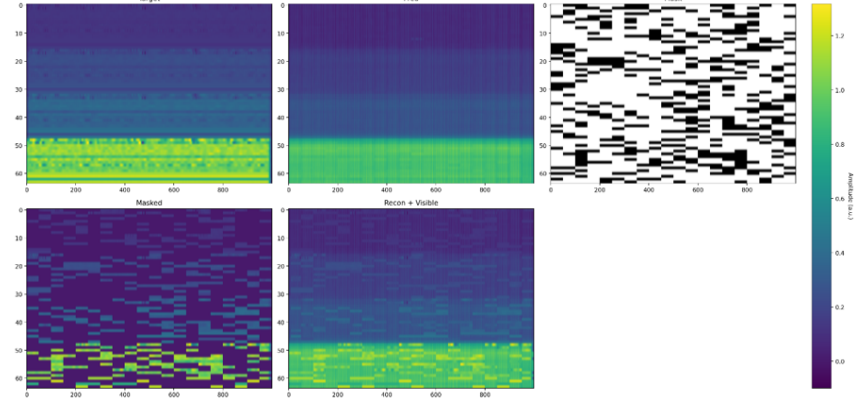


Figure 8: Reconstruction results for the 20th training epoch and the 1000th batch. This image shows the pretraining process at a later stage, where the model continues to restore missing information with increasing accuracy. The ability to restore the wavelet decomposition at this stage is further refined.

Figure 8 displays the results for the 20th training epoch and the 1000th batch of the EMG pretraining process. At this stage, the model shows improved performance in reconstructing the masked regions, indicating its enhanced understanding of the signal’s multi-scale features and its ability to restore more complex signal components.

These visualizations highlight the progression of the model’s learning ability during the pretraining process. The first figure 7 demonstrates the model’s early-stage capability to restore missing multi-scale features, while the second figure 8 shows the improvements made by the model as it continues training. This process emphasizes the model’s capacity to learn to restore wavelet-decomposed features, which is critical for downstream applications like EMG signal analysis and classification.

E.2 Visualization of EPN612 Experimental Results

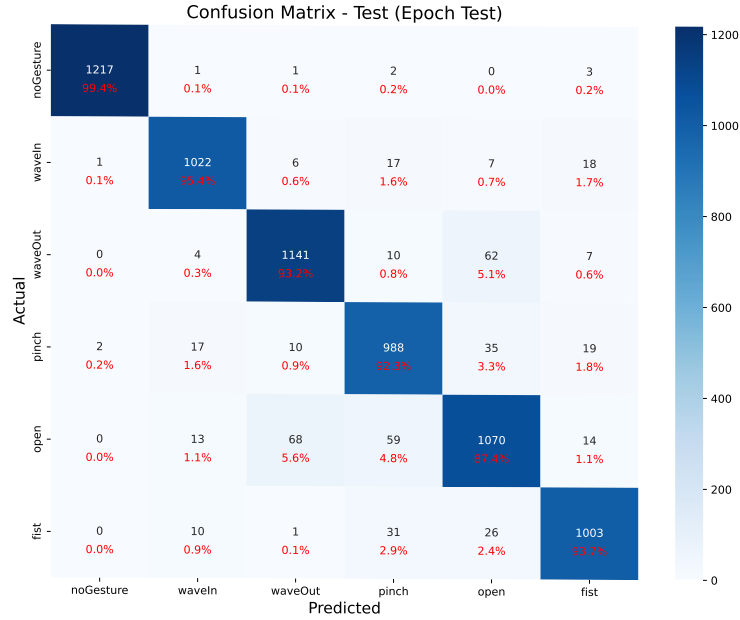


Figure 9: Confusion matrix on the EPN612 test set after final training.

Figure 9 shows the test confusion matrix for the EPN612 dataset. Per-class recalls remain consistently high ($\geq 87.4\%$, typically $> 92\%$), with the highest recall achieved for noGesture (99.4%). Most

misclassifications occur between semantically similar dynamic gestures: (a) open is occasionally confused with waveOut and pinch, and (b) pinch is sometimes predicted as open. The sparse distribution of off-diagonal entries indicates that the model has successfully learned discriminative representations for the remaining gesture classes.

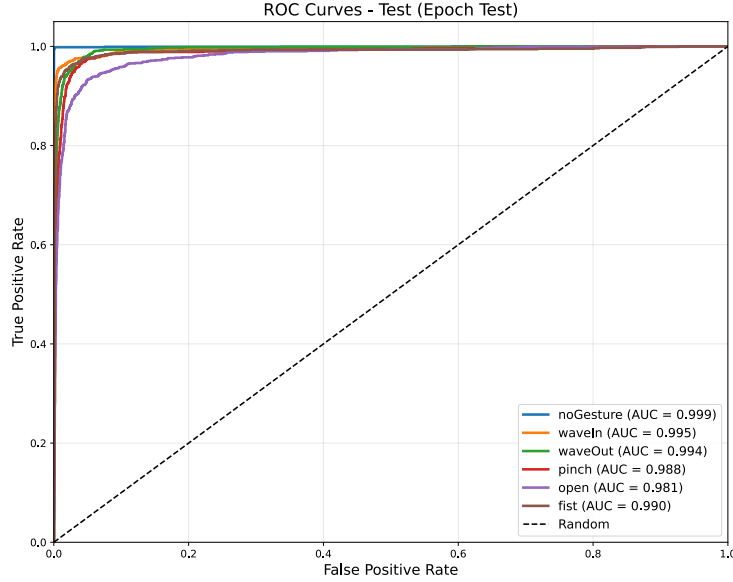


Figure 10: ROC curves for all gesture classes on the test set after final training.

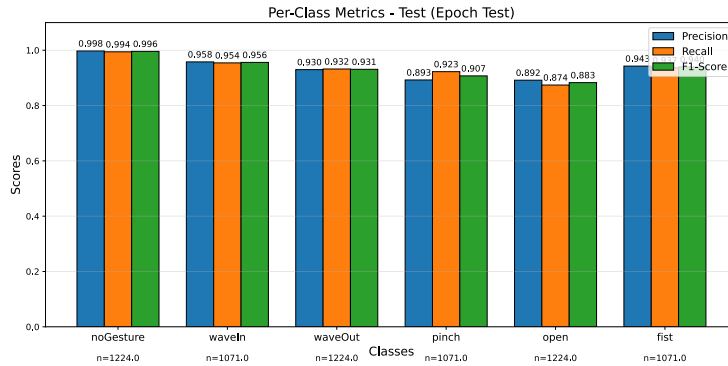


Figure 11: Per-class precision, recall, and F1-score metrics on the test set after final training.

Figure 10 presents the ROC curves for all six gesture classes on the test set. All models demonstrate excellent discriminative performance with AUC values ranging from 0.981 to 0.999. The noGesture class achieves the highest AUC of 0.999, followed by waveIn (0.995) and waveOut (0.994). The curves are positioned well above the random classifier diagonal, indicating strong separation between positive and negative classes across all gesture types.

Figure 11 shows the detailed per-class performance metrics. The noGesture class achieves near-perfect performance across all metrics (precision: 0.998, recall: 0.994, F1-score: 0.996). Dynamic gesture classes show consistently high performance, with F1-scores ranging from 0.883 (open) to 0.956 (waveIn). The open gesture exhibits the lowest recall (0.874) among all classes, while maintaining reasonable precision (0.892), suggesting some difficulty in detecting this particular gesture pattern.

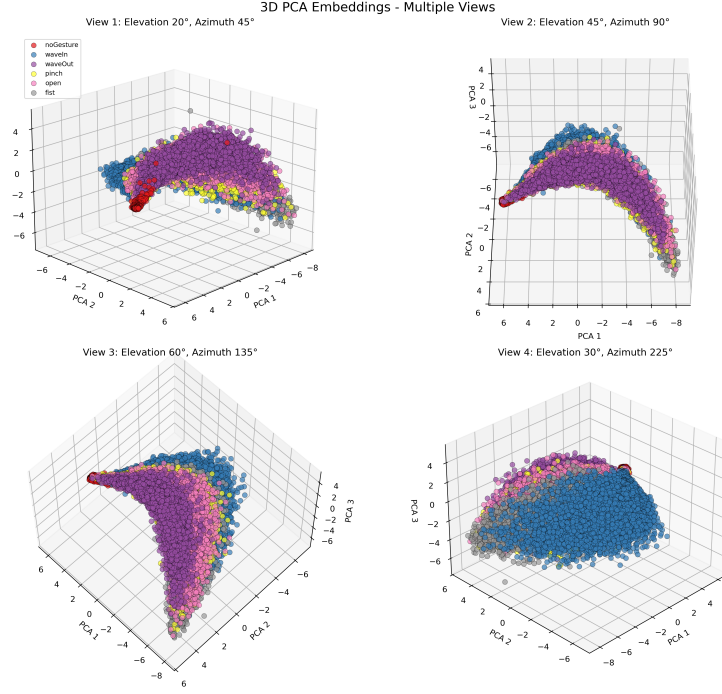


Figure 12: 3D PCA embeddings visualization from multiple viewing angles showing feature representations learned by the WaveletTransformer model.

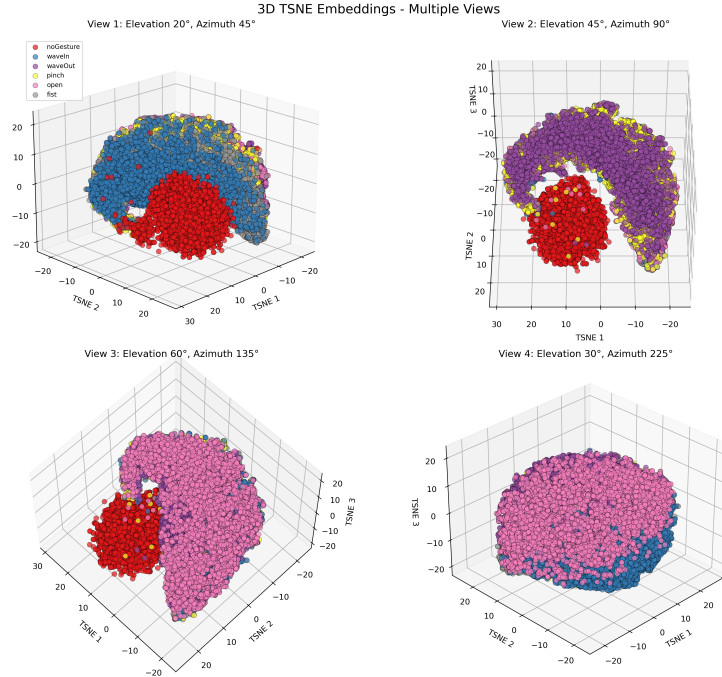


Figure 13: 3D t-SNE embeddings visualization from multiple viewing angles demonstrating non-linear clustering patterns in the learned feature space.

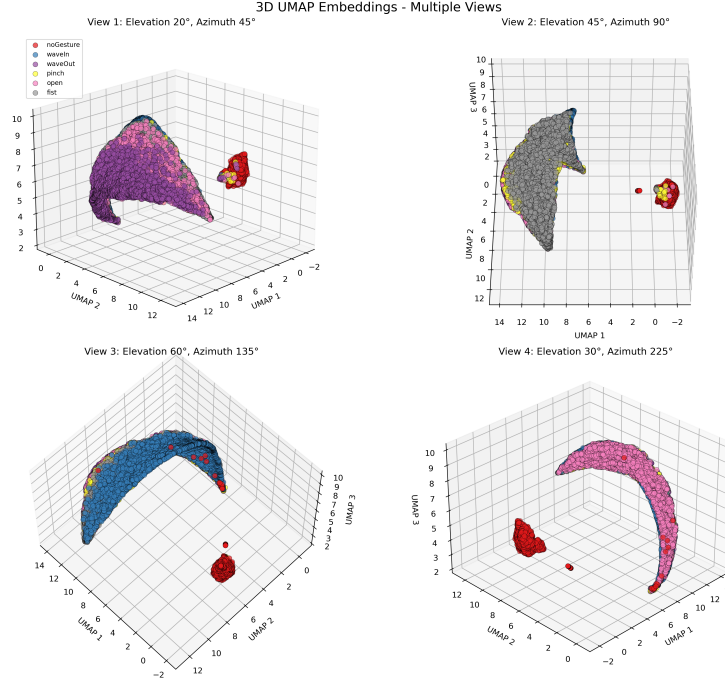


Figure 14: 3D UMAP embeddings visualization from multiple viewing angles revealing the topological structure of gesture representations in the feature space.

Figures 12, 13, and 14 present comprehensive 3D visualizations of the learned feature embeddings using three different dimensionality reduction techniques: Principal Component Analysis (PCA), t-Distributed Stochastic Neighbor Embedding (t-SNE), and Uniform Manifold Approximation and Projection (UMAP). Each visualization displays the same feature space from four distinct viewing angles (elevation/azimuth combinations of 20°/45°, 45°/90°, 60°/135°, and 30°/225°) to provide complete spatial understanding of the clustering patterns.

The PCA visualization (Figure 12) reveals the linear structure of the feature space, showing how gesture classes are distributed along the principal components of maximum variance. The `noGesture` class (red) forms a distinct, compact cluster that is well-separated from dynamic gesture classes, while the active gesture classes (`waveIn`, `waveOut`, `pinch`, `open`, `fist`) exhibit more distributed but still distinguishable patterns.

The t-SNE visualization (Figure 13) emphasizes local neighborhood relationships and reveals non-linear clustering structures. The method successfully preserves local similarities, creating tight, well-separated clusters for each gesture class. Notably, the `noGesture` class forms a dense, spherical cluster at the center, while dynamic gestures are arranged in distinct regions around the periphery, suggesting strong discriminative power in the learned representations.

The UMAP visualization (Figure 14) balances both local and global structure preservation, revealing the topological organization of the feature space. UMAP shows excellent class separation with `noGesture` forming a highly concentrated cluster, and dynamic gesture classes organized in a manifold-like structure that preserves both local neighborhoods and global relationships between semantically related gestures.

Across all three visualization methods, several consistent patterns emerge: (1) the `noGesture` class demonstrates exceptional separability from active gestures, (2) dynamic gesture classes maintain distinct clustering while showing logical spatial relationships based on gesture similarity, and (3) the learned feature representations exhibit strong discriminative properties that facilitate effective classification. The multi-view presentation confirms the robustness of these clustering patterns across different spatial perspectives.

F LIMITATIONS

While the proposed PhysioWave architecture represents a significant advancement in the processing of physiological signals, it is not without its limitations. Our current approach focuses on large-scale models specifically trained for electromyography (EMG) and electrocardiography (ECG) signals, both of which have demonstrated state-of-the-art performance across several downstream tasks. However, this approach is currently limited to these two modalities, and other important physiological signals, such as electroencephalography (EEG) and photoplethysmography (PPG), remain underexplored.

Another key limitation lies in the fact that our work primarily focuses on separate models for different physiological signals. Although our unified framework integrates pre-trained EMG and ECG models with an existing EEG encoder, the design is not fully generalized across all biosignal modalities. This calls for further exploration into the development of a universal, multi-modal model capable of seamlessly processing a wide variety of physiological signals. A model of this nature could function as a comprehensive "physiological diagnostic" system, akin to a highly specialized medical expert, diagnosing and interpreting a broad spectrum of physiological signals across different conditions. Developing such a universal model would not only enhance the robustness of signal interpretation but also streamline the diagnostic process across different sensor modalities.

We believe that addressing these gaps by expanding the range of modalities incorporated into our framework and further investigating the potential for a unified, multi-modal biosignal model will significantly improve the versatility and applicability of our approach in real-world clinical and health monitoring settings. Future research could focus on training models for a wider array of biosignals, as well as enhancing the multi-modal integration capabilities to create a truly universal model for physiological signal processing.