OCA-SENTINEL: MULTIMODAL AGE GROUP PREDICTION SYSTEM

Bootstrap Ensemble Approach

OVERVIEW

This system predicts age groups (20s-70s, 6 classes) from dual-modality arterial pressure waveforms (Aortic and Brachial) using a transformer-based ensemble architecture with adaptive attention masking for missing data handling.

DATA PROCESSING PIPELINE

1. Signal Preprocessing:
   - Butterworth 4th-order low-pass filter (fs=500Hz, cutoff=25Hz) applied to valid data segments
   - Missing value detection and masking (preserving NaN positions)
   - Segment-wise filtering to handle incomplete sensor readings

2. Normalization:
   - StandardScaler normalization fitted on non-missing values only
   - Per-modality scaling (separate for Aortic and Brachial pressures)
   - Missing values filled with zeros post-normalization (masked in attention)

3. Data Augmentation via Bootstrap Sampling:
   - 10 independent bootstrap samples with replacement (N=2700 → 2700 each)
   - Each sample contains ~63% unique subjects with duplicates
   - Enables variance reduction and model diversity

ALGORITHM DESCRIPTION

Architecture (per model):

- Dual-stream transformer encoders (one per modality)
- Input projection: 1D time series → 128-dimensional embeddings
- Positional encoding with sinusoidal patterns (max_len=336)
- 4-layer transformer encoder per modality (8 attention heads, 512 FFN dim)
- Adaptive Attention Masking: Boolean masks prevent attention to missing time points (inspired by AIM methodology)
- Cross-modal fusion: Concatenate encoded representations [256-dim]
- Classification head: Dropout (0.5) → FC (256→6) → Softmax

Ensemble Strategy:

- Bootstrap Aggregating (Bagging) with 10 independent models
- Each model trained on different bootstrap sample (separate random data)
- Prediction: Probability averaging across all 10 models, then argmax
- Training: 120 epochs, ReduceLROnPlateau scheduler, early stopping
- Loss: CrossEntropyLoss, Optimizer: AdamW (lr=0.0001, weight_decay=0.01)

Missing Data Handling:

- Attention-based masking prevents gradient flow from missing positions
- Models learn robust representations despite incomplete sensor data
- No imputation required—architecture handles sparsity natively

DEVELOPMENT & VALIDATION

Training Configuration:

- Dataset: 2700 subjects with dual-modality pressure waveforms (336 timesteps)
- Train/Validation Split: 80/20 per bootstrap sample
- Hardware: NVIDIA GPU (CUDA-enabled), batch size 32
- Convergence: Mean validation accuracy 84.4% ± 2.4% across 10 models
- Individual model range: 80.9%-89.2% validation accuracy

Performance Metrics:

- Ensemble validation accuracy: ~85-87% (probability averaging)
- Prediction diversity: All 6 age groups represented (14-19% each)
- Inference time: ~15 minutes (875 test samples, CPU)
- Model size: 21 MB per checkpoint (206 MB total ensemble)

Key Innovations:

1. Adaptive attention masking for incomplete multimodal sensor data
2. Bootstrap ensemble reduces overfitting and improves generalization
3. Signal preprocessing tailored to arterial pressure waveform characteristics
4. No imputation—native missing data support through architecture design