Variable-View Multi-Instance Learning for Breast Cancer Diagnosis on Mammograms

ZGT Science Day 2022

Shreyasi Pathak
PhD candidate

Supervisors:
Prof. Dr. Christin Seifert (UT, UDE), Dr. Ir. Maurice van Keulen (UT), Dr. Jörg Schlötterer (UDE)
Drs. Onno Vijlbrief (ZGT), Dr. Han Hegeman (ZGT), Ing. Jeroen Geerdink (ZGT)

Universitätsmedizin Essen
Institut für KI in der Medizin (IKIM)

zgt
Topzorg voor uw levenskwaliteit

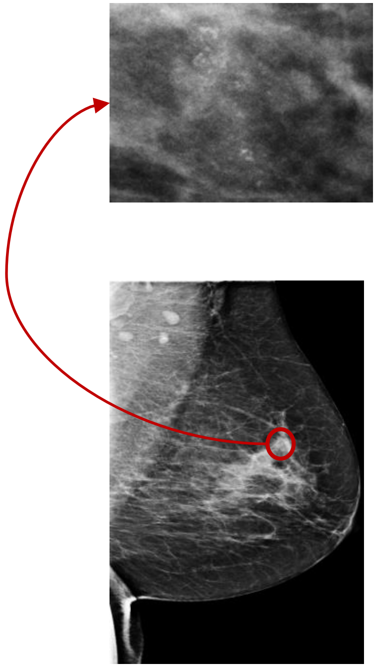
UNIVERSITY OF TWENTE.

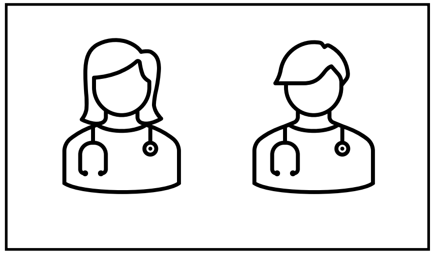
Disclosure-slide voor sprekers op nascholingsbijeenkomsten

Disclosure belangen spreker	
(potentiële) Belangenverstrengeling	✓ Geen / Zie hieronder
Voor bijeenkomst mogelijk relevante relaties met bedrijven[1]	**Bedrijfsnamen**
• Sponsoring of onderzoeksgeld[2] • Honorarium of andere (financiële) vergoeding[3] • Aandeelhouder[4] • Andere relatie, namelijk …[5]	• • • •

Vision

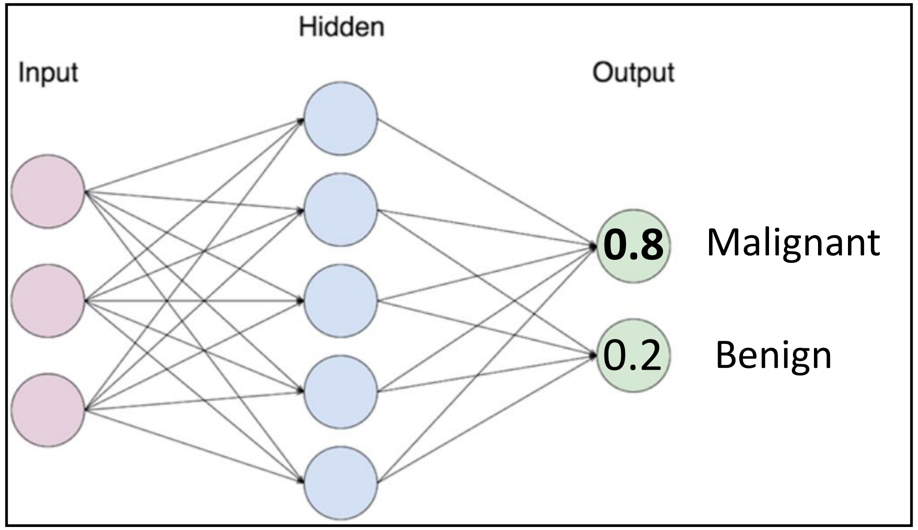
How can machine learning help doctors for breast cancer identification?





Assumption: Mammogram alone can identify malignancy

Malignant/Benign

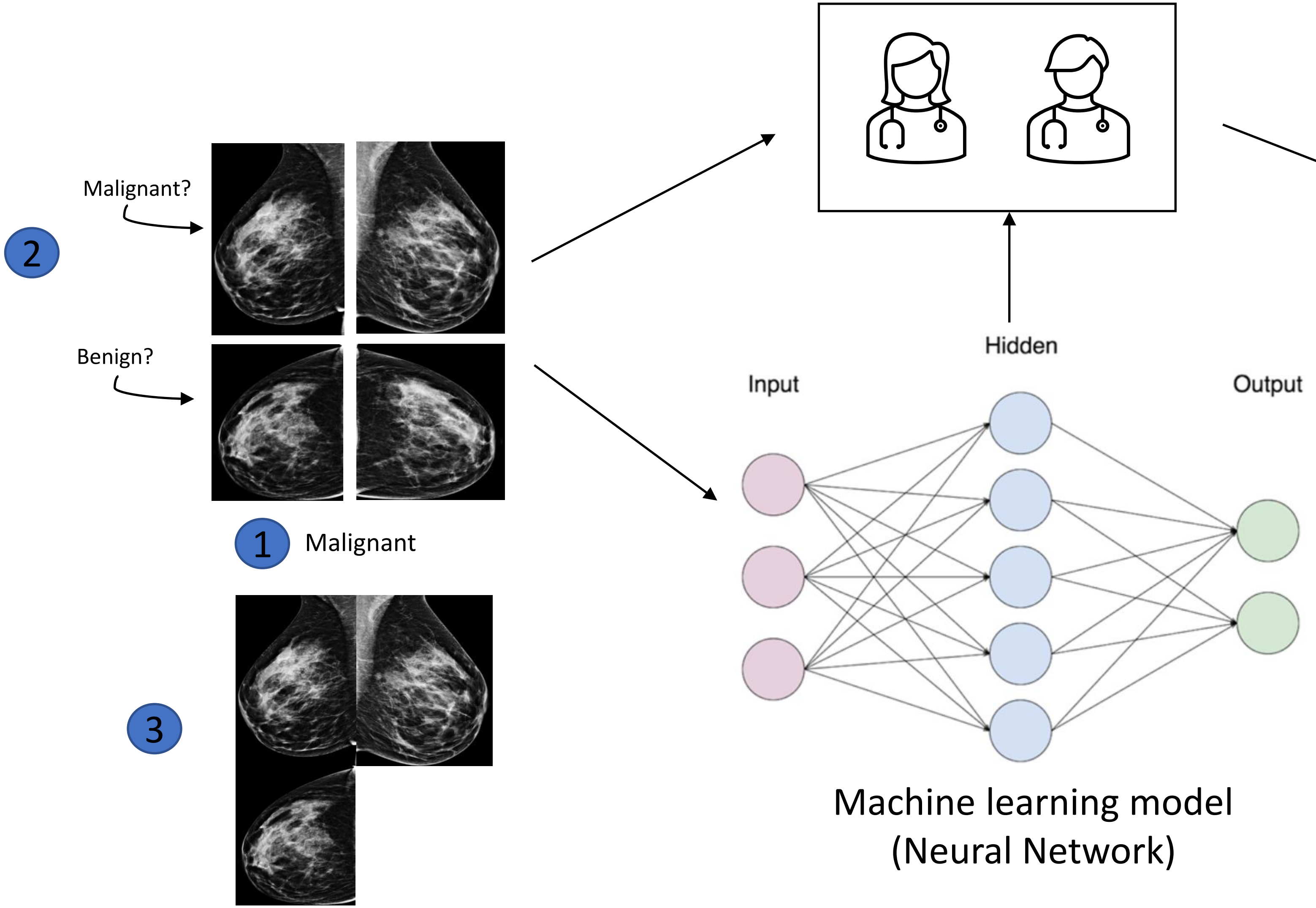


Machine learning model
(Neural Network)*

A machine learning model could help in reducing the workload of the doctors!

Challenges

What happens in a real-world hospital setting for breast cancer prediction?



Machine learning model
(Neural Network)

Real-world challenges for creating a machine learning:

1 *We have case-level labels and not image-level labels.*

2 *Malignancy may not be visible in all images in a case*

3 *Variable number of images per case*

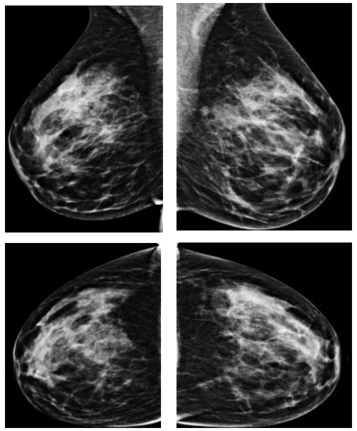
Introduction

Gap with related work, Goal & Dataset

Goal

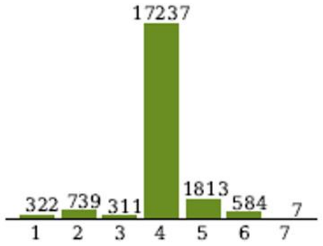
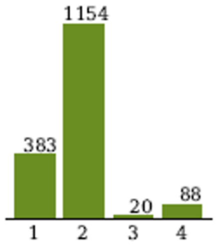
Predict the probability of breast cancer (malignant or benign) in a realistic setting

1. *We have case-level labels and not image-level labels.*
2. *Malignancy may not be visible in all images in a case*
3. *Variable number of images per case*



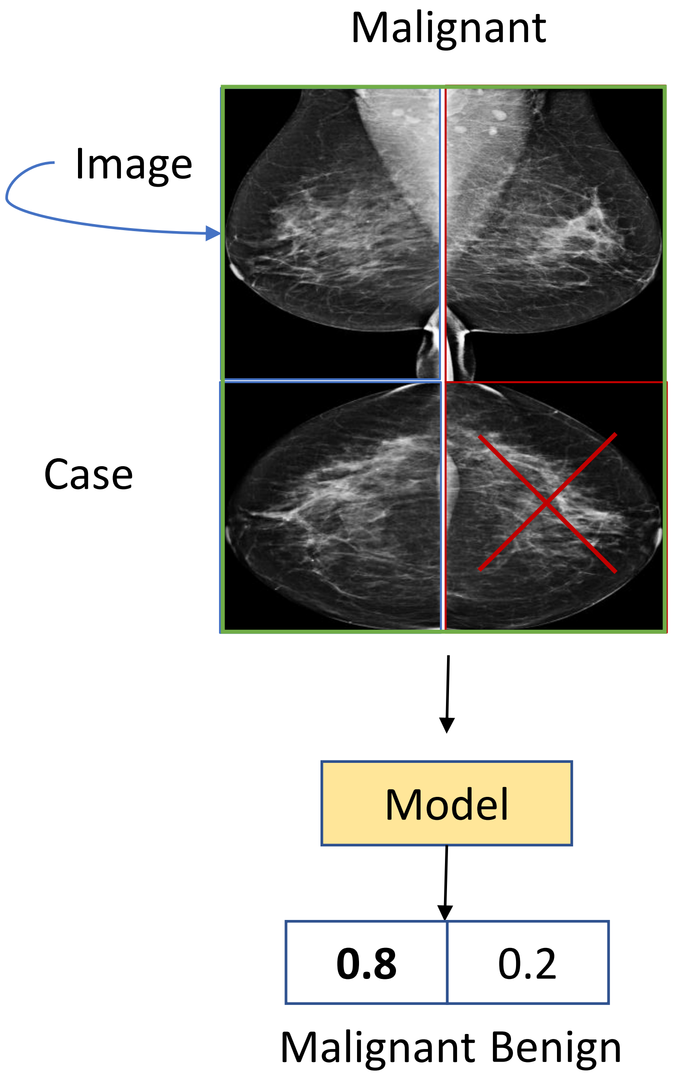
Malignant

Dataset

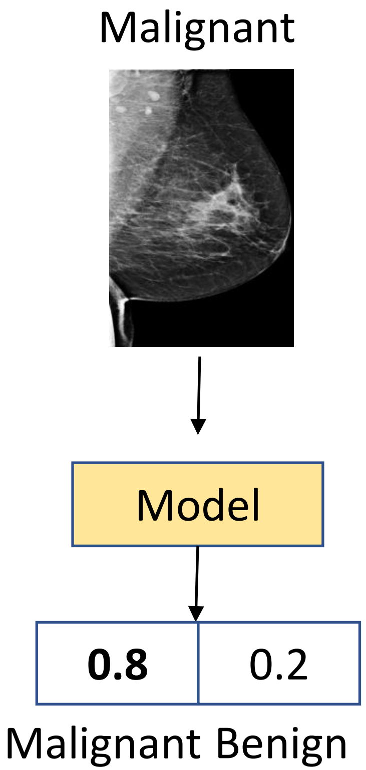
	ZGT	**CBIS-DDSM**
Cases	21,013	1,645
Images per case distribution		

Methodology

Single-instance learning vs Multi-instance learning



Variable-view
Multi-instance
learning

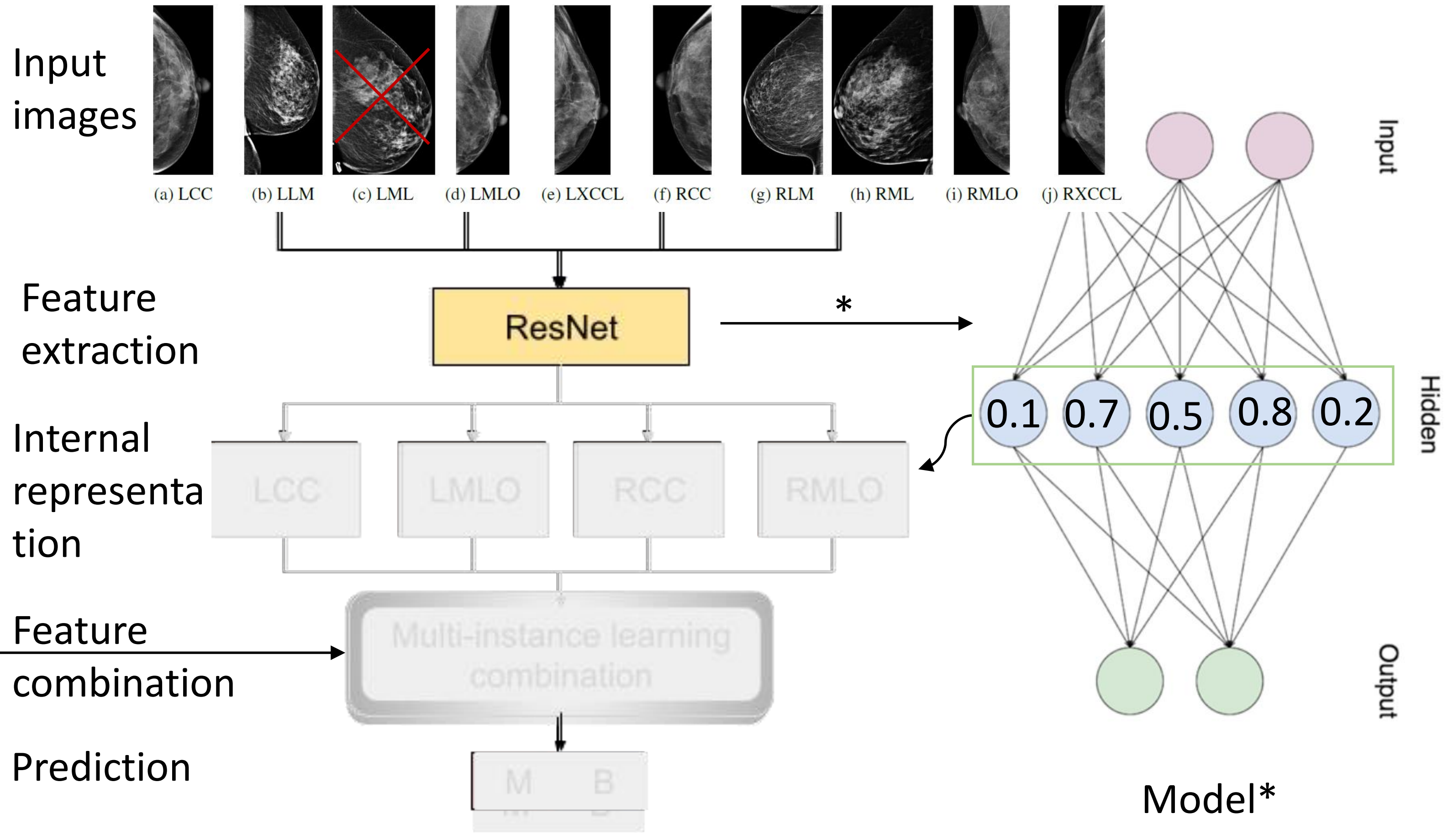


Single-instance
learning

Methodology

Multi-instance model

1. *We have case-level labels and not image-level labels.*
2. *Malignancy may not be visible in all images in a case*
3. *Variable number of images per case*



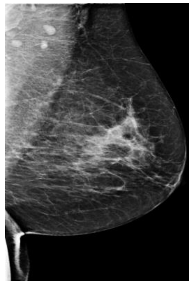
Model*

*This is a simplistic figure. ResNet are more complex with more hidden layers.

Evaluation of our model

Performance score

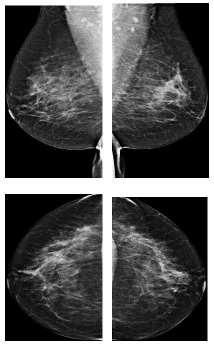
Single-instance Model
Malignant



Model

0.8	0.2
Malignant	Benign

Multi-instance Model
Malignant



Model

0.8	0.2
Malignant	Benign

score 1 is best and 0 is worst

Model	ZGT F1	CBIS-DDSM F1
Single-instance: per-image label (our)	-	0.61 ± 0.03
Single instance: per-image label = case label (our)	0.39 ± 0.02	0.62 ± 0.04
Multi-instance model (our)	**0.54** ± 0.02	**0.64** ± 0.01
Baseline multi-instance model [1]	0.45 ± 0.02	0.58 ± 0.02

We found case labels to be sufficient for breast cancer prediction, suggesting that image-level annotation may not be needed.

[1] *Kim, Eun-Kyung, et al. "Applying data-driven imaging biomarker in mammography for breast cancer screening: preliminary study." *Nature Scientific reports* 8.1 (2018): 1-8.

Conclusion

1. We developed a breast cancer prediction model for mammogram cases.

2. One of the first works to create a breast cancer prediction model on realistic scenario **without excluding any image type/view**. (this work is currently under review for publication)

3. Associated Challenges:
   1. Extracting good quality dataset from the hospital is very hard
   2. Real world dataset is very different from simple dataset (like cats/dogs dataset).
   3. Interpretability: How do you explain the reasoning behind the model's decision?

4. Future work: We are investigating the reasoning behind the model's prediction.

This work would not have been possible without!

Universitätsmedizin Essen
Institut für KI in der Medizin (IKIM)

zgt
Topzorg voor uw levenskwaliteit

UNIVERSITY OF TWENTE.

Prof. Dr. Christin Seifert
IKIM, UDE, DE

Dr. Ir. Maurice van Keulen
DMB group, UT, NL

Dr. Joerg Schlötterer
PostDoc, IKIM, UDE

Cross-country collaboration

Very thankful to all the people, especially to ZGT for all the support and funding,
for being enthusiastic in doing innovative work!

Happy to be part of the team!

Drs. Onno Vijlbrief
Neuro Radiologist, ZGT

Drs. Rob Bourez
Breast Radiologist, ZGT

Dr. Jeroen Veltman
Breast Radiologist, ZGT

Dr. Danny Evers
Oncology Surgeon, ZGT

Dr. Han Hegeman
Trauma Surgeon, ZGT

Ing. Jeroen Geerdink
Innovation Manager, ZGT

Sander ten Hoeve
PACS Admin, ZGT

Raymond Bouwman
IT, ZGT

Erik Butterhoff
IT, ZGT