



Deep Learning For Condition Detection In Chest Radiographs: A Performance Comparison Of Different Radiograph Views And Handling Of Uncertain Labels

Mubashir Ahmad¹, Kheng Lee Koay¹, Yi Sun¹, Farshid Amirabdollahian¹, Vijay Jayaram² and Ganesh Arunachalam²

¹Department of Computer Science, University of Hertfordshire, Hatfield, UK

²The Princess Alexandra Hospital, Harlow, UK

MUBASHIR AHMAD

mubashir.ahmad21@herts.ac.uk





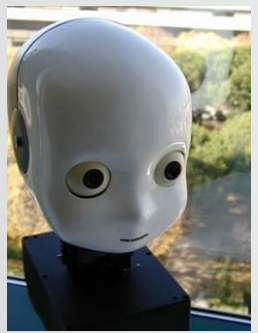
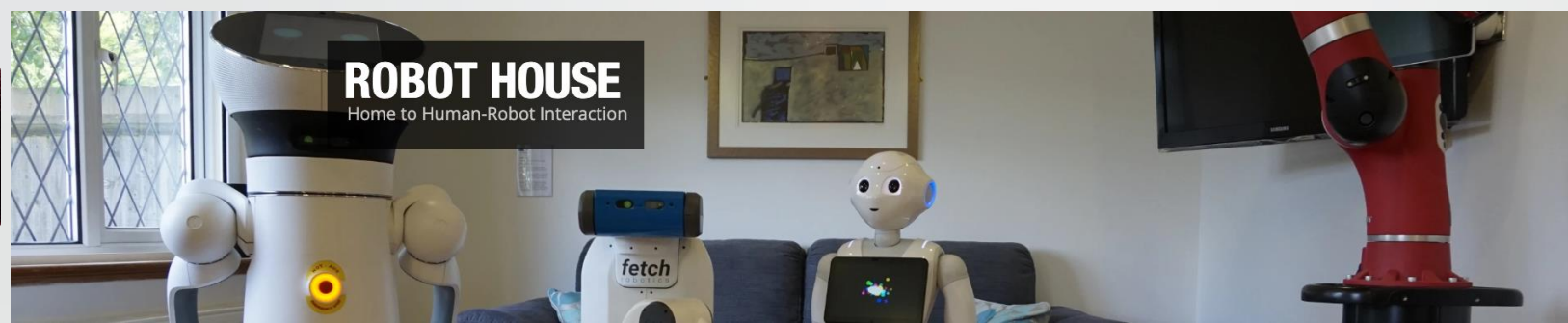
Mubashir Ahmad

- MSc in Artificial Intelligence with Robotics (2017-2019)
- 3rd year PhD researcher in department of computer science, University of Hertfordshire
- Data Scientist at Big Data Technologies Innovation Lab

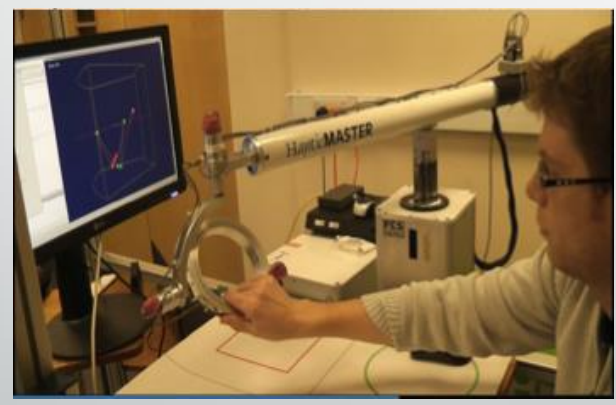
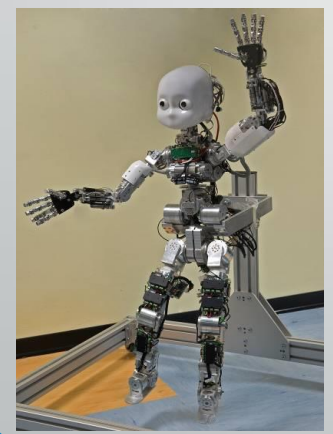
Interests

- Artificial Intelligence, Deep learning, Medical Imaging





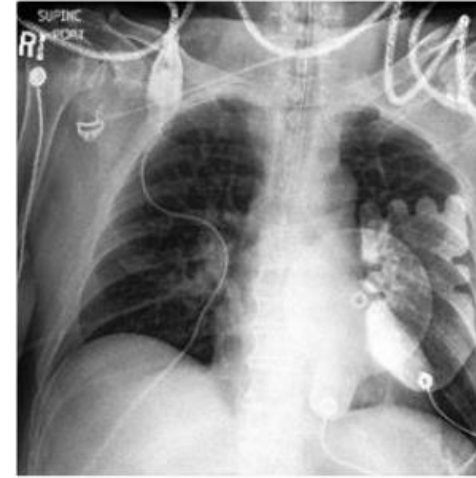
Robots in UH Robot House and Robotics Research Group



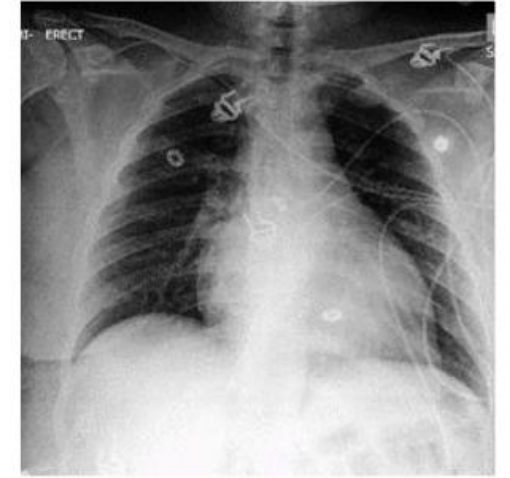
Introduction

- Chest Radiograph Interpretation
- Chexpert Dataset
- AP, PA and Lateral Projections
- Multilabel Classification
- Deep Learning for Image Classification
- Five Clinically Significant Conditions
 - Cardiomegaly
 - Consolidation
 - Atelectasis
 - Pleural Effusion
 - Oedema

(a) Supporting Devices



(b) Cardiomegaly



(c) Edema



(d) Multiple



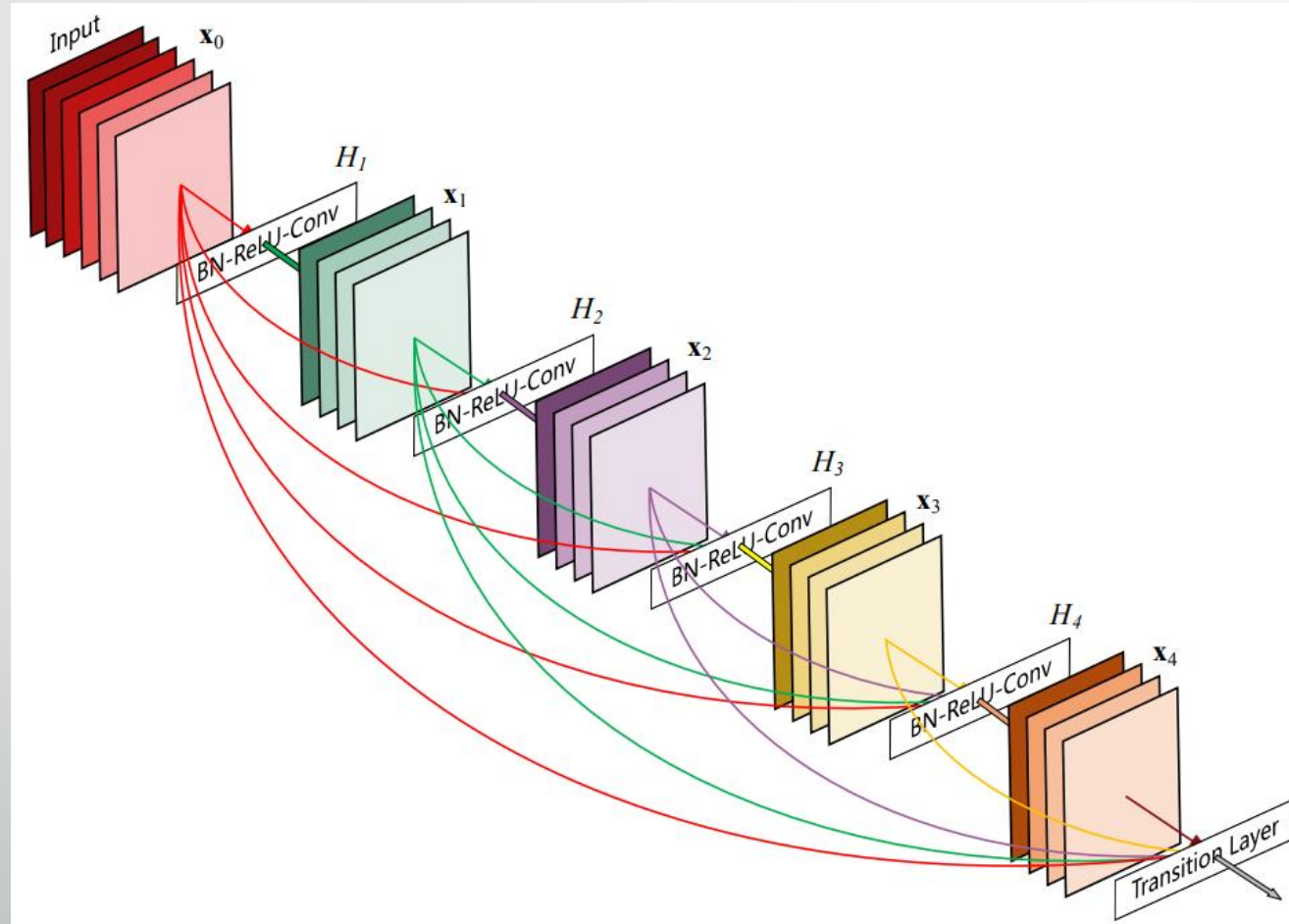
Images from CheXpert Dataset [1]

Methodology

- DenseNet121
- Each Projection Separately Considered
- Transfer Learning
- Multiscale Template Matching
- Data Augmentation
- Labelling Uncertain Samples



Methodology – DenseNet121



Five Layer Dense Block From DenseNet121 [2]



Methodology – ALL Views

AP



PA



Lateral

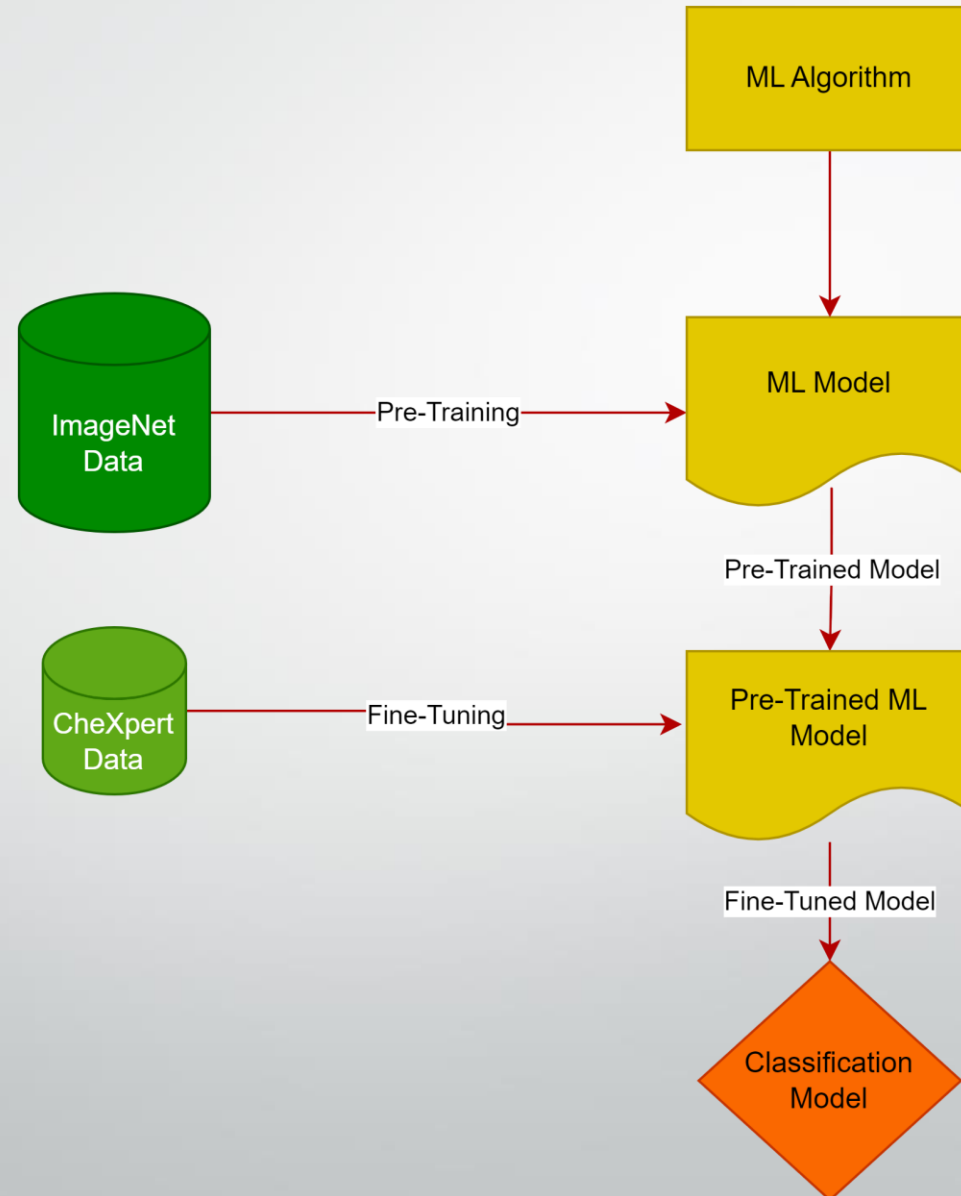


Different projections of radiographs of same patient from CheXpert data Set [1]

- Different orientation of Discriminative Features
- Heart size in AP and PA

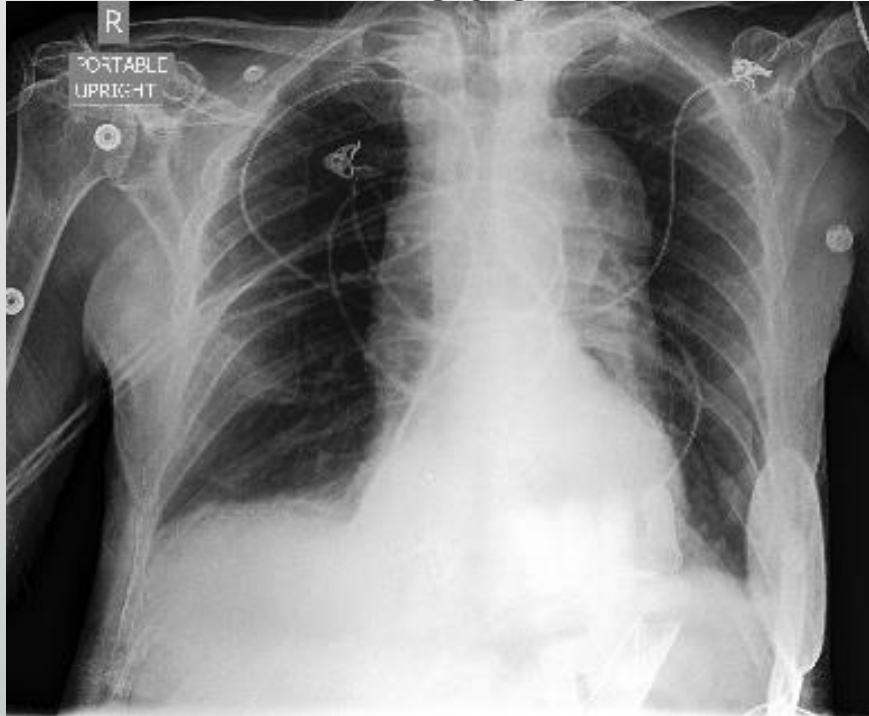


Methodology – Transfer Learning



Methodology – Template Matching

Before



After



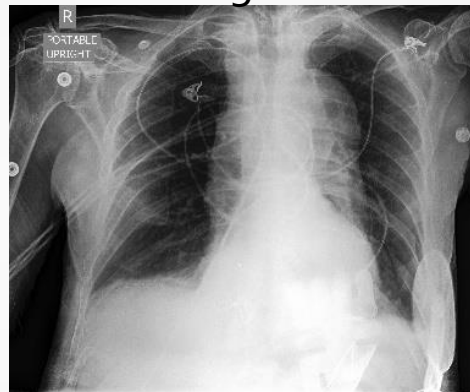
Same radiograph before and after applying template Matching [1]



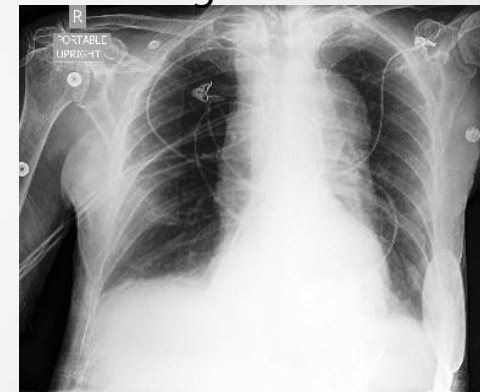
Methodology – Augmentation

- Enhance data
- Increase data diversity
- Multiple Techniques (Zooming, Brightness, Flipping, etc.)

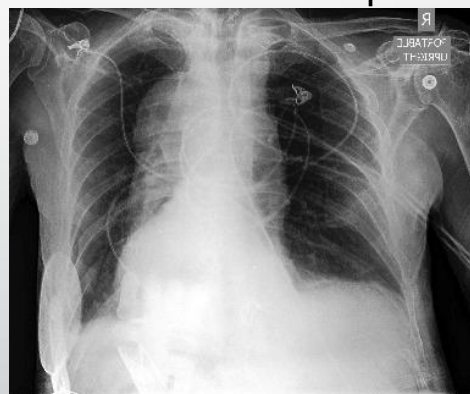
Original



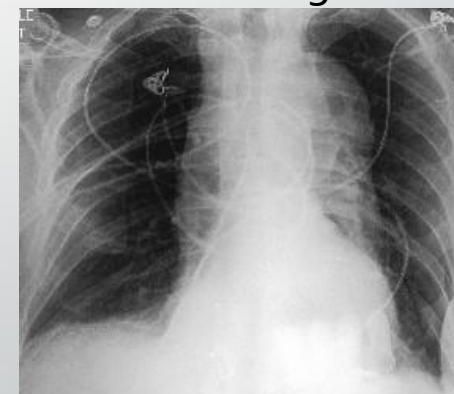
Brightness



Horizontal Flip



Zooming



Methodology – Label Uncertain with GMM

- Trained GMM for each condition and view separately
- Classify uncertain samples
- Included them in the training set



Results – Best Model

Anteroposterior					
Exp	DN121	DN121_TM	DN121_TL	DN121_AUG	DN121_TM_TL_AUG
1	0.85	0.79	0.76	0.87	0.84
2	0.79	0.74	0.81	0.76	0.85
3	0.76	0.75	0.86	0.79	0.82
4	0.78	0.81	0.8	0.8	0.83
5	0.76	0.81	0.84	0.84	0.83
6	0.76	0.72	0.9	0.86	0.83
7	0.8	0.79	0.67	0.8	0.88
8	0.82	0.63	0.8	0.84	0.85
9	0.81	0.79	0.82	0.82	0.86
10	0.74	0.78	0.81	0.8	0.88
Avg	0.79	0.76	0.81	0.82	0.85
Std	0.03	0.05	0.06	0.03	0.02

- Analysis of Variance (ANOVA)

$$[F(4, 45) = 5.504, p = 0.001]$$



Results – Comparison Between Views

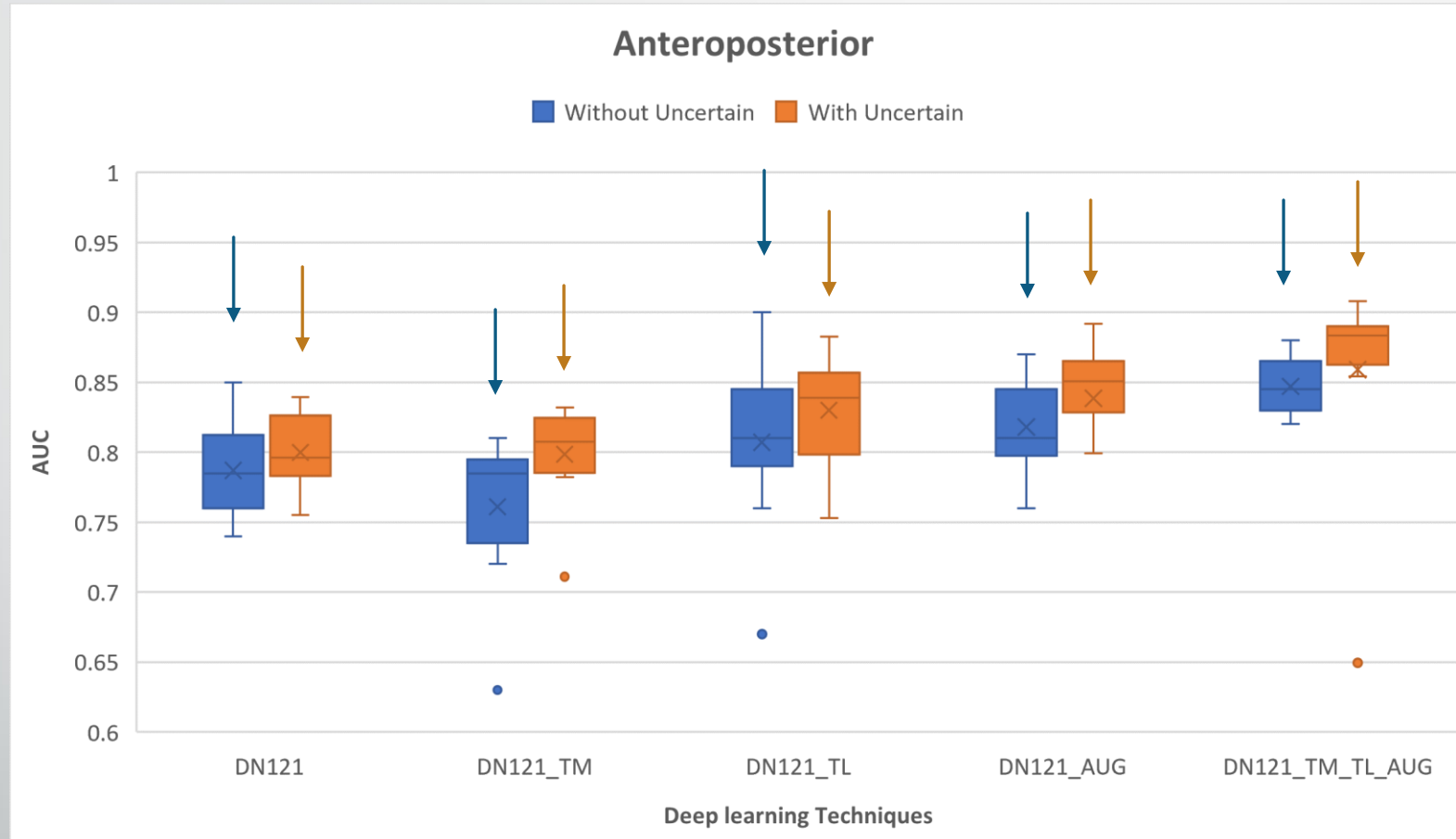
Exp	Anteroposterior(AP)	Posteroanterior(PA)	Lateral
1	0.84	0.69	0.79
2	0.85	0.73	0.9
3	0.82	0.74	0.84
4	0.83	0.74	0.78
5	0.83	0.74	0.87
6	0.83	0.73	0.82
7	0.88	0.73	0.84
8	0.85	0.69	0.86
9	0.86	0.7	0.82
10	0.88	0.72	0.81
Avg	0.85	0.72	0.83
Std	0.02	0.02	0.04

- Analysis of Variance (ANOVA)

[F(2, 27) = 64.677, p < 0.001]



Results – After Removing Uncertainty



Limitations and Future Work

Limitations:

- Insufficient data for each projection
- Same hospital data

Future Work:

- Other deep learning techniques such as transformers
- Co-design studies with radiologists
- Integrate in clinical work flow



Conclusion

- AP out performs PA and Lateral views
- Added techniques improve the model performance
- Relabelling the uncertain with GMM works
- These models can assist radiologist



References

- 1) Irvin, J., Rajpurkar, P., Ko, M., Yu, Y., Ciurea-Ilicus, S., Chute, C., ... & Ng, A. Y. (2019, July). Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 33, No. 01, pp. 590-597).
- 2) Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4700-4708)



THANK YOU

