Stage 2: MRI-Enhanced Stress Profiling

In this second stage, we elevate our foundational stress detection model by integrating contextual variables specific to MRI environments — a crucial real-world setting where patients frequently experience heightened stress due to the acoustic conditions.

Key Environmental Stressors

We focus on two primary acoustic stressors that directly impact patient stress levels during MRI scans:

- **Peak Decibel Level (PDB):** The maximum acoustic intensity experienced during the scan.
- **Noise Bursts per Minute (NBM):** The frequency of sudden, loud acoustic events within the MRI suite.

Contextual Data Generation via LLMs

To realistically simulate these MRI conditions, we generated separate CSV datasets for each feature using LLM-guided data generation. Carefully crafted prompts explicitly described typical MRI scenarios where patients exhibit a range of stress responses influenced by the acoustic environment.

This approach produced values spanning low, moderate, and high noise levels, capturing a rich gradient of stress states from calm to highly stressed individuals. The generation process prioritized:

- **Variability:** Reflecting the natural fluctuations in MRI noise.
- **Realism:** Grounded in physiological and acoustic plausibility.
- **Semantic coherence:** Leveraging the LLM's ability to generate contextually meaningful, consistent data that aligns with known medical patterns.

Note: Starting with separate LLM-generated CSV files is optional. The pipeline is adaptable—you can also initiate generation directly within the existing CSV from Stage 1. However, isolating feature generation allows for cleaner semantic control and more modular data handling.

Statistical Validation

Each generated feature underwent rigorous statistical validation using:

- **Kernel Density Estimation (KDE)**
- **Boxplots**
- **Q–Q plots**

to ensure distributions closely match medically expected profiles in MRI settings.

Iterative Feature Injection and Semantic Validation

Features were integrated sequentially into the Stage 1 dataset (dataset_v1.csv) as follows:

1. **Injection:** Each MRI-contextual feature (PDB first, then NBM) was added one at a time.
2. **Semantic Checking:** After injection, the LLM (via training/llm_check.py) validated coherence between raw synthetic data, engineered features, and the new environmental variables, ensuring physiological and contextual consistency.
3. **Reorganization:** The LLM then refined and reorganized data points (using training/llm_organize.csv), generating new coherent samples that realistically reflect MRI-related stress scenarios.
4. **Distance Metrics:** Wasserstein distance was calculated to quantify similarity between checked and organized data, maintaining tight distributional alignment.
5. **Sample Augmentation:** Leveraging these insights, new stress-contextualized samples were synthesized (training/llm_generate.py).

Generative Modeling with RCGAN

The enriched dataset was fed into a Recurrent Conditional GAN (RCGAN) for robust modeling of MRI-related stress patterns:

- **Training:** The generator and discriminator engaged in adversarial training (training/rcgan_train.py), with the discriminator improving stress detection sensitivity and the generator striving to produce indistinguishable synthetic data.
- **Evaluation:** Every eval_interval , Wasserstein distance between generated and real data assessed generation quality.
- **Early Stopping:** Training ceased if the discriminator weakened excessively or loss dropped below thresholds to avoid mode collapse or overfitting.
- **Output:** Once converged, synthetic data was decoded, scaled back to original units, and saved as dataset_v2.csv.

All training metrics, loss curves, and plots are archived under training/plots/.

Validation of Generated Data

To confirm that generated samples reflect **realistic stress patterns**, a separate LLM-based classification model (classify_with_llm.py) assessed the stress state of each new instance. Results were stored in classified_output.csv.

Classification Metrics Summary

Metric	Value
Accuracy	0.920
Macro F1 Score	0.922
Macro Recall	0.927
Macro Precision	0.922
Macro AUC	0.955

Confusion matrix:

[[380 10 10]

 [15 310 15]

 [5 15 230]]

- **Balanced precision and recall (~92–93%)** indicate the model robustly distinguishes stress states without bias.
- **Matthews Correlation Coefficient (MCC) near 0.9** confirms strong predictive correlation.
- **AUC ≥ 0.95** signals excellent class separability.

Interpreting the Metrics

- **Accuracy (92%)** means the model correctly classifies stress states in 92% of cases.
- **Macro averages** (Precision, Recall, F1) treat all classes equally, ensuring no single class dominates performance.
- Confusion matrix insights reveal typical borderline cases where “borderline stress” may be misclassified—an area for potential threshold tuning or feature enrichment.

Summary of Stage 2 Impact

By embedding MRI-specific acoustic context into our stress detection model, we have:

- Created a richer, physiologically plausible dataset combining metadata, physiological signals, engineered features, and MRI environmental variables.
- Demonstrated a modular pipeline that leverages LLMs for data generation, semantic validation, and augmentation.
- Successfully trained and validated a GAN-based generative model that produces realistic synthetic stress data tailored to MRI conditions.
- Established robust evaluation protocols combining statistical, adversarial, and LLM-based assessments.

With dataset_v2.csv finalized, containing nuanced MRI-contextualized stress profiles, we are poised to advance to the next stage .