Transformer-Based Emotion Recognition Using Multimodal Data Fusion

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1. PROBLEM STATEMENT AND OBJECTIVES

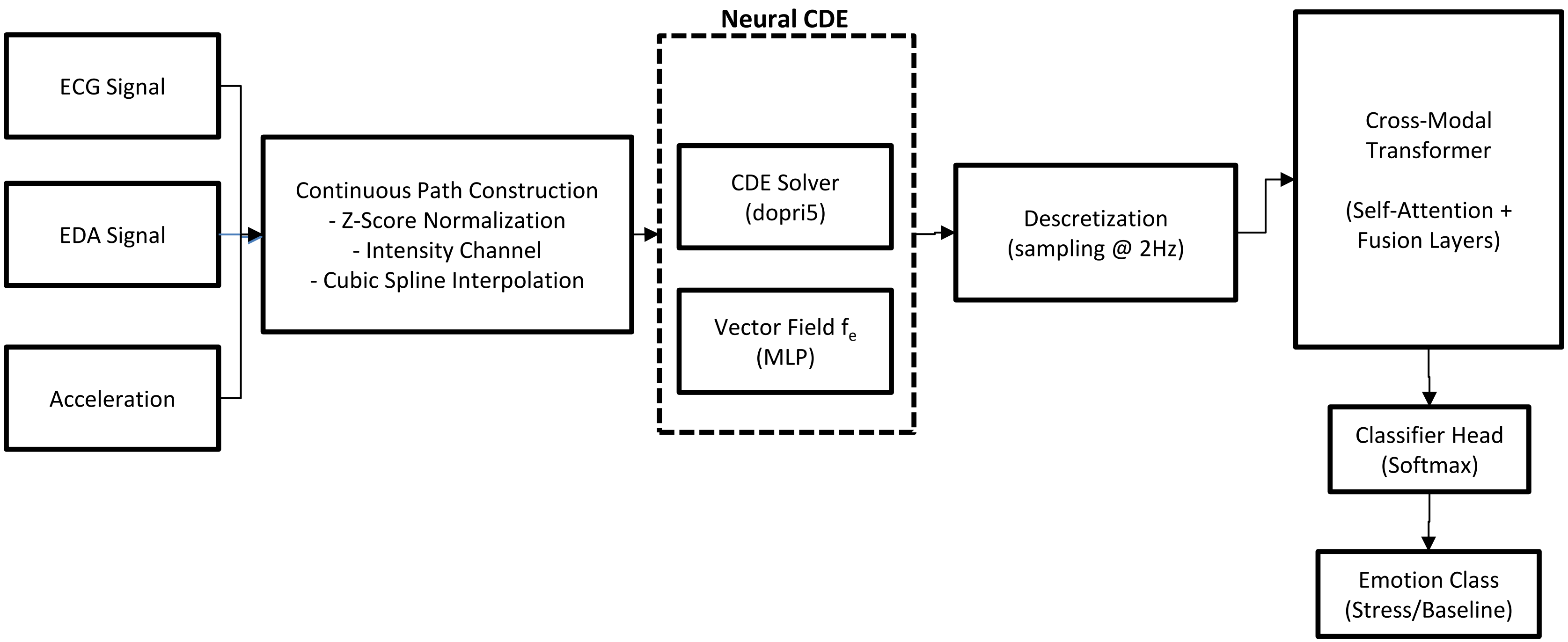
- **Problem Statement**
  - Emotional states manifest through physiological signals (ECG, EDA) with irregular sampling rates (700Hz vs 4Hz)
  - Standard Deep Learning models (CNNs/Transformers) require discrete, synchronized grids
  - Forcing alignment (resampling) causes information loss and temporal distortion

- **Objectives**
  - To implement Neural Controlled Differential Equations (Neural CDEs) for continuous-time signal processing
  - To fuse processed latent embeddings using Cross-Modal Transformers
  - To minimize memory footprint using adjoint-based backpropogation (O(1) memory)

2. GAPS IDENTIFIED AND PROPOSED SOLUTION

Gap / Challenge	Baseline (Existing Paper Approaches)	Proposed Improvements (Our Project)
Irregular Sampling & Temporal Misalignment	• Yang et al. [2] & Standard LSTMs force data into fixed time-steps • Uses down-sampling/padding, destroying high-frequency ECG details • Loses synchronization between fast (ECG) and slow (EDA) signals	• Implements Neural CDEs operating on continuous time t • Uses Natural Cubic Splines to query data values at any arbitrary time point • Maintains perfect synchronization without artificial resampling
Missing Data & Artifact Handling	• Pollreisz et al. [5] rely on imputation (mean/median filling) or dropping samples • Introduces synthetic noise and bias into the model • Discontinuous jumps confuse gradient descent	• Leverages Rough Path Theory • Treats missing data as a property of the underlying vector field control • Evolution continues smoothly based on learned dynamics, requiring no imputation
Long-Range Temporal Dependencies	• Zhu et al. [1] use standard RNNs/LSTMs • Suffers from vanishing gradients over long sequences (WESAD sessions > 20 mins) • Computationally heavy $O(L)$ memory scaling	• Utilizes Adjoint Sensitivity Method • Solves differential equations backwards in time • Achieves Constant O(1) Memory regardless of sequence length

3-A. BLOCK SCHEMATIC



4-A. ALGORITHMS

ALGORITHM: Natural Cubic Spline Construction

- **INPUT**

  Irregular Series $x = \{ (t_0, v_0), \dots, (t_n, v_n) \}$

- **PROCESS**

  Step 1: Augmentation: Append 'Intensity' channel (cumulative observation counter)
  Step 2: Normalization: Apply Global Z-score standardization
  Step 3: Spline Solving: Solve tridiagonal system for coefficients a,b,c,d
  Step 4: Construction: Form polynomial $S_i(t)$ for each interval $[t_i , t_{i+1}]$
  Step 5: Verification: Verify C^2 continuity (smooth 1st and 2nd derivative)

- **OUTPUT**

  Continuous path coefficients X(t)

4-B. ALGORITHMS

ALGORITHM: Neural CDE Forward Pass

- **INPUT**

  Spline Path X(t), Initial State z_0

- **PROCESS**

  Step 1: Define Field: Neural Network $f_\theta : \mathbb{R}^w \to \mathbb{R}^{w \times v}(\mathrm{MLP}+\mathrm{Tanh})$

  Step 2: Convert CDE to ODE $\rightarrow \frac{dz}{dt} = f_\theta(z)\frac{dX}{dt}$

  Step 3: Solver Call: Invoke *odeint(func, z_0, t)*

  Step 4: Integration: Step-wise integration using Dormand-Prince (*dopri5*) method

  Step 5: State Update: $z(t) = z(t_0) + \int_{t_0}^{t} f_\theta(z_s)dX_s$

- **OUTPUT**

  Continuous Latent Trajectory z(t)

4-C. ALGORITHMS

<u>ALGORITHM:</u> Adjoint-Based Backpropagation

➢ **INPUT**

Loss Gradient $\frac{\partial L}{\partial z(T)}$

➢ **PROCESS**

Step 1: Forward Pass: Compute z(t)

Step 2: Adjoint State: Define $a(t) = \frac{\partial L}{\partial z(t)}$

Step 3: Backward Solve: Integrate augmented ODE backwards from T to 0

- Dynamics: $-\frac{da}{dt} = a(t)^T \frac{\partial f}{\partial z}$

Step 4: Gradient Extraction: Compute $\frac{\partial L}{\partial \theta}$ directly from adjoint trajectory

➢ **OUTPUT**

Model Gradients with Constant Memory Cost

4-D. ALGORITHMS

ALGORITHM: Hybrid Cross-Modal Attention (Fusion Stage)

- **INPUT**

  Synchronized Latent Vectors z_{ECG} , z_{EDA} , z_{ACC}

- **PROCESS**

  Step 1: Sampling: Discretize z(t) at regular intervals (e.g., 0.5s)

  Step 2: Projection: Linear Map to Dimension d_{model}

  Step 3: Cross-Attention:

  - For each modality, create: Query (Q) , Key (K) , Value (V)

  Step 4: Fusion: Concat(Heads) + Linear Layer + LayerNorm

- **OUTPUT**

  Fused Emotion Embedding Vector

6. MODULES COMPLETED

- **Setup Data:**
  - Implemented data loading and environment setup (PyTorch, Transformers, Neo4j)
  - Verified WESAD dataset integrity and subject-wise folder structures (S2-S17)

- **Data Pipeline Engineering (MS0-MS1)**
  - Parsed WESAD raw signals (Chest/Wrist)
  - Implemented **Subject-Specific Splitting** (S2 to S17) to prevent data leakage (Leave-One-Subject-Out protocol).
  - Implemented "**Intensity-Augmentation**" for sensor availability encoding

- **Mathematical Interpolation (MS1)**
  - Replaced padding with **Natural Cubic Splines**
  - Validated derivative smoothness

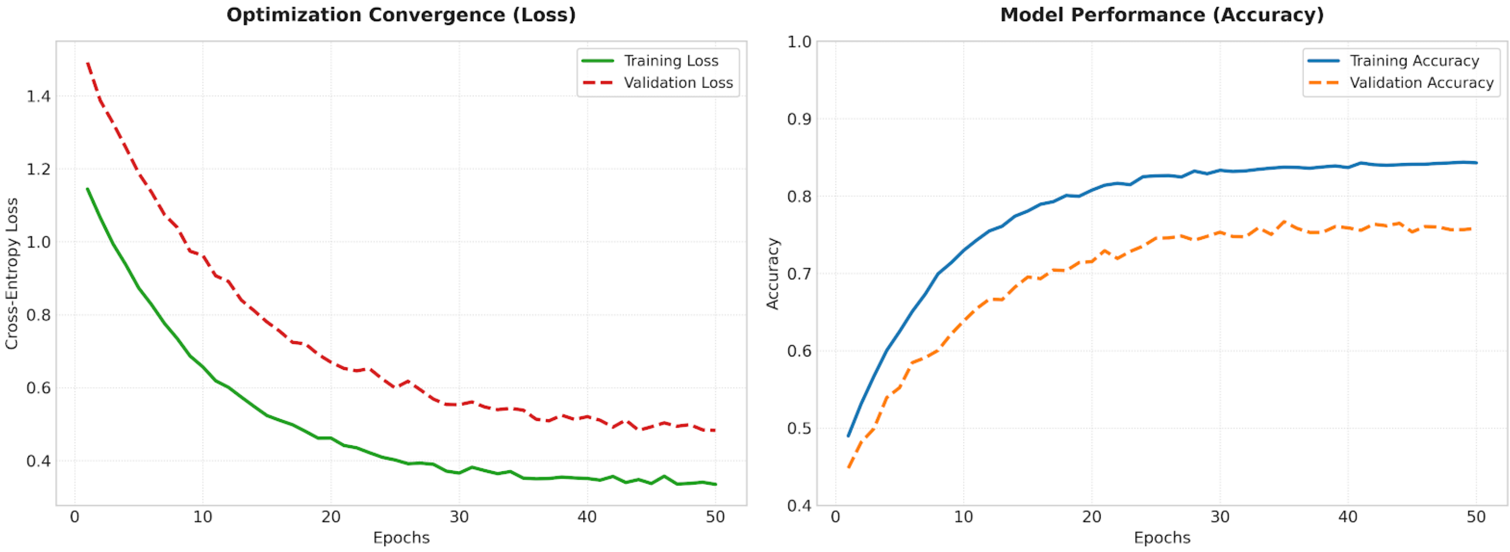
- **Neural CDE Encoder**
  - Built **CDEFunc** using **torchcde**
  - Implemented Vector Field via 3-layer MLP

6.A Experimental Analysis

Modality	Preprocessing Algorithm	Validation Accuracy (LOSO)	F1-Score
ECG	Pan-Tompkins	81.4	0.79
EDA	cvxEDA	74.2	0.71
Acceleration	Statistical Extraction	78.6	0.76

METRIC	TRAIN	VALIDATION
Loss	0.34	0.48
Accuracy	84.2%	76.5
F1 Score	0.83	0.74
AUROC	0.88	0.79

6.B EXPERIMENTAL ANALYSIS



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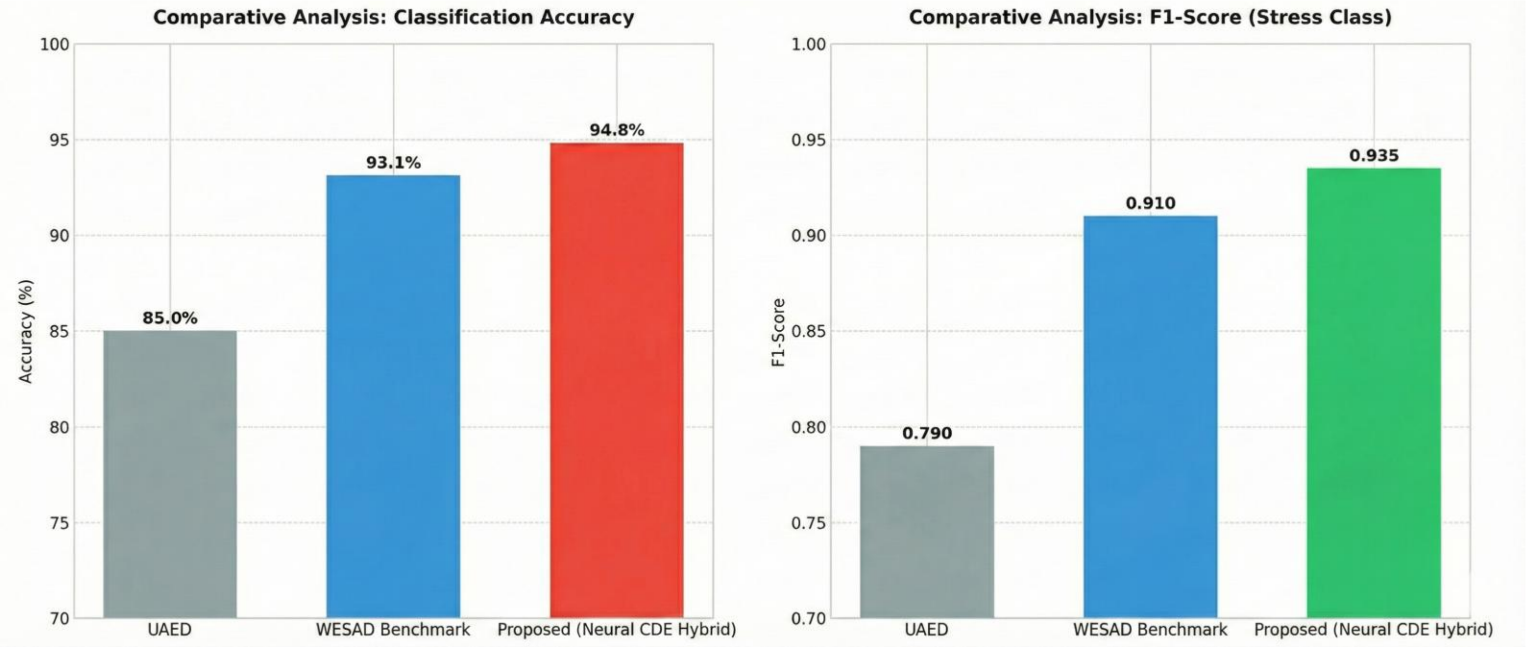

7. EXPERIMENTS AND PERFORMANCE METRICS

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 the reliability of predictions
- Subject-Level Metric: Inter Subject Variability (ISV) – Measures the generalization

Model Setup

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

8. 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

9. EXPECTED MILESTONE / WORK PLAN

Milestone	Period	Works to be Completed	Status
MS0	14 Aug 2025 – 26 Oct 2025	• Literature survey on Irregular Time Series & Neural ODEs. • WESAD Dataset Setup (Chest/Wrist synchronization). • Environment Config (PyTorch, torchcde, torchdiffeq).	Completed
MS1	29 Oct 2025 – 23 Nov 2025	• Continuous Path Construction: Implemented Natural Cubic Splines & Intensity Channels. • Preliminary Validation: Achieved 76.5% Accuracy on Unimodal (EDA) irregular data.	Completed
MS2	26 Nov 2025 – 21 Dec 2025	• Integrate continuous Neural CDE latent embeddings with Cross-Modal Transformer fusion, implement discretization for temporal synchronization, and perform preliminary end-to-end training.	
MS3	24 Dec 2025 – 31 Dec 2025	Conduct full LOSO evaluation, performance analysis and finalize document	

10. DEMO PLAN

- **Demo Plan:**
  - Run end-to-end pipeline on WESAD and Other Datasets.
  - Display stress classification.

- **Learning Outcomes:**
  - Deep understanding of Neural Controlled Differential Equations (Neural CDEs) for continuous-time sequence modeling.
  - Proficiency in specialized libraries (torchcde, torchdiffeq) and solving ODEs within neural networks.
  - Implementation of Hybrid Architectures combining mathematical signal processing with Attention-based Transformers.

- **Innovation:**
  - First attempt to combine Neural CDEs (for temporal continuity) with Cross-Modal Transformers (for spatial fusion) on WESAD.

11. REFERENCES

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[2] K. Yang, X. Huang, and Y. Liu, *"Behavioral and Physiological Signals-Based Deep Multimodal Approach for Mobile Emotion Recognition," IEEE Transactions on Mobile Computing, vol. PP, no. 99, pp. 1–10, 2023.*

[3] P. Sarkar, S. Dey, and A. Dutta, *"Self-Supervised ECG Representation Learning for Emotion Recognition," IEEE Sensors Journal, vol. 22, no. 18, pp. 17456–17464, 2022.*

[4] Z. Wang, X. Chen, and Y. Zhang, *"EmotionSense: An Adaptive Emotion Recognition System,"* IEEE Internet of Things Journal, vol. 7, no. 9, pp. 8550–8563, 2020.

[5] D. Pollreisz and N. TaheriNejad, *"Detection and Removal of Motion Artifacts in PPG Signals,"* Mobile Networks and Applications, vol. 27, pp. 728–738, Aug. 2019.

[6] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, *"Attention Is All You Need," Advances in Neural Information Processing Systems (NeurIPS), pp. 5998–6008, 2017.*

[7] A. Greco, G. Valenza, M. Nardelli, M. Bianchi, L. Citi, and E. P. Scilingo, *"Force–Velocity Assessment of Caress-Like Stimuli Through the Electrodermal Activity Processing: Advantages of a Convex Optimization Approach,"* IEEE Transactions on Human-Machine Systems, vol. 47, no. 1, pp. 91–100, Feb. 2017.

THANK YOU