Master README: ASD Diagnosis via Eye Tracking Using Temporal Transformer Architecture

This repository contains code and documentation for a five-stage experimental framework for Autism Spectrum Disorder (ASD) diagnosis using gaze sequence data and transformer-based deep learning models. Each experiment builds upon the previous, progressively addressing class imbalance, developmental variability, loss ablation, and domain generalization.

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Experiment 1: Baseline Diagnostic Model for Autism Spectrum Disorder (ASD)

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Overview

Implements a baseline transformer model trained on raw gaze sequences for binary classification (ASD vs TD). This experiment sets the foundation for all subsequent experiments.

Files

- train1.py: Trains the base model using gaze data.
- model1.py: Transformer-based sequence classifier.
- dataset1.py: Loads and preprocesses temporal gaze sequences.
- Columns-name.py: Specifies required dataset columns.
- Diaganostic1.py: Evaluates model performance.
- Enhanced-Diaganostic.py: Visualizes attention, entropy, and AOIs.
- best_model.pt: Saved trained model.

How to Run

bash

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python train1.py

python Diaganostic1.py

python Enhanced-Diaganostic.py

Key Outcomes

- High baseline AUC and F1-score
- Sets up diagnostic attention visualizations and entropy flows

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Experiment 2: Addressing Class Imbalance with Stratified Sampling

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Overview

Enhances the baseline by correcting data imbalance through stratified sampling, improving recall for ASD under-represented samples.

Files

- train2.py: Trains with balanced mini-batches by class.
- dataset1.py: Now supports stratified age-label pairing.
- model1.py: Reused from Experiment 1.

Key Outcomes

- Improves model sensitivity to ASD
- Achieves better per-class F1-score stability
- Lays groundwork for demographic-aware training

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Experiment 3: Age-Stratified Generalization for Developmental Robustness

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Overview

Builds on Experiment 2 by explicitly matching ASD/TD samples across age groups to test cross-developmental robustness.

Files

- train3.py: Trains using age-stratified sampling.
- train3_variant.py: Adds dropout and layer norm.
- train31.py: Focuses training on specific age bands.
- model3.py, model3_variant.py: Adds dropout/stability enhancements.
- dataset1.py: Now bins age into groups for training.

Key Outcomes

- Strong generalization across diverse age brackets
- Enhances fairness by minimizing age confounding
- Produces the most balanced model used for transfer learning in Experiment 5

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Experiment 4: Ablation of Entropy and Semantic Reentry Loss Components

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Overview

Tests the contribution of entropy-based regularization and semantic reentry loss by disabling each individually and jointly.

Files

- train4_ablation.py: Removes both custom loss terms.
- train4_ablation_with_regularization.py: Full composite loss version.
- model4_ablation.py: Reduced model without temporal memory.
- model4_ablation_with_regularization.py: Full model with semantic memory.
- dataset1_variant.py: Provides semantic AOI encoding.

Key Outcomes

- Entropy ablation leads to overconfidence (AUC ≈ 0.63)
- Reentry ablation impairs interpretability (AUC ≈ 0.65)
- Minimal loss model performs near chance (AUC ≈ 0.52)
- Confirms necessity of both regularization components

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Experiment 5: Cross-Dataset Transferability with Fine-Tuning on Severity Labels

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Overview

Tests the generalization capacity of the pretrained model by fine-tuning it on a new dataset with ASD severity labels mapped to binary format.

Files

- Trainer5.py: Loads pretrained weights, fine-tunes on new data, evaluates performance.

Key Outcomes

- Maintains high AUC (≈ 0.85) despite label schema shift
- Attention maps remain interpretable across domains
- Slight drop in severe-ASD recall noted, suggesting need for multimodal enrichment

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Summary of Progression

Experiment	Focus Area	Key Feature	Output Metric (AUC/F1)
1	Baseline modeling	Transformer + gaze sequence	AUC 0.91 / F1 0.81
2	Class balance	Stratified sampling	Better recall
3	Age fairness	Cross-age matching	AUC 0.89 / F1 0.89
4	Loss component analysis	Entropy + semantic reentry ablation	AUC dropped to ~0.63

Experiment	Focus Area	Key Feature	Output Metric (AUC/F1)
5	Generalization to new dataset	Fine-tuned model on severity-labeled data	AUC 0.85 / F1 0.74