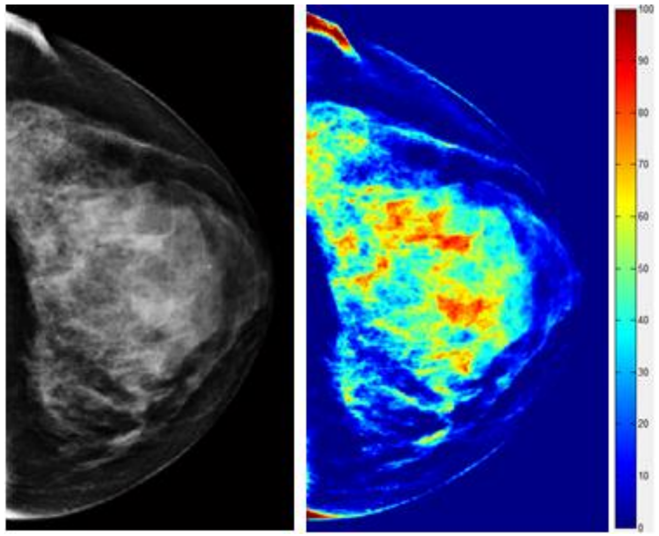
New Quantitative Imaging Markers to Predict Breast Cancer Risk in Women

Background :

- Breast cancer: Most common cancer in women
- Early detection methods can improve overall survival
- Current risk assessment models do not accurately predict individual risk
- Radiographic image features in mammograms change as suspicious breast abnormalities develop



Example of segmented fibro-glandular tissue volume on a BIRADS D digital mammogram

Targets:

- Develop new image feature analysis-based cancer risk prediction model
- New risk model that takes prior screenings into account
- New model for short-term individualized screening recommendations (e.g., 1 to 2 years)

Speaker:

- Dr. Maxine Tan, Monash University Malaysia

New Quantitative Imaging Markers to Predict Breast Cancer Risk in Women

Project Members :

Maxine Tan
Monash University
Malaysia

Hwee Kuan Lee
A*STAR
Singapore

Kartini Rahmat
UM
Malaysia

Project Duration :

- 17 months

Project Budget:

- USD 29,510

Project Activities: List of activities

Dataset compilation/collation

- Dr. Maxine Tan (Monash University Malaysia)
- Prof. Kartini Rahmat (University of Malaya)

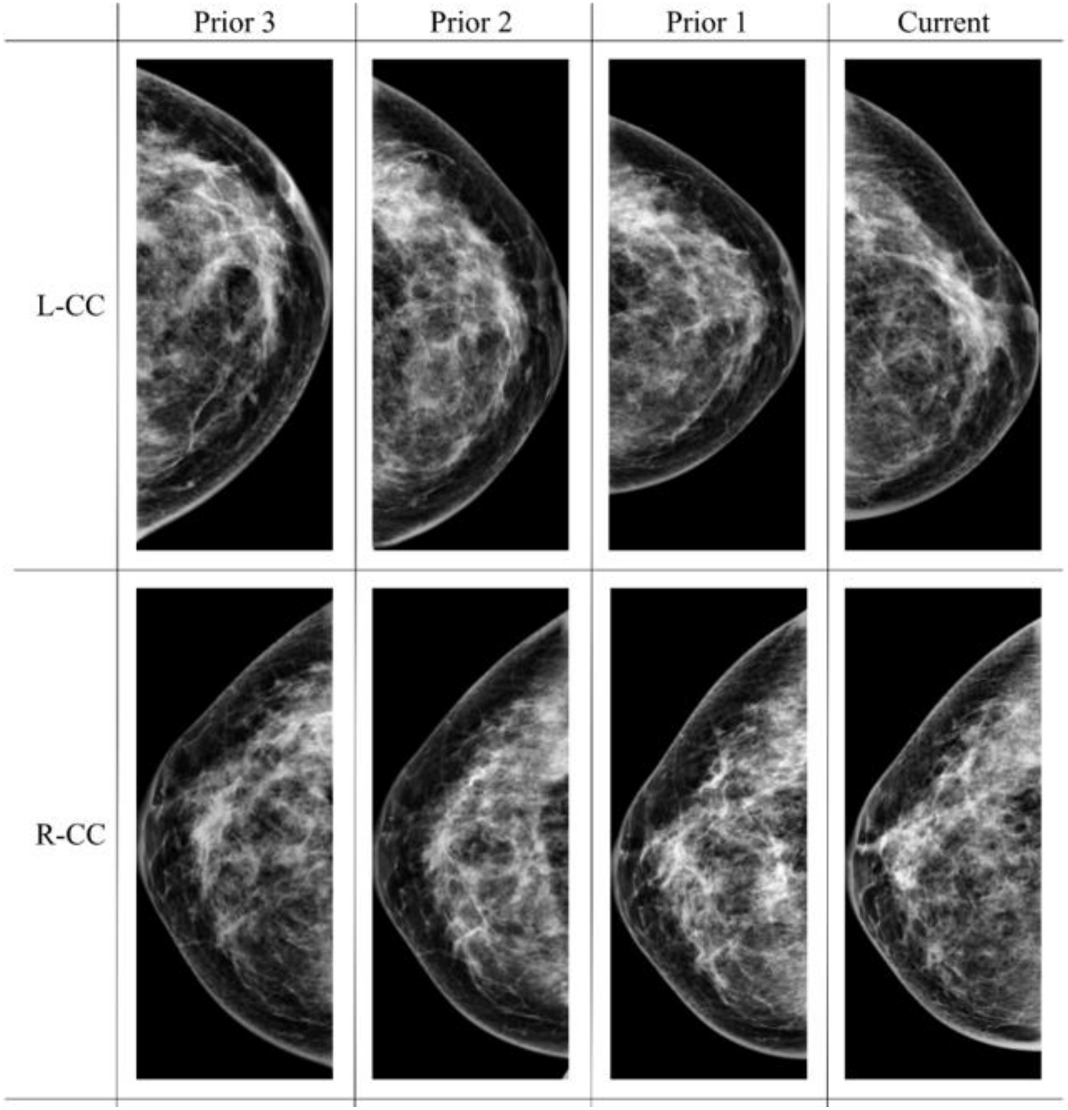
Multi-radiomics deep learning cancer risk prediction model

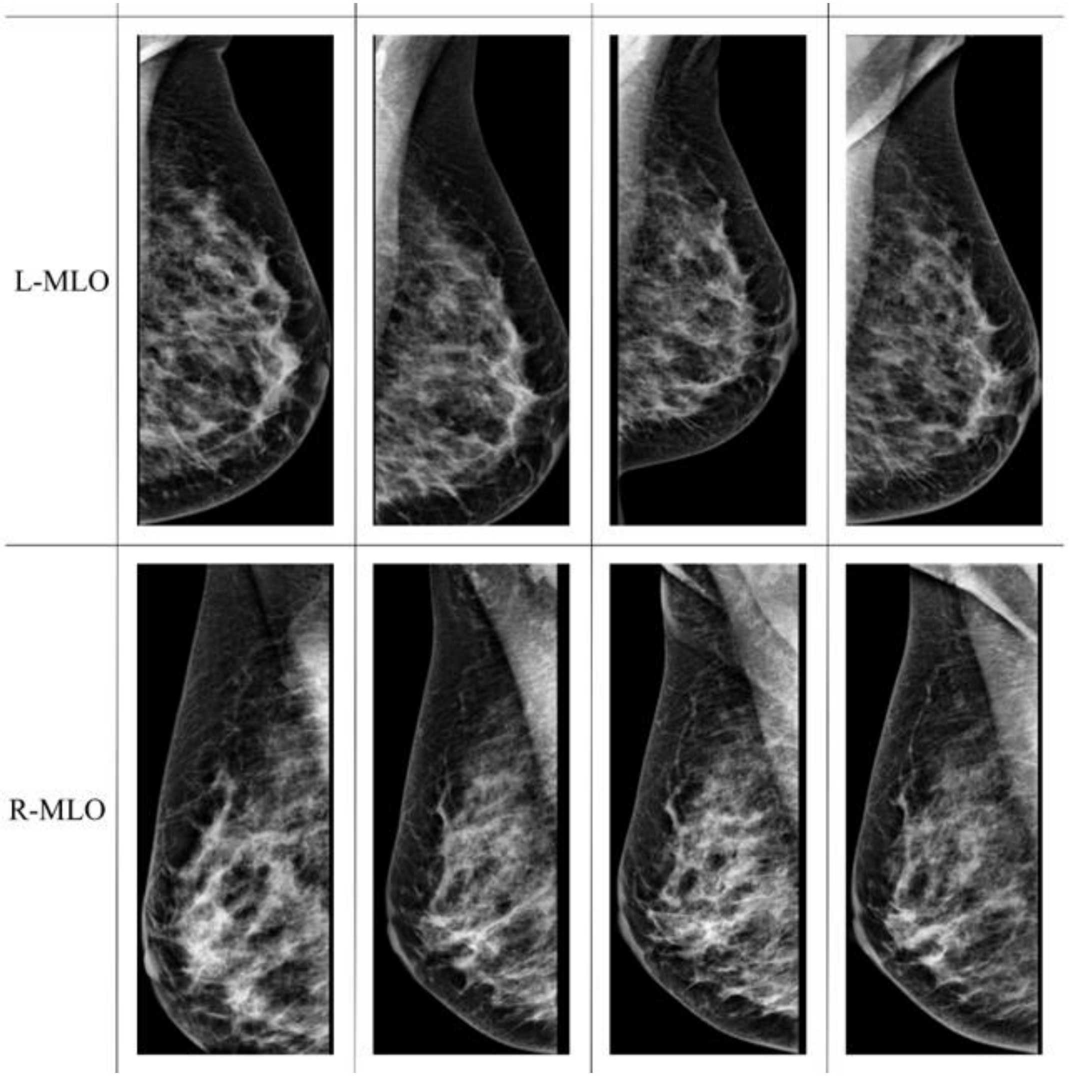
- Dr. Maxine Tan (Monash University Malaysia)
- Prof. Kartini Rahmat (University of Malaya)

New deep learning networks combined with clinical risk factors to improve risk prediction

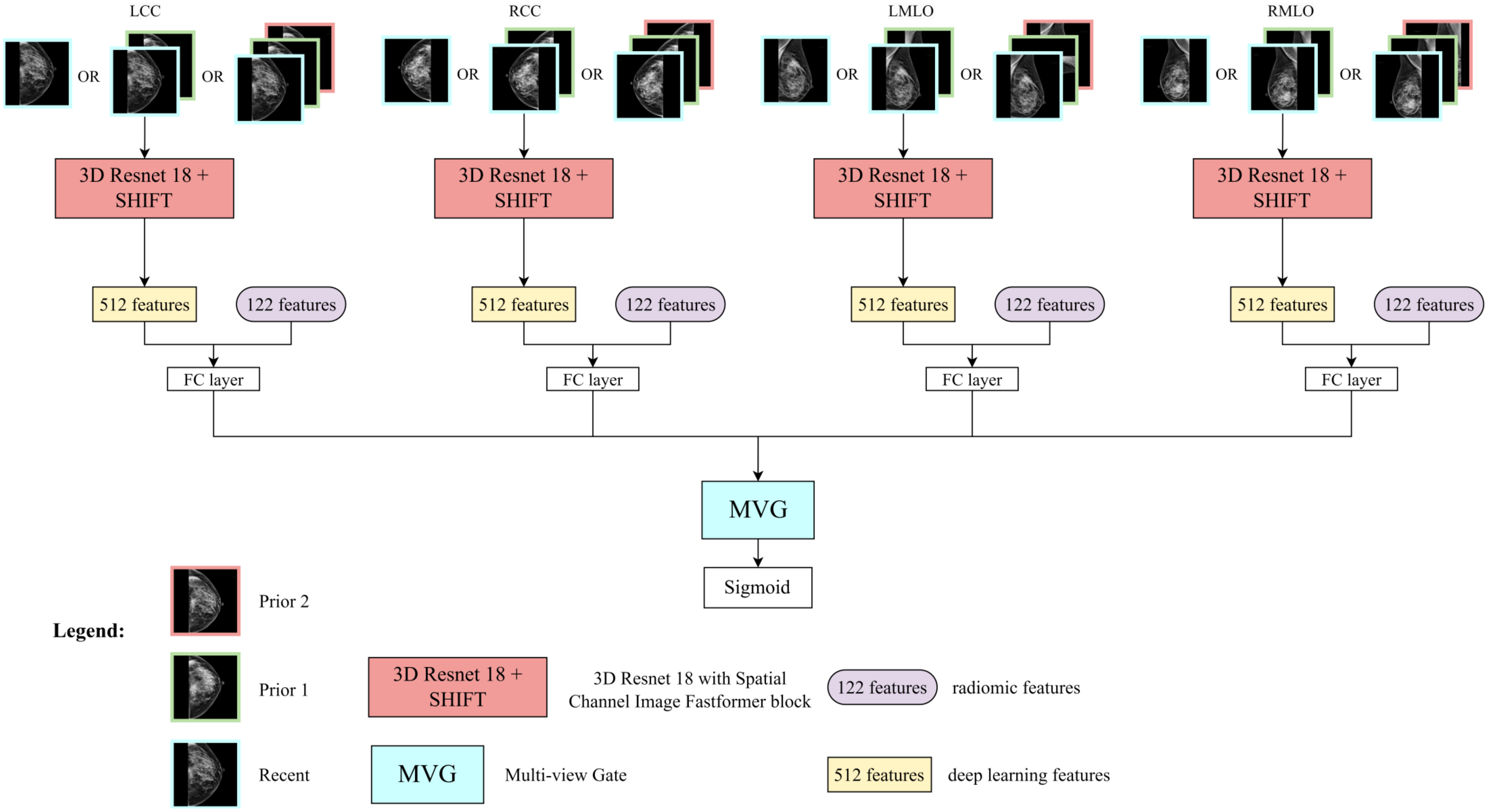
- Dr. Maxine Tan (Monash University Malaysia)
- Prof. Kartini Rahmat (University of Malaya)
- Dr. Hwee Kuan Lee (A*STAR, Singapore)

Project Activities: Dataset compilation/collation

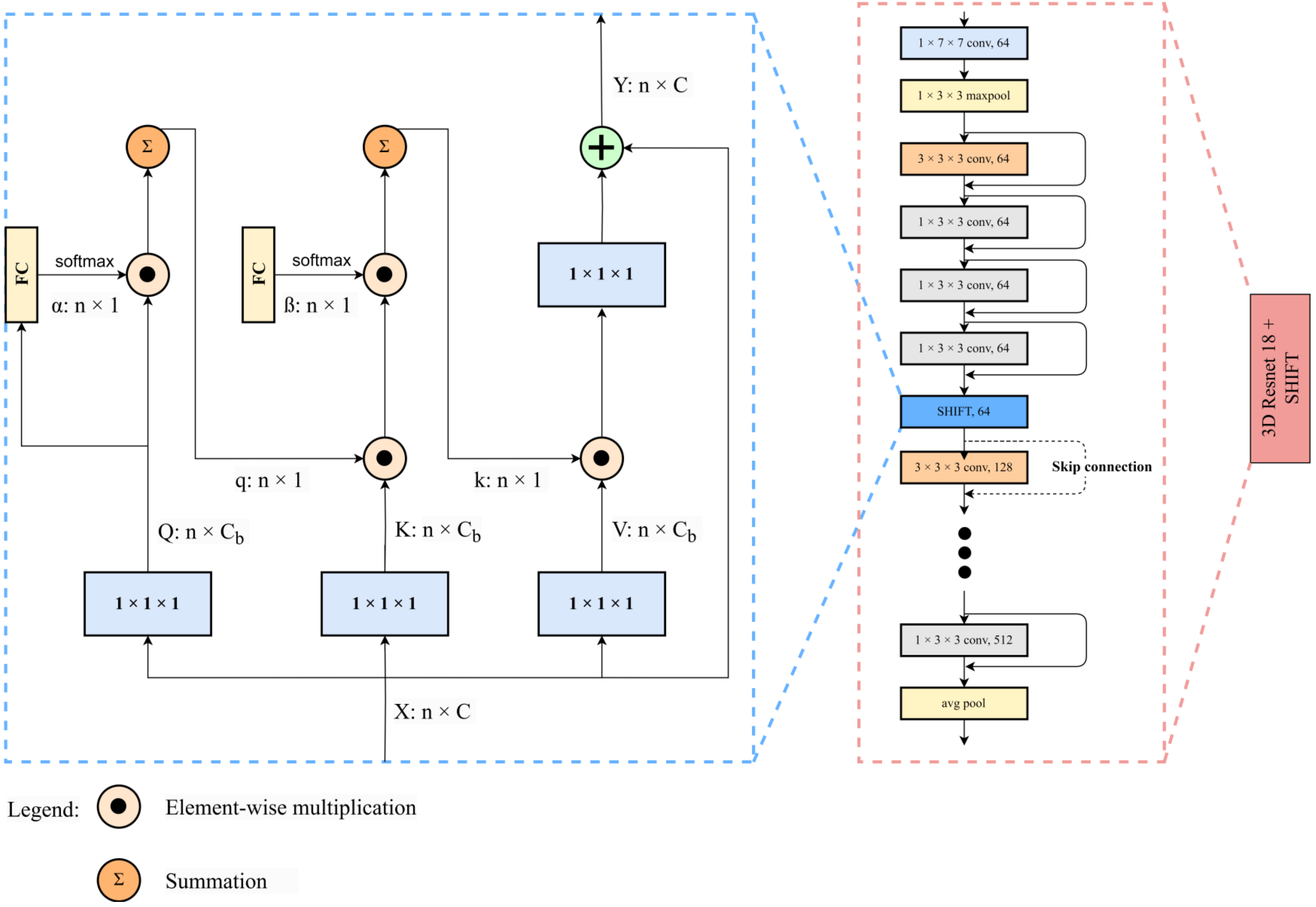




Project Activities: Multi-radiomics deep learning cancer risk prediction model



Project Activities: Multi-radiomics deep learning cancer risk prediction model



New SHIFT block and its placement in the 3D Resnet-18 network

Project Activities: Multi-radiomics deep learning cancer risk prediction model

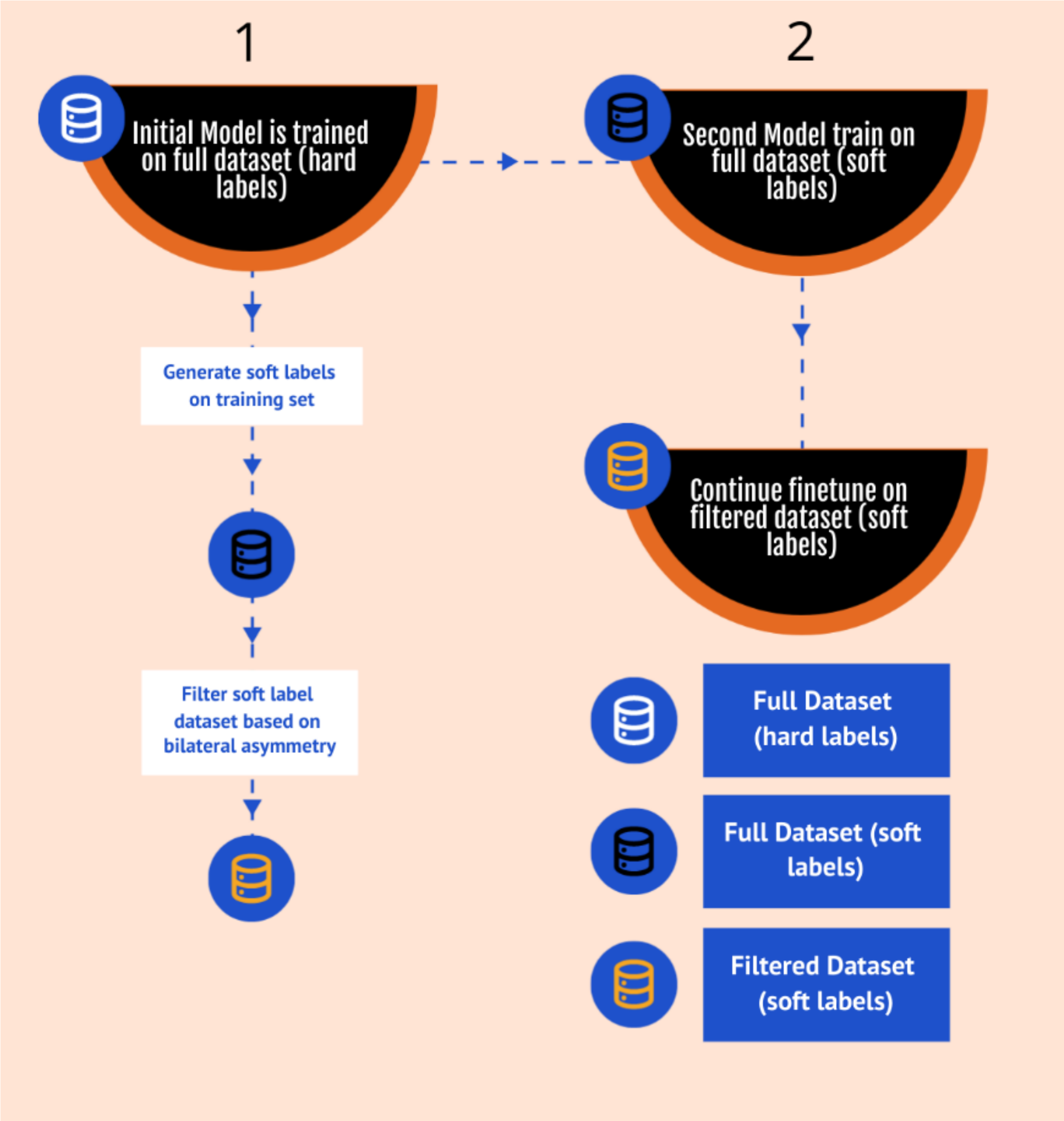
Feature group/type	Feature number/quantity	Description
First Order	18	Energy, Total Energy, Entropy, Minimum, 10th Percentile, 90th Percentile, Maximum, Mean, Median, Interquartile Range, Range, Mean Absolute Deviation, Robust Mean Absolute Deviation, Root Mean Squared, Skewness, Kurtosis, Variance, Uniformity
Gray Level Co-occurrence Matrix (GLCM)	23	Autocorrelation, Joint Average, Cluster Prominence, Cluster Shade, Cluster Tendency, Contrast, Correlation, Difference Average, Difference Entropy, Difference Variance, Joint Energy, Joint Entropy, Informational Measure of Correlation 1, Informational Measure of Correlation 2, Inverse Difference Moment, Maximal Correlation Coefficient, Inverse Difference Moment Normalized, Inverse Difference, Inverse Difference Normalized, Inverse Variance, Maximum Probability, Sum Entropy, Sum Squares
Gray Level Size Zone Matrix (GLSZM)	16	Small Area Emphasis, Large Area Emphasis, Gray Level Non-Uniformity, Gray Level Non-Uniformity Normalized, Size Zone Non-Uniformity, Size Zone Non-Uniformity Normalized, Gray Level Variance, Zone Variance, Zone Entropy, Low Gray Level Zone Emphasis, High Gray Level Zone Emphasis, Small Area Low Gray Level Emphasis, Small Area High Gray Level Emphasis, Large Area Low Gray Level Emphasis, Large Area High Gray Level Emphasis
Gray Level Run Length Matrix (GLRLM)	14	Short Run Emphasis, Long Run Emphasis, Gray Level Non-Uniformity, Gray Level Non-Uniformity Normalized, Run Length Non-Uniformity, Run Length Non-Uniformity Normalized, Run Percentage, Gray Level Variance, Run Variance, Run Entropy, Low Gray Level Run Emphasis, High Gray Level Run Emphasis, Short Run Low Gray Level Emphasis, Short Run High Gray Level Emphasis, Long Run Low Gray Level Emphasis, Long Run High Gray Level Emphasis
Neighbouring Gray Tone Difference Matrix (NGTDM)	5	Coarseness, Contrast, Busyness, Complexity, Strength
Gray Level Dependence Matrix (GLDM)	15	Small Dependence Emphasis, Large Dependence Emphasis, Gray Level Non-Uniformity, Dependence Non-Uniformity, Dependence Non-Uniformity Normalized, Gray Level Variance, Dependence Variance, Dependence Entropy, Low Gray Level Emphasis, High Gray Level Emphasis, Small Dependence Low Gray Level Emphasis, Small Dependence High Gray Level Emphasis, Large Dependence Low Gray Level Emphasis, Large Dependence High Gray Level Emphasis

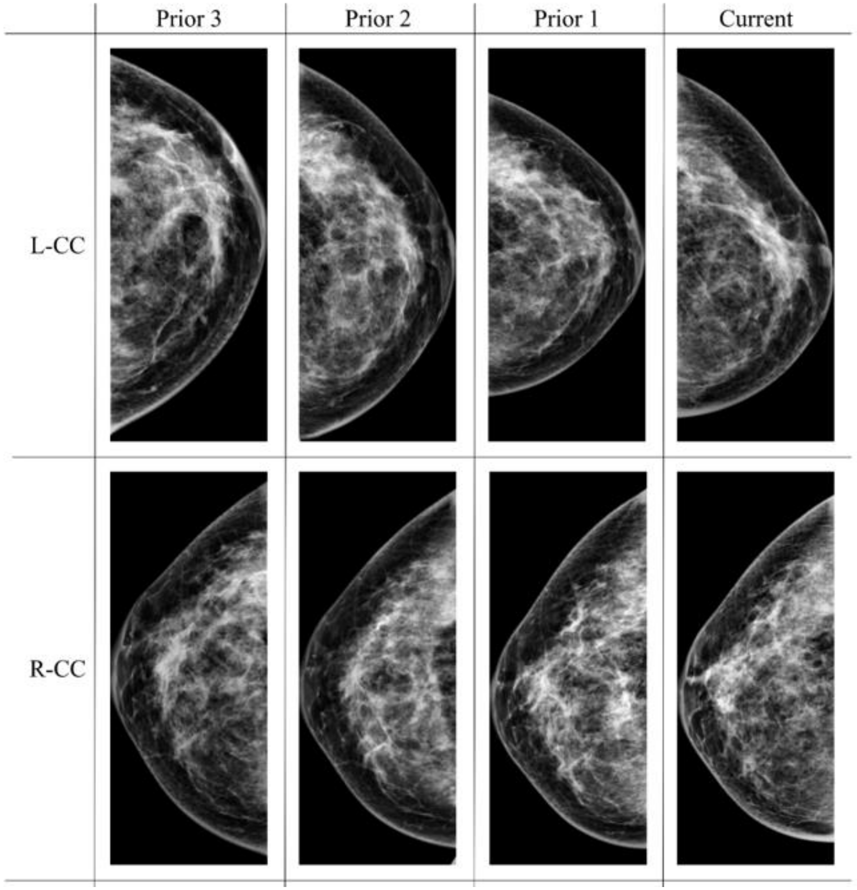
91 radiomics features from Pyradiomics library

30 new DCT and FFT frequency domain statistical features

Feature group/type	Feature number/ quantity	Description
Discrete Cosine Transform (DCT) Fast Fourier Transform (FFT)	30	Mean, Maximum, Variance, Skew, Kurtosis, Entropy, Energy, Root Mean Square, Uniformity, Minimum, Median, Range, Interquartile Range, Mean Absolute Deviation, Median Absolute Deviation

Project Activities: Multi-radiomics deep learning cancer risk prediction model





Flowchart of bilateral asymmetry based finetuning

R&D results: Patient dataset distribution & Prior screening results

Table 1: Patient distribution in Training, Validation and Testing sets of 5-fold CV setup

CV fold	Training set		Validation set		Testing set	
	Cases	Controls	Cases	Controls	Cases	Controls;
1	552 (10%)	5021 (90%)	143 (10%)	1258 (90%)	178 (10%)	1571 (90%)
2	553 (10%)	5023 (90%)	142 (10%)	1256 (90%)		
3	558 (10%)	5024 (90%)	137 (10%)	1255 (90%)		
4	558 (10%)	5024 (90%)	137 (10%)	1255 (90%)		
5	559 (10%)	5024 (90%)	136 (10%)	1255 (90%)		

Table 2: Tabulated results by taking different numbers of mammographic screenings

Model	Number of Screenings	1-year AUC (95% CI)	2-year AUC (95% CI)	> 2-year AUC (95% CI)
Baseline	3	0.882 (0.853-0.913)	0.855 (0.829-0.886)	0.849 (0.823-0.878)
	2	0.879 (0.85-0.91)	0.839 (0.811-0.871)	0.835 (0.81-0.866)
	1	0.877 (0.849- 0.909)	0.831 (0.798-0.863)	0.823 (0.793-0.853)

R&D results: Attention mechanism results & Ablation studies

Table 3: Results summary for Non-Local networks, SHIFT and no attention mechanisms

Attention Mechanism	Resnet Layer	1-year AUC (95% CI)	2-year AUC (95% CI)	> 2-year AUC (95% CI)
-	-	0.879 (0.85-0.91)	0.839 (0.811-0.871)	0.835 (0.81-0.866)
Non-Local	1	Out of Memory		
	2	0.881 (0.822-0.91)	0.840 (0.811-0.875)	0.837 (0.81-0.867)
SHIFT	1	0.887 (0.86-0.917)	0.848 (0.82-0.876)	0.844 (0.818-0.872)
	2	0.880 (0.85-0.911)	0.842 (0.811-0.873)	0.839 (0.812-0.867)

Table 4: Result compilation of new model additions

Model Configuration	Radiomics	1-year AUC (95% CI)	2-year AUC (95% CI)	> 2-year AUC (95% CI)
SHIFT + Gate + BAF	✓	0.905	0.872	0.866
SHIFT + Gate	✓	0.902	0.863	0.861
SHIFT	✓	0.888	0.854	0.853
Baseline	✓	0.880	0.845	0.844
Baseline	-	0.879	0.839	0.835
Radiomics Only	✓	0.714	0.719	0.715
Mirai [8]	-	0.877	0.834	0.830
SHIFT = Spatial Channel Image Fastformer, BAF = Bilateral Asymmetry based Finetuning				

R&D results: Ablation studies (ROC curves)

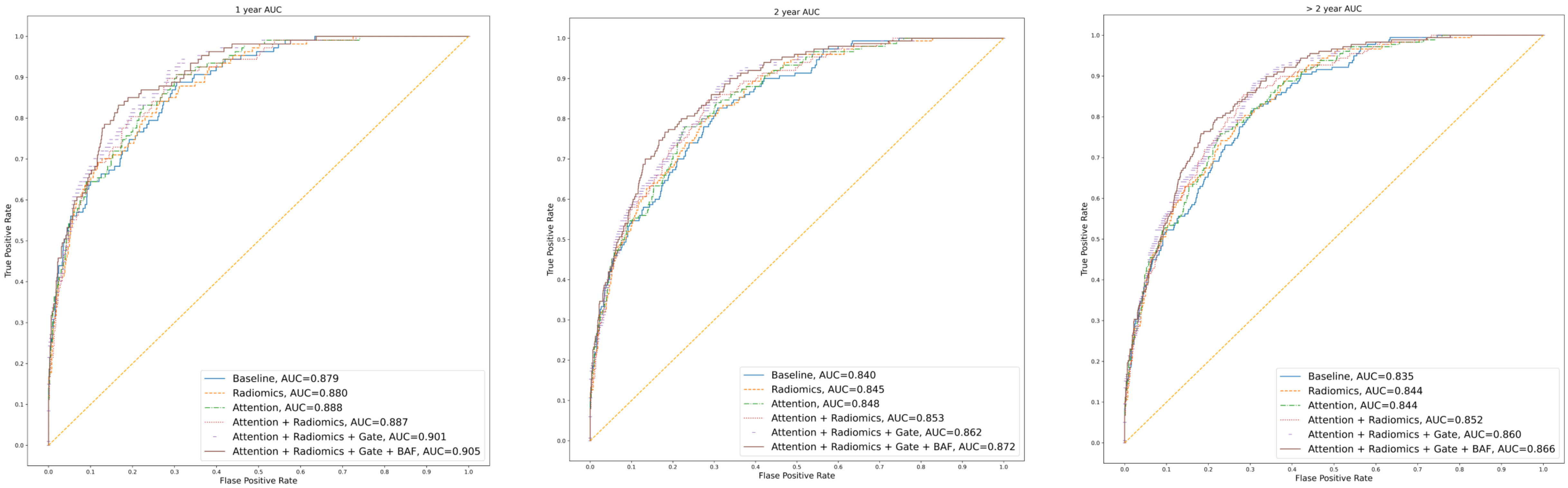


Fig. 1: ROC curves of ablation study results corresponding to 1-year, 2-year and >2-year AUC categories

Scientific Contribution: Submitted journal paper

Since the project has only been running for 6 months, we do not yet have a scientific contribution (international conferences and journal articles).

However, we have submitted a Journal Paper:

No:	Paper title:	Author names	Affiliations	Journal name:	The publisher of the Journal	The volume number and Pages
1	A multi-radiomics deep learning based breast cancer risk prediction model using sequential mammographic images with image attention and bilateral asymmetry refinement	Hong Hui Yeoh, Andrea Liew, Raphaël Phan, Fredrik Strand, Kartini Rahmat, Tuong Linh Nguyen, John L. Hopper, Maxine Tan	Monash University Malaysia, Karolinska Institute, University of Malaya, The University of Melbourne	Engineering Applications of Artificial Intelligence	Elsevier	Submitted

Societal Impact

Societal impact of project:

- Breakthrough towards early cancer detection
- Risk assessment model for individualized risk
- Personalized screening recommendations for women
- Reduced patient mortality rates
- Reduced false-positives, over-diagnosis and high healthcare costs through unnecessary biopsies, etc.

Conclusion

Conclusions:

- Using attention-based multiple sequential screenings improves risk prediction performance
- New radiomics features improves overall performance
- New gating mechanism effectively combines both CC and MLO views
- Bilateral asymmetry fine tuning improves model generalizability
- On comprehensive screening dataset consisting of 8,723 patients (34,892 mammograms), new risk model outperforms state-of-the-art methods in literature

Future Work

Future work:

- We duplicated missing screening mammograms in the dataset (due to patients not going for regular screening)
  - Evaluate our model's performance on larger datasets
- Cases in category 1: Patients diagnosed with cancer at <= 60 days from screening – Presented as 1-year AUC results
  - Omit these cases: Perform future studies with bigger datasets
- If possible, perform clinical testing on model's utility and impact in assisting radiologists