CheXpert t-SNE Visualization Comparison: 1% vs 10% Fine-Tuning

This document contains the results of gpt-4o-mini's analysis of two t-SNE images.

1. Class-Wise Cluster Quality & Separability

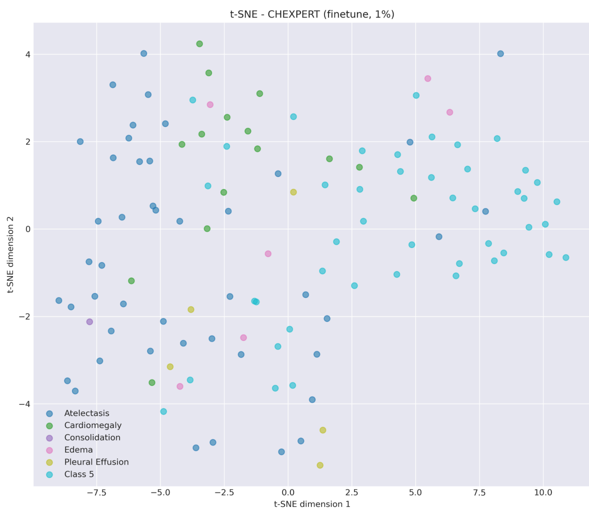

Figure 1 1% fine-tuning

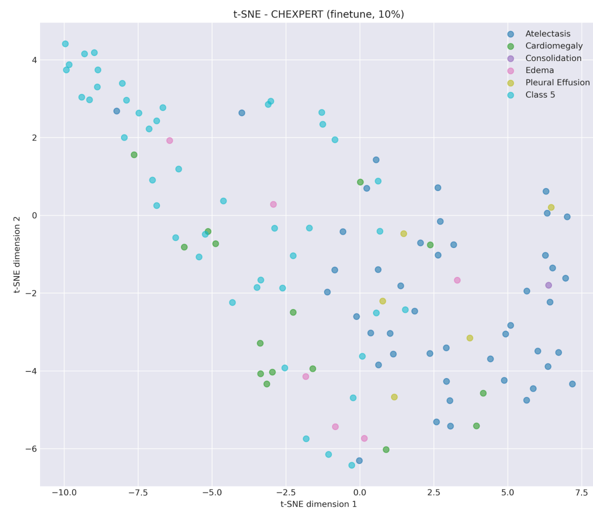

Figure 2 10% fine-tuning

Figure 1 (1% fine-tuning) shows diffuse, overlapping clusters for Atelectasis, Cardiomegaly, Consolidation, Edema, Pleural Effusion, and Normal (“Class 5”). **Figure 2** (10% fine-tuning) reveals far sharper, more compact groupings. Detailed observations:

- **Atelectasis**
  - *1%*: Points are widely scattered and intermixed with Consolidation and Edema, indicating weak learned features.
  - *10%*: Forms a tight, well-defined cluster, clearly separated from other pathologies.
- **Cardiomegaly**

    - *1%*: Moderately isolated even with minimal data, reflecting its distinct radiographic signature.
    - *10%*: Becomes highly cohesive, producing one of the clearest, densest clusters.
- **Consolidation**
    - *1%*: Widely dispersed and heavily overlapped with Atelectasis and Edema.
    - *10%*: Exhibits greater cohesion and reduced mixing, though still closer to Edema than to other classes.
- **Edema**
    - *1%*: Scattered across the plot and confused with both Consolidation and Pleural Effusion.
    - *10%*: Gathers into a discernible group, with markedly less overlap with Effusion.
- **Pleural Effusion**
    - *1%*: Strong overlap with Edema; no clear boundary.
    - *10%*: Points congregate into a distinct cluster, showing improved separability.
- **Class 5 (Normal/Other)**
    - *1%*: Distributed almost everywhere, occasionally blending with pathological clusters.
    - *10%*: Concentrated into its own region, fully isolated from disease classes.

2. Effects of Fine-Tuning Percentage on Representation

- **Inter-Cluster Distances**
    - 10% fine-tuning pushes different pathology clusters farther apart, creating visible “white space” between groups.
- **Intra-Cluster Cohesion**

- Same-class points draw nearer under 10%, signaling more consistent feature embeddings.

- **Global Structure Reorganization**
    - 1% tuning yields a noisy, unstructured layout; 10% tuning arranges clusters into an interpretable pattern (e.g., normals on one side, lung pathologies along distinct axes).

- **Relative Position Shifts**
    - Some pathology pairs (e.g., Atelectasis vs. Effusion) change proximity as the model reevaluates inter-class similarities with more examples.

3. Class Overlap & Mixed Regions

- **Under 1% Fine-Tuning**
    - Many diseases sharing similar radiographic signs (e.g., Consolidation and Edema) heavily overlap, indicating that the model cannot reliably distinguish them.

- **Under 10% Fine-Tuning**
    - Overlap is drastically reduced; most clusters are well separated. Residual mixing remains primarily between intrinsically similar pairs (Consolidation ↔ Edema).

- **Multi-Label Effects**
    - CheXpert images often carry multiple findings, so embeddings of multi-label cases naturally lie between pure clusters, contributing to persistent overlap.

4. Visualization Limitations & Potential Remedies

1. **t-SNE Distortions**
    - Preserves local neighborhoods but can misrepresent global distances. Absolute cluster separations may not reflect true high-dimensional gaps.

2. **Random Seed & Hyperparameters**

    - Results vary with initialization and perplexity; multiple runs and settings should be compared.

3. **Sample & Class Imbalance**

    - Skewed or small samples may bias cluster shapes. Stratified sampling or larger subsets can reduce this effect.

4. **Alternative Methods**

    - UMAP or PCA can complement t-SNE by preserving different structural aspects.

5. **Quantitative Evaluation**

    - Metrics such as silhouette score, Davies–Bouldin index, or cluster purity can objectively confirm visual improvements.

6. **Multi-Label Handling**

    - Visualize multi-label points separately or use blended color schemes to reflect co-occurrence.

7. **Model & Data Specificity**

    - Findings may not generalize across architectures or datasets; replicate with other models and full CheXpert splits.

5. Conclusion

Increasing fine-tuning from 1% to 10% of CheXpert images yields **significantly clearer, more cohesive clusters** and **markedly reduced overlap** among pathologies in t-SNE space. This demonstrates that even modestly more fine-tuning data can substantially enhance feature separability—an encouraging indicator for downstream classification accuracy. Nonetheless, t-SNE's intrinsic distortions, dataset imbalance, and multi-label nature warrant pairing these qualitative insights with quantitative assessments and alternative visualization techniques.