Transformer-Based Emotion Recognition Using Multimodal Data Fusion

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1. PROBLEM STATEMENT, OBJECTIVES & MOTIVATION

➢ Problem Statement

- To develop robust multimodal emotion recognition system using Transformer-based architecture that effectively models cross-modal dependencies and temporal dynamics across physiological signals.

➢ Objectives

- To design Transformer-based multimodal system.
- To fuse ECG, EDA and acceleration features to predict emotions.
- To reduce the artifacts in the signals.
- To improve accuracy.

➢ Motivation

- To enhance human-computer interaction.
- To bridge gap between laboratory validations and real-world deployment.
- To support affective computing.

2-A. LITERATURE SURVEY

S.No	Paper Details	Techniques Used	Gaps Identified
1.	**Title:** "UAED: Unsupervised Abnormal Emotion Detection Network Based on Wearable Mobile Device" **Author:** *J. Zhu et al.* ***Year:*** *2023*	• Gaussian Mixture VAE • 2D-CNN with stacking • Whitening distance anomaly scoring • Unsupervised training	• Unimodal approach - Uses only ECG signals. • No cross-modal attention – Cannot leverage multiple physiological signals. • Limited emotion granularity - Only binary anomaly detection. • Fixed window processing - No adaptive temporal modeling.
2.	**Title:** "Self-supervised ECG Representation Learning for Emotion Recognition" **Author:** *P. Sarkar et al.* ***Year:*** *2022*	• Self-supervised learning • Contrastive pre-training • CNN-LSTM architecture • Transfer learning fine-tuning	• Single modality dependency - ECG-only approach. • No multimodal fusion - Misses complementary signal information. • Supervised requirement - Needs labeled data for fine-tuning. • Short-term focus - Limited long-range temporal context.

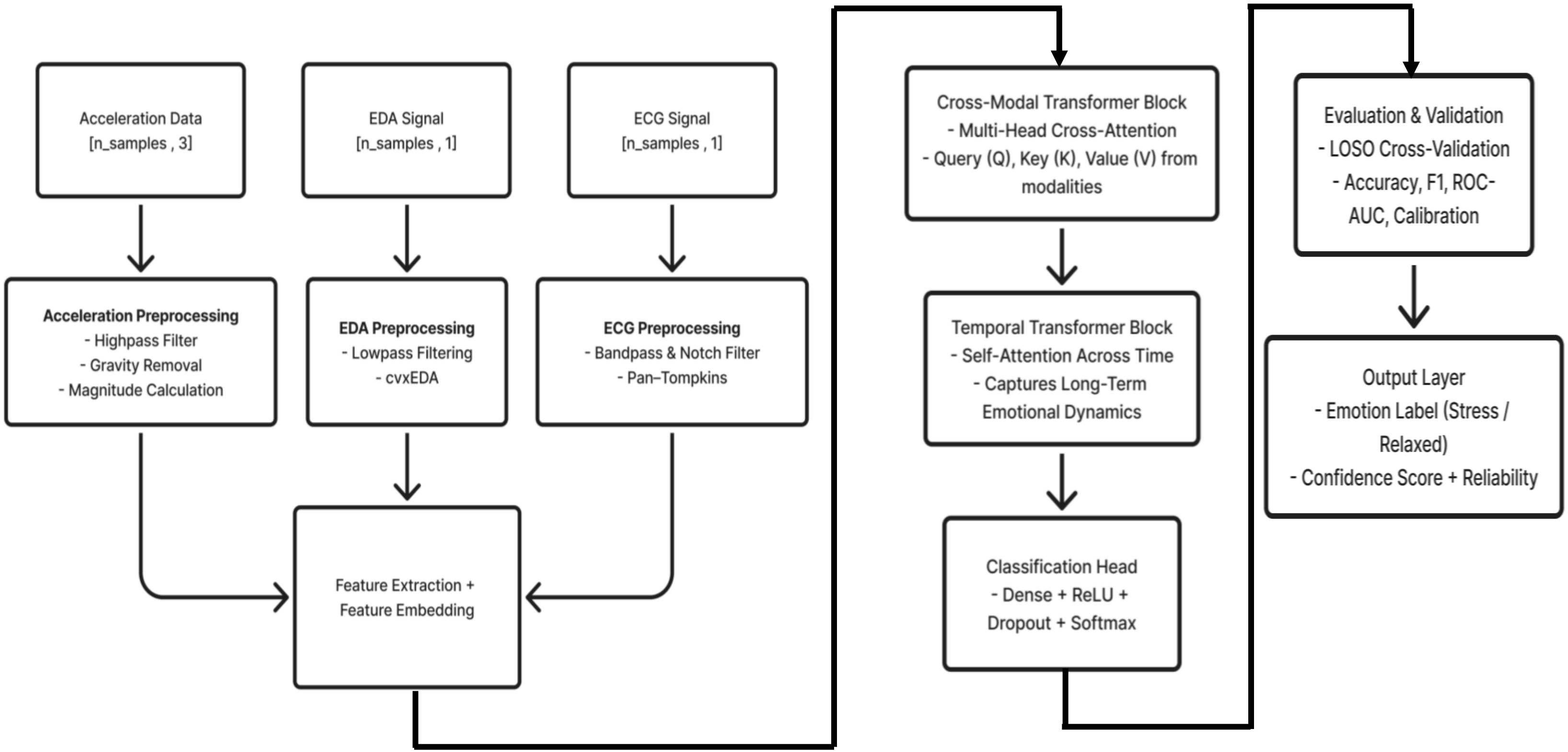
2-B. LITERATURE SURVEY CONTD.

S.No.	Paper Details	Techniques Used	Gaps Identified
3.	**Title:** "Behavioral and Physiological Signals-Based Deep Multimodal Approach for Mobile Emotion Recognition" **Author:** *K. Yang et al.* ***Year:*** *2023*	• LSTM with attention • Multimodal fusion • Mobile deployment optimization • Behavioral + physiological signals	• Limited temporal context - LSTM struggles with long sequences. • Sequential processing - Inherent RNN limitations. • Shallow fusion - Basic attention on temporal dimension only. • Limited physiological coverage - Focuses more on behavioral sensors.
4.	**Title:** "EmotionSense: An Adaptive Emotion Recognition System" **Author:** *Z. Wang et al.* ***Year:*** *2020*	• Random Forest classifiers • Wearable sensor integration • Context-aware recognition • Personalization approach	• Shallow models - Limited feature learning capacity. • Traditional ML limitations - Poor scalability with complex data. • Feature engineering dependency - Manual feature extraction required. • No deep temporal modeling - Cannot capture complex temporal patterns.

2-C. LITERATURE SURVEY CONTD.

S.No.	Paper Details	Techniques Used	Gaps Identified
5.	**Title: "Attention Is All You Need"** **Author:** A. Vaswani et al. ***Year:*** *2017*	• Transformer Architecture • Scaled Dot-Product Attention • Multi-Head Attention • Positional Encoding • Encoder-Decoder Structure	• High Computational Complexity ($O(n^2)$ with sequence length). • No Native Multimodal Support - Designed for NLP. • Large Data Requirements for effective training. • No Domain Adaptation for physiological signals.

3-A. BLOCK SCHEMATIC



4-A. ALGORITHMS

ALGORITHM: Pan-Tompkins + Heart Rate Variability (HRV) Feature Extraction

- **INPUT**
  - Raw ECG signal x(t) sampled at 700 Hz.

- **PROCESS**
  - **Step 1:** Apply a bandpass filter to remove baseline wander and high-frequency noise.
  - **Step 2:** Use the Pan-Tompkins algorithm to detect R-peaks:
    - Differentiate → Square → Moving window integration → Threshold.
    - Output is a list of detected R-peak indices.
  - **Step 3:** Compute R–R intervals to estimate beat-to-beat timing.
  - **Step 4:** Derive Heart Rate Variability (HRV) features, such as mean RR, SDNN, RMSSD, etc.

- **OUTPUT**
  - Clean ECG signal with noise removed

4-B. ALGORITHMS CONT.

ALGORITHM: : Convex Optimization (cvxEDA Decomposition)

- **INPUT**
  - Raw EDA signal $y(t)$y(t) collected from wrist sensor.
- **PROCESS**
  - **Step 1:** Apply a low-pass filter (cutoff = 2 Hz) to remove high-frequency fluctuations.
  - **Step 2:** Use cvxEDA (Convex Optimization-based Decomposition) to split the signal
  - into:
    - Tonic component (T): slow baseline skin conductance.
    - Phasic component (P): fast changes linked to emotional arousal.
  - **Step 3:** Detect Skin Conductance Response (SCR) peaks from the phasic component r.
  - **Step 4:** Extract statistical features — mean, standard deviation, and number of SCR peaks.
- **OUTPUT**
  - Clean ECG signal with noise removed

4-C. ALGORITHMS CONT.

ALGORITHM: Convex Optimization (cvxEDA Decomposition)

➢ **INPUT**

- 3-axis acceleration signal $a_x(t)$, $a_y(t)$, $a_z(t)$.

➢ **PROCESS**

- **Step 1:** Apply a high-pass filter (cutoff = 0.5 Hz) to remove gravitational components.
- **Step 2:** Compute the magnitude of the resultant acceleration.
- **Step 3:** Segment the signal into small time windows (e.g., 4–6 s).
- **Step 4:** Extract activity-level features such as mean, variance, energy, and entropy.

➢ **OUTPUT**

- Clean ECG signal with noise removed

4-D. ALGORITHMS CONTD..

ALGORITHM: Cross-Modal Transformer with Multi-Head Attention (Fusion Stage)

- **INPUT**
  - Embedded feature sequences for each modality: e_{ECG}, e_{EDA}, e_{ACC} obtained from CNN encoders or preprocessing.
- **PROCESS**
  - **Step 1:** Prepare attention inputs:
    - For each modality mm, create:
    - Query (Qm) , Key (Km) , Value (Vm)
  - **Step 2:** Compute attention weights:
    - Use scaled dot-product attention to decide how strongly one signal should focus on another.
  - **Step 3:** Use multiple attention heads:
    - Several parallel "heads" learn different kinds of relationships
  - **Step 4:** All heads are concatenated and linearly combined.
- **OUTPUT**
  - The model outputs a single fused vector F_{fusion}

4-E. ALGORITHMS CONTD..

ALGORITHM: Temporal Transformer Block (Sequential Modeling)

- **INPUT**
  - Sequence of fused embeddings $F_{fusion,t}$ obtained from the Cross-Modal Transformer.
- **PROCESS**
  - **Step 1:** Add positional information:
    - Since Transformers don't know time order naturally, add positional encodings
  - **Step 2:** Compute self-attention across time:
    - For every time window, compute attention.
  - **Step 3:** Residual + Layer Normalization.
    - Maintains stable gradients and keeps temporal context consistent.
  - **Step 4:** A small network refines each time-step's contextual embedding, strengthening temporal coherence.
- **OUTPUT**
  - Final time-dependent emotional embedding $F_{temporal}$

5. EXPERIMENTS & PERFORMANCE METRICS

- **Experimental Setup**
  - Dataset: WESAD (primary) and AffectiveROAD (supplementary)
  - Training:
    - ECG/EDA CNN: 100 epochs × 32 batch size
    - Acceleration CNN: 50 epochs × 64 batch size
    - Optimizer: AdamW (weight decay=0.01, β_1=0.9, β_2=0.999, ε=1e-8)
    - Validation: LOSO Cross Validation

- **Performance Metrics**
  - Core Metrics: Accuracy, ROC-AUC, PR-AUC.
  - Calibration Metric: Expected Calibration Error (ECE) – assesses reliability of predictions.
  - Subject-Level Metric: Inter Subject Variability (ISV) – measures generalization.

- **Model Setup**
  - Modality specific CNN encoders for ECG, EDA and Acceleration.
  - Cross-Modal Transformer Fusion + Temporal Transformer for sequence modeling.

6. IMPLEMENTATION ENVIRONMENT

- **Hardware**
  - **Processor:** Intel i7 / AMD Ryzen 7 (8-core, 3.0GHz+)
  - **RAM:** 16 GB minimum
  - **Storage:** 500 GB NVMe SSD
  - **GPU:** NVIDIA RTX 4060 (12 GB VRAM) or equivalent CUDA-enabled GPU
  - **Operating System:** Windows 11 (64-bit)
- **Software & Libraries**
  - **Language:** Python 3.10.x
  - **IDE:** Visual Studio Code
  - **Core Framework:** PyTorch (with CUDA support)
  - **Deep Learning Models:**
    - NeuroKit2/SciPy Essential for robust ECG R-peak detection, cvxEDA decomposition, and HRV analysis.
    - Transformers (for implementing attention mechanisms)
  - **Data Handling & Processing:** NumPy, Pandas, OpenCV, Open3D
  - **Visualization Tools:** Matplotlib, TensorBoard, Seaborn

7. EXPECTED MILESTONE / WORK PLAN

Milestones	Period	Work to be completed
MS0	14 Aug 2025 – 26 Oct 2025	Literature survey, tool & language selection, dataset setup (WESAD/AffectiveROAD), sensor level study, bio-signal study, algorithm selection, and project planning.
MS1	29 Oct 2025 – 23 Nov 2025	Implement preprocessing for ECG, EDA, and acceleration (filtering, HRV, SCR, activity features) and begin 1D-CNN feature extraction.
MS2	26 Nov 2025 – 21 Dec 2025	Integrate feature embeddings and Transformer-based fusion, temporal modeling, and perform preliminary training and validation.
MS3	24 Dec 2025 – 31 Dec 2025	Conduct full LOSO evaluation, performance analysis and finalize document.

8. REFERENCES

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THANK YOU…