**1. Automated Identification of Thoracic Pathology from Chest Radiographs with Enhanced Training Pipeline — DSouza, Abidin, Wismüller (2020)**

**Conclusion**

* The modifications in training (variable image sizes, restart schedules, good learning rate choice) help improve performance, especially helping reduce overfitting.
* Using ResNet34 with those training enhancements, they achieve AUCs for many disease labels that match or beat prior state-of-the-art on ChestX-ray14.
* However, some labels still lag (e.g. Infiltration, Nodule) showing room for further improvement.

**2. Multi-Label Classification of Chest X-ray Abnormalities Using Transfer Learning Techniques — J. Kufel et al. (2023)**

**Conclusion**

* EfficientNet models + good data augmentation + transfer learning produce very strong performance on ChestX-ray14 for the 14 disease classes.
* Their model outperforms previous works on many labels, indicating that newer architectures + well-tuned training pipelines still yield gains even for widely-studied datasets.
* The study notes that some classes still have lower performance; possible limits include label noise, overlap between disease manifestations, and image quality variation.

**3. Anatomy-XNet: Anatomy Aware Convolutional Neural Network for Thoracic Disease Classification in Chest X-rays — Kamal, Zunaed, Nizam, Hasan (2021)**

**Conclusion**

* Integrating anatomical attention (making the model aware of organ regions) improves classification of thoracic diseases compared to models that just treat whole image uniformly.
* Using semi-supervised organ annotations helps in guiding attention even when organ-level labels are sparse.
* The method generalizes well across datasets (NIH, CheXpert, MIMIC) showing cross-dataset robustness.
* Remaining challenges: capturing very small lesions (nodules), overlapping pathologies, noisy labels, and further improving localization.

**4. ChestNet: A Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography — Hongyu Wang & Yong Xia (2018)**

**Conclusion**

* ChestNet’s two-branch architecture (classification + attention) significantly improves diagnosis accuracy over just classification alone.
* When trained and tested *only* on ChestX-ray14 without extra data, ChestNet achieves higher AUCs per disease compared to other comparable methods.
* Attention branch helps localize and focus on pathological regions despite weak supervision (i.e. no bounding boxes), improving performance.

**5. Automated Identification of Thoracic Pathology from Chest Radiographs with Enhanced Training Pipeline — Adora M. DSouza, Anas Z. Abidin, Axel Wismüller (2020)**

**Conclusion**

* The enhancements in training pipeline (variable image sizing, restarts in optimization, careful learning rate scheduling) give measurable improvements, e.g. reduce overfitting and help rare/weak labels.
* Using ResNet-34 with those enhancements reaches or exceeds prior state-of-the-art performance on many disease classes of ChestX-ray14.
* Some labels still underperform (for example Infiltration, Nodule), showing room remains for better architecture, better data, perhaps better localization or more precise supervision.