

A Multimodal Wearable Biomedical Sensor System for Early Prediction of Autistic Meltdowns

An innovative approach to early intervention through biomedical sensor fusion and deep learning

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ISEF Category

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The Problem

Autistic meltdowns are involuntary neurophysiological responses to overwhelming sensory or emotional stimuli. They're frequently misunderstood as behavioral issues, particularly in schools and public environments, leading to inappropriate disciplinary actions, emotional distress, and safety risks.



Why It Matters

- **Current detection methods rely on observation or video, which are intrusive and impractical**
- **Caregivers and educators lack early-warning tools**
- **Misinterpretation of meltdowns contributes to stigma and harm**



Our Goal

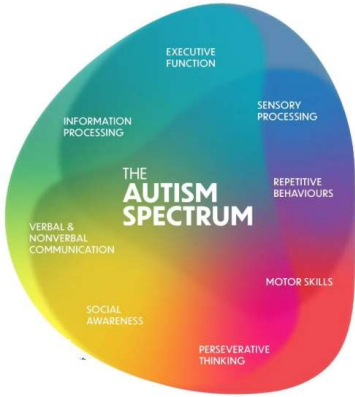
Develop a privacy-preserving, wearable-based system that can predict meltdowns before they occur, enabling timely intervention and improved quality of life for autistic individuals and their support networks.



Introduction

Autism Spectrum Disorder (ASD) affects approximately 1 in 31 children in the United States, with many experiencing meltdowns triggered by sensory overload, stress, or environmental factors. Current prediction methods rely heavily on camera-based monitoring, limiting real-world applicability.

This study developed a wearable sensor–based machine learning system to predict autistic meltdowns using physiological signals such as heart rate and electro-dermal activity. Among four models evaluated, a CNN-LSTM achieved the best performance (99.0% accuracy, 0.95 recall), highlighting the feasibility of real-time, non-invasive meltdown prediction to support timely intervention in everyday settings.



Methods

Data Acquisition & Ethics

- Medical data access was limited due to strict privacy regulations, especially for pediatric autism data.
- Used a public, de-identified dataset from Autism Together (hackathon), avoiding additional IRB approval while ensuring ethical compliance.

Data Sources

- Biometric sensors: Accelerometer (ACC), Blood Volume Pulse (BVP), Electrodermal Activity (EDA), Heart Rate (HR), Inter-Beat Interval (IBI), Skin Temperature
- Environmental data: UV Index, Discomfort Index

Preprocessing

- Sensor synchronization, missing-data handling, feature engineering
- Class balancing and normalization for effective model training

Machine Learning Models

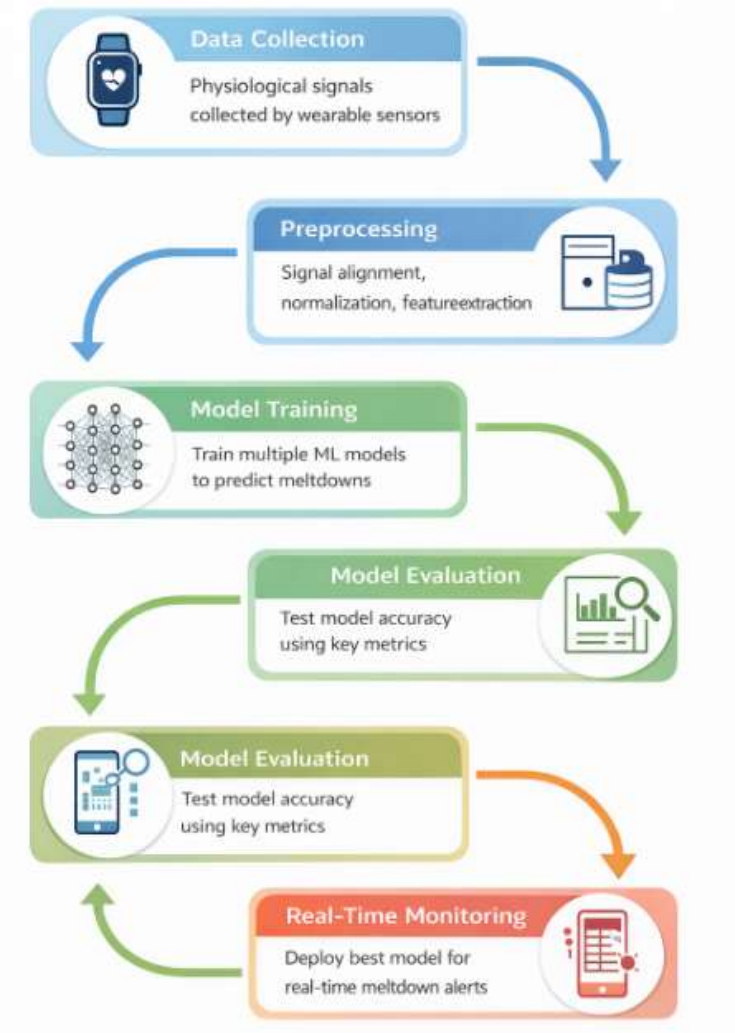
- Logistic Regression: Interpretable baseline
- Random Forest: Handles non-linear relationships, provides feature importance
- LSTM: Captures temporal patterns leading up to meltdowns
- CNN-LSTM: Extracts local signal patterns + temporal dependencies; robust to noise

Implementation

- Python (scikit-learn, TensorFlow/Keras, pandas, NumPy)
- AI-assisted coding with manual validation and optimization

Evaluation Metrics

- Accuracy, Precision, Recall, F1-Score
- Recall prioritized to minimize missed meltdowns and enable timely intervention

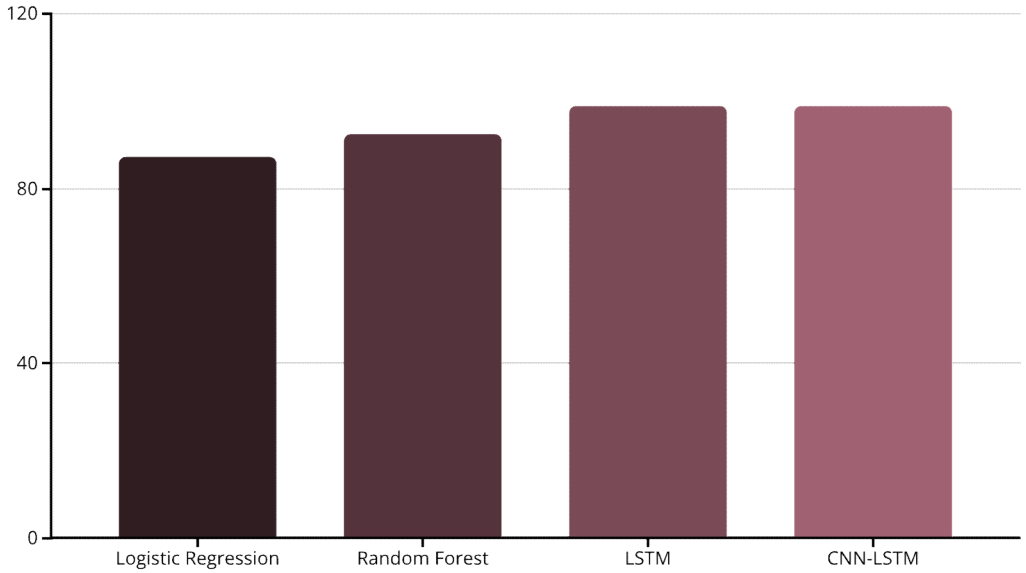


Results: Model Performance Comparison

- **Logistic Regression** performed poorly, with only 43% recall, making it unsuitable for practical meltdown prediction
- **Random Forest** showed substantial improvement (92% recall) and offers good interpretability
- **LSTM** achieved excellent performance (96% recall), demonstrating the value of temporal sequence modeling
- **CNN-LSTM** achieved the highest overall accuracy (99.0%) with 95% recall, providing the best balance of performance and robustness

Model	Accuracy	F1 (Meltdown)	Recall (Meltdown)	Notes
Logistic Regression	0.91	0.56	0.43	Insufficient for real-time use; misses 57% of meltdowns
Random Forest	0.98	0.93	0.92	Good balance; interpretable; misses 8% of meltdowns
LSTM	0.989	0.96	0.96	Excellent temporal modeling; detects 96% of meltdowns
CNN-LSTM	0.990	0.95	0.95	Highest accuracy; robust to noise; detects 95% of meltdowns

Results & Key Findings



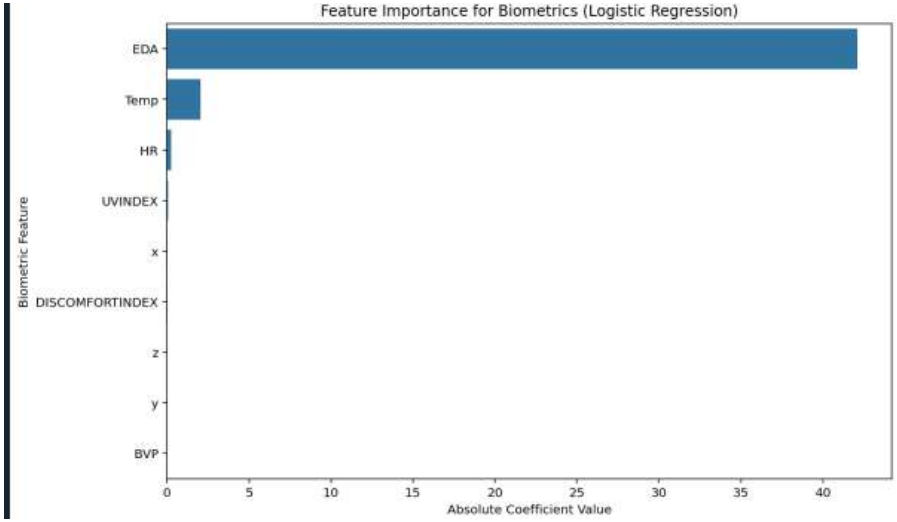
Performance Highlights

- **CNN-LSTM Accuracy: 99.0%**
- **LSTM Accuracy: 98.9%**
- Recall for meltdown detection: ~0.95–0.96
- Heart rate and EDA emerged as strongest predictors

Temporal models significantly outperformed non-temporal approaches, aligning with known sympathetic nervous system activation patterns during stress responses.

Results: Feature Importance

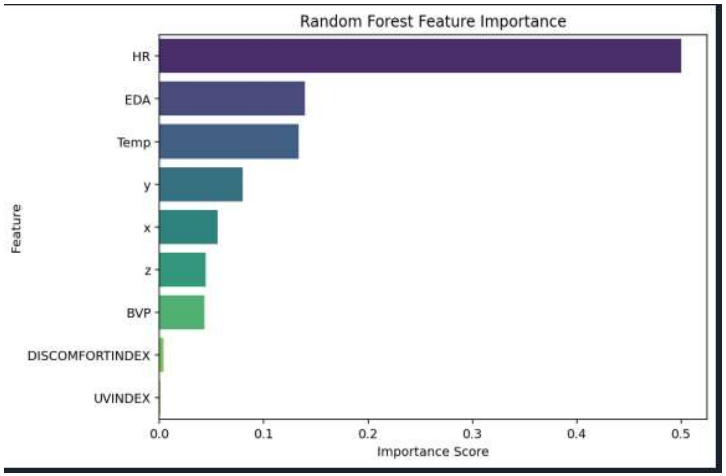
Feature Importance - Logistic Regression



Most Important: Electro-dermal Activity (EDA)

EDA reflects sympathetic nervous system arousal and showed the strongest linear relationship with meltdown occurrence in this model

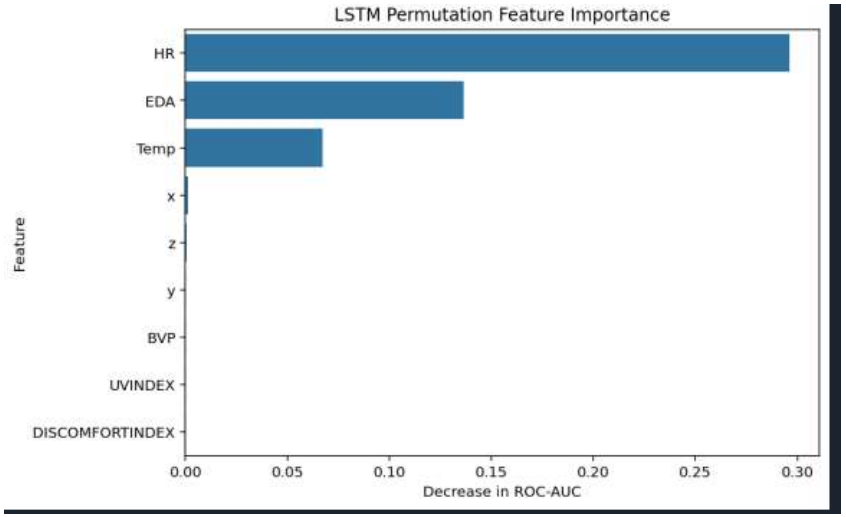
Feature Importance - Random Forest



HR emerged as the dominant predictor, consistent with sympathetic activation during meltdowns

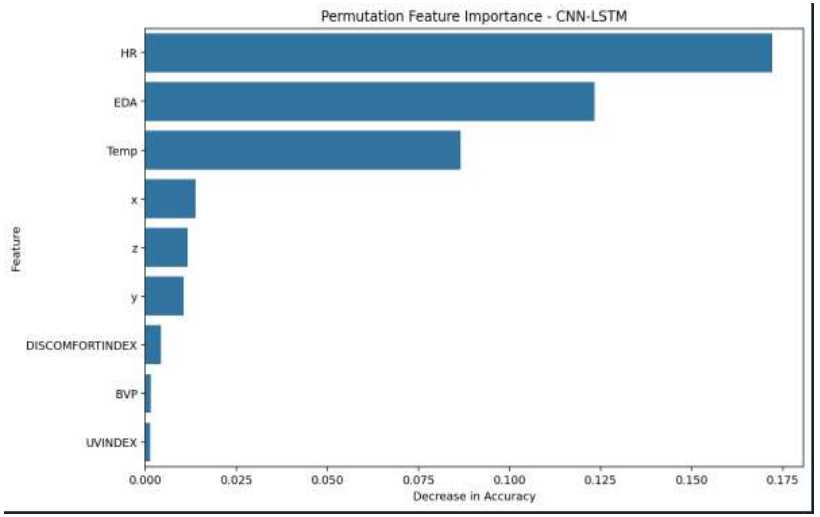
Results: Feature Importance - Continued

Feature Importance - LSTM



Most Important: Heart Rate (HR)
Temporal patterns in HR provided the strongest predictive signal in the sequence model

Feature Importance – CNN-LTSM



Most Important: Heart Rate (HR)
The hybrid architecture also identified HR as the primary predictor, with EDA and temperature as secondary contributors

- Three of four models identified **heart rate** as the most important feature for meltdown prediction.
- This finding aligns with the neurophysiological understanding of meltdowns as sympathetic nervous system activation events.

Discussion

Model Performance and Selection

Temporal models significantly outperformed non-temporal approaches, aligning with known sympathetic nervous system activation patterns during stress responses.

Physiological Insights: The Primacy of Heart Rate

Heart rate was the strongest predictor across all models, supporting a sympathetic “fight-or-flight” mechanism underlying meltdowns.

This aligns with insular cortex dysfunction in autism, leading to heightened autonomic reactivity.

Practical advantage: Heart rate is easy, continuous, and non-invasive to measure with wearables.

Supporting signals: EDA and temperature add complementary information and improve reliability

Why LSTM and CNN-LSTM Excel

- **Temporal Dependencies:** Meltdowns do not occur instantaneously; they develop over seconds to minutes as physiological stress accumulates. LSTM networks are specifically designed to model such temporal sequences, capturing how heart rate, EDA, and other signals evolve leading up to a meltdown.
- **Multi-Signal Integration**: The CNN component in the hybrid model can identify local patterns across multiple sensor channels simultaneously, while the LSTM component tracks how these patterns evolve over time.
- **Noise Robustness:** Wearable sensors in real-world settings generate noisy data due to motion artifacts and environmental interference. The CNN-LSTM architecture is more robust to these issues than simpler models

Clinical Impact

- **Enables early intervention for autistic individuals**
- **Preserves privacy—no cameras or audio required**
- **Supports caregivers, educators, and clinicians with actionable insights**
- **Reduces misinterpretation and stigma through objective data**



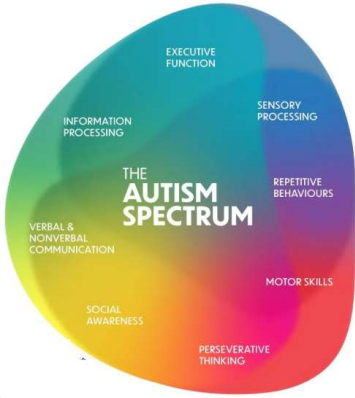
Next Steps

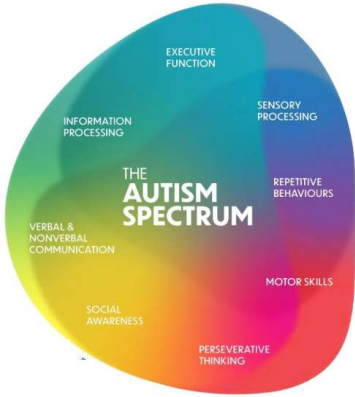
- **Real-time implementation on commercial wearable devices (e.g., smartwatch)**
- **Personalization of models for individual user patterns**
- **Integration into parent and educator alert dashboards**
- **Prospective validation with new datasets and populations**



Conclusion

This study shows that **wearable sensor data + machine learning** can accurately predict autistic meltdowns (up to **99% accuracy, 95–96% recall**), with **heart rate** as the key physiological marker of sympathetic nervous system activation. Compared to camera-based systems, the approach is **more private, portable, and continuous**, with strong potential benefits in schools, families, and community settings. Despite current dataset and deployment limitations, the results provide a strong foundation for ethical, user-centered tools that improve safety, reduce misinterpretation, and promote better support for autistic individuals by distinguishing meltdowns from behavioral misconduct.





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