A Dual-Branch Convolutional Neural Network with Gated Recurrent Units Network for Enhanced Multimodal Stress Monitoring from Wearable Physiological Signals

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Why Continuous Stress Monitoring?

Health Impact

Chronic stress contributes to cardiovascular disease, hypertension, depression, and immune dysfunction.

Wearable Opportunity

BVP and EDA signals can be captured unobtrusively from wrist-worn devices like Empatica E4 or Fitbit — no lab required.

Existing Gaps

ML methods rely on handcrafted features that fail to generalize. DL methods often use heavy models or complex image transforms, unsuitable for wearables.

Goal

A lightweight, real-time deep learning model deployable on resource-constrained devices using only BVP + EDA.

Dataset & Physiological Signals

WESAD Dataset

Subjects	15 (12M / 3F)
BVP Sampling	64 Hz
EDA Sampling	4 Hz
Window	30-second segments
Validation	Leave-One-Subject-Out

Blood Volume Pulse (BVP)

Measures peripheral blood volume changes. Heart rate and pulse-rate variability can be derived from BVP and reflect the balance between sympathetic activation and parasympathetic recovery regulation.

Electrodermal Activity (EDA)

Measures skin conductance changes mainly driven by sympathetic sweat-gland activity. Higher EDA suggests increased physiological arousal, but unchanged EDA does not prove absence of stress.

Autonomic nervous system: **Sympathetic = “gas pedal”** stress / alertness / arousal **Parasympathetic = “brake”** rest / recovery / slowing down

Together: complementary autonomic insights for robust stress estimation

Proposed CNN-GRU Architecture

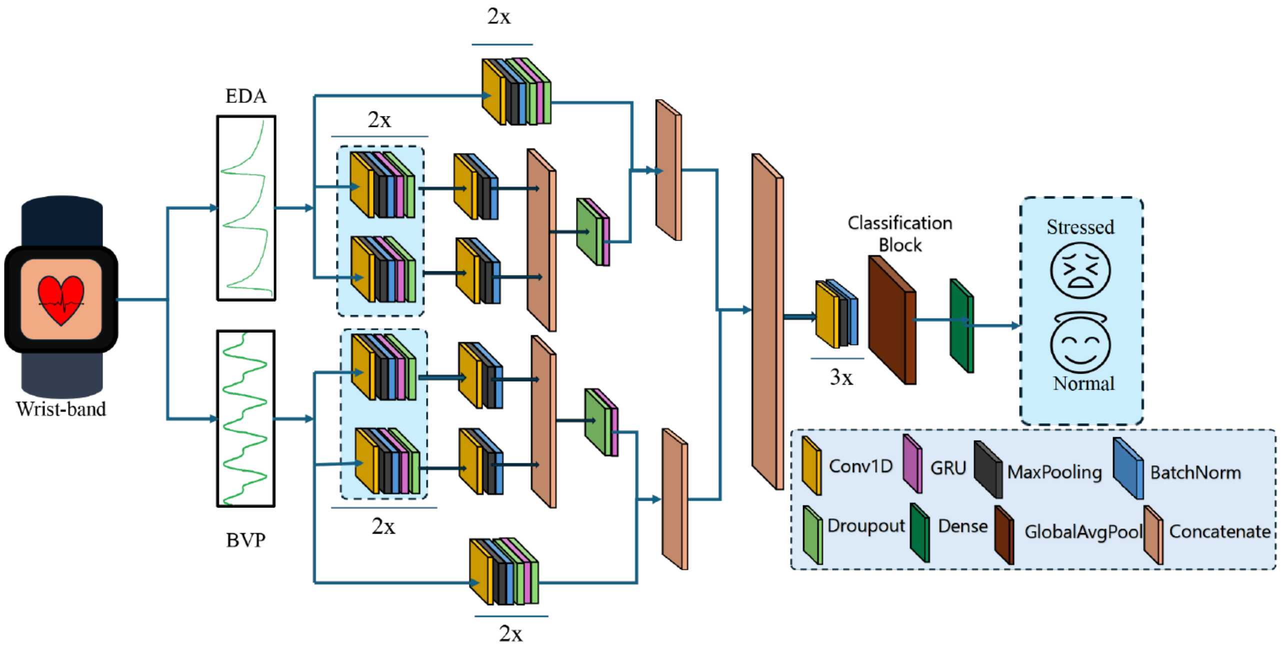


Figure 1: Proposed lightweight CNN-GRU architecture for stress detection using multimodal physiological signals. The model processes simulated normal signals through parallel convolutional and recurrent pathways, incorporating Conv1D, MaxPooling1D, BatchNormalization, GRU, and Dense layers. Feature representations are integrated via concatenation and global average pooling for final classification.

Data Preprocessing & Augmentation

1 Segmentation

Raw BVP and EDA signals divided into non-overlapping 30-second windows.

2 Normalization

Z-score normalization applied to minimize inter-subject amplitude variation.

3 Class Imbalance Identified

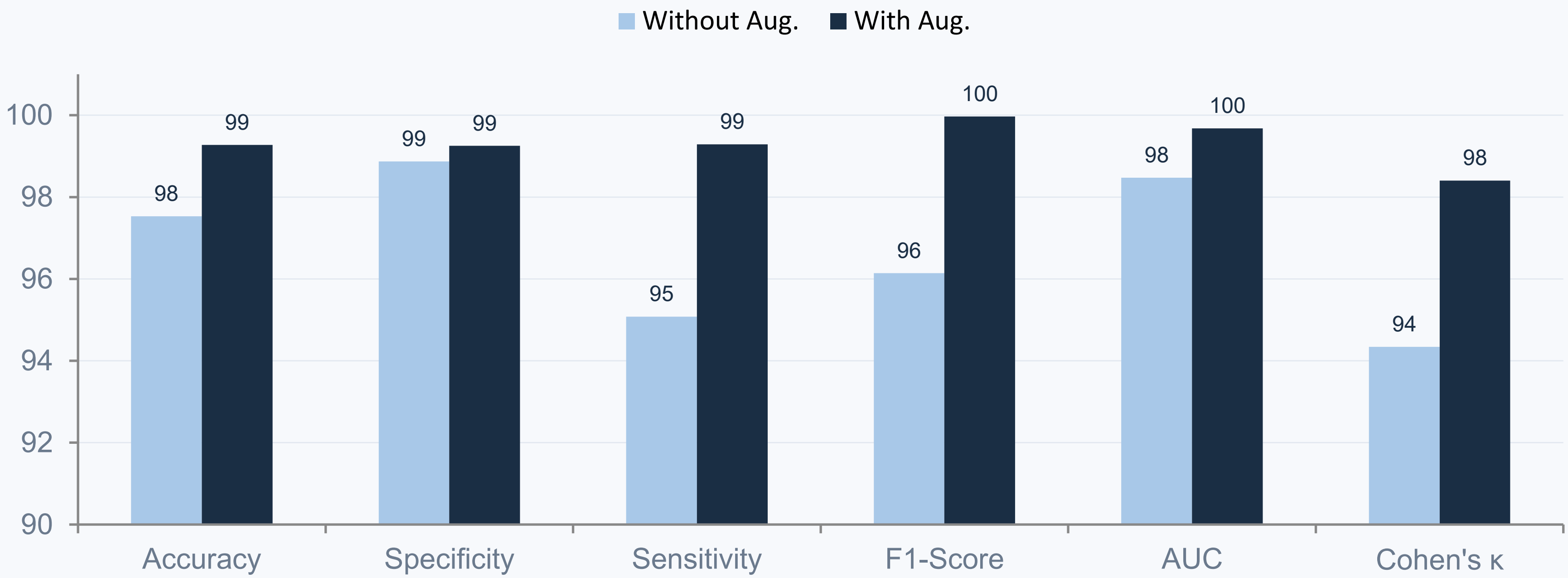
Normal samples significantly outnumber stressed samples, limiting minority class detection.

4 Sliding Window Augmentation

Additional samples were generated for the minority (stressed) class by sliding overlapping windows, improving training stability and generalization.

Augmentation is critical: sensitivity for the stressed class jumped from 95.08% → 99.29%

Results — With & Without Augmentation



Gains from augmentation: Accuracy: +1.74% · Specificity: +0.38% · Sensitivity: +4.21% · F1-Score: +3.83% · AUC: +1.21% · Cohen's κ: +4.06%

Ablation Study — Signal Contribution

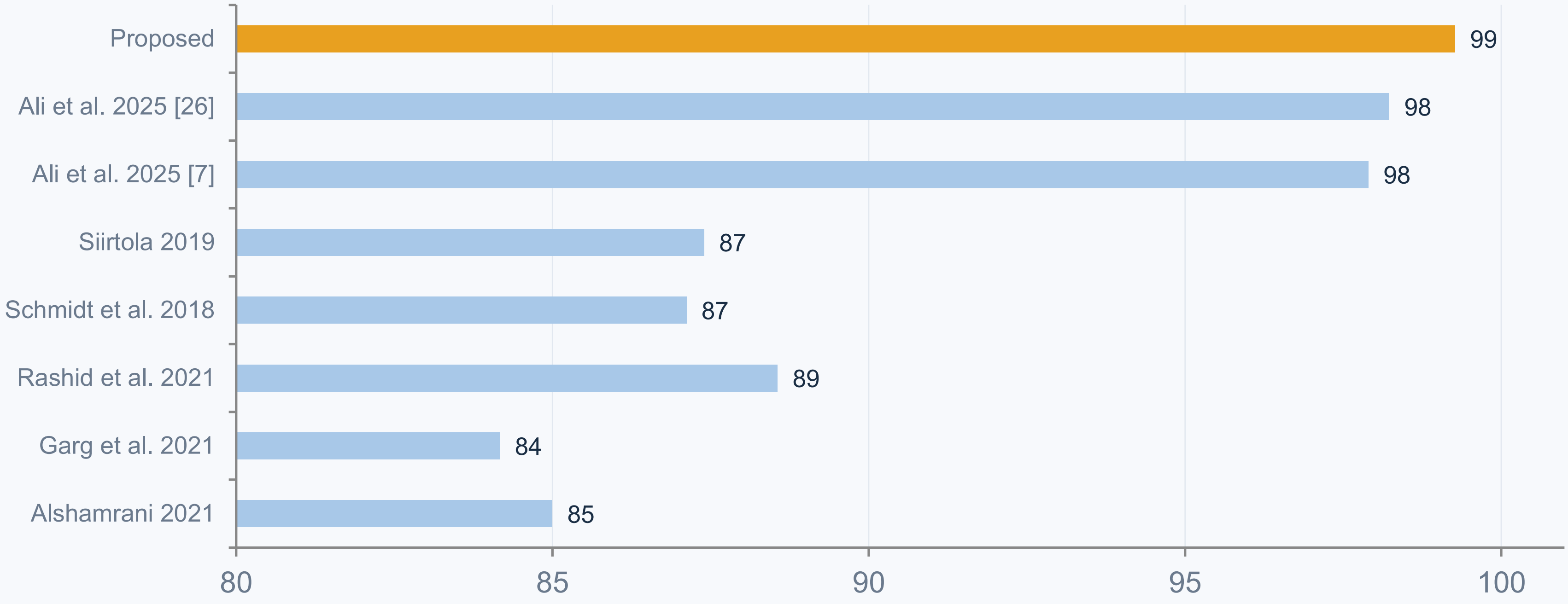
Signal	Accuracy	Specificity	Sensitivity	F1-Score	AUC	Cohen's κ
EDA only	93.55%	94.34%	92.05%	90.47%	95.92%	85.61%
BVP only	97.37%	98.11%	96.21%	96.01%	98.93%	94.05%
BVP + EDA ✓	**99.27%**	**99.25%**	**99.29%**	**99.97%**	**99.68%**	**98.40%**

EDA captures sympathetic arousal but alone is insufficient (93.55% accuracy).

BVP provides stronger temporal information — 97.37% accuracy with good AUC.

Combining BVP + EDA yields 99.27% accuracy and 98.40% Cohen's κ — the best of both modalities.

Comparison with Prior Work



Proposed model outperforms all prior work on WESAD — while using only 2 signals and 0.43M parameters.

Conclusion

1. Lightweight dual-branch CNN-GRU using BVP + EDA for real-time wearable stress detection.
2. Achieves 99.27% accuracy and 98.40% Cohen's κ on WESAD via LOSO cross-validation.
3. Sliding-window augmentation is key — sensitivity for stressed class improved by 4.21%.
4. Only 0.43M parameters (1.64 MB) — suitable for deployment on resource-constrained devices.
5. Outperforms all compared prior work while using fewer signals.

Future Work: Multiclass stress detection · Cross-dataset validation · Embedded hardware implementation