

Bayesian Network Framework for Mammographic Multi-View Analysis

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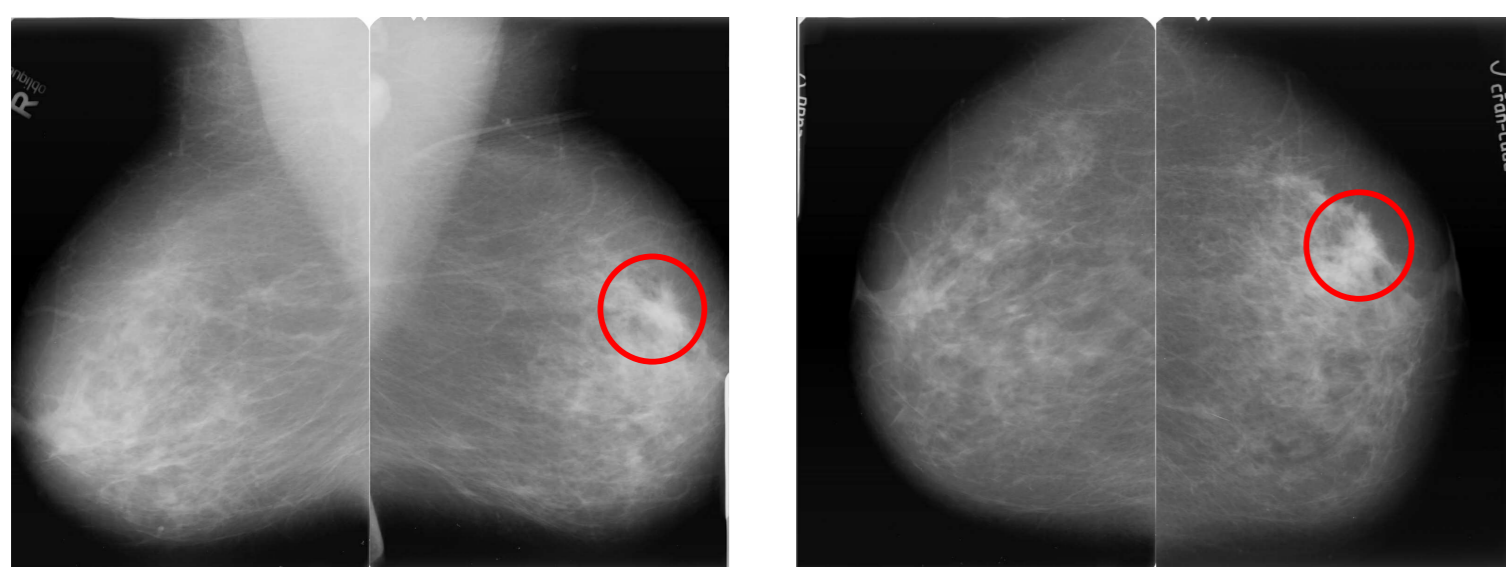
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Problem definition

In reading mammograms, radiologists judge for the presence of a lesion by comparing at least two breast projections (views) as a lesion is to be observed in both of them. Most computer-aided detection (CAD) systems, on the other hand, treat single views independently and thus they fail to account for the interaction between the breast views. This limits the usability and the trust in the performance of such systems.

Mammography: CANCEROUS CASE



Mediolateral oblique (MLO) view Cranio-caudal (CC) view

Aims

We propose an approach for exploiting mammographic multi-view dependencies based on a Bayesian network framework to improve the breast cancer detection rate at a case level upon a single-view CAD system.

The main idea is to model the context information about each breast, represented as the regions detected by a single-view CAD system in MLO and CC, to obtain a single likelihood measure for a case being cancerous.

Bayesian networks

Definitions. A Bayesian network $BN = (G, P)$ is defined as an acyclic directed graph $G = (V, E)$ with set of nodes V , corresponding to a set of random variables, and set of arcs E , representing the direct causal relationships between the variables.

Causal independence. Causal independence arises in cases where multiple causes (parent nodes) lead to a common effect (child node). The approach described in [1] is a way of representing causal independence by qualitative encoding within the network structure.

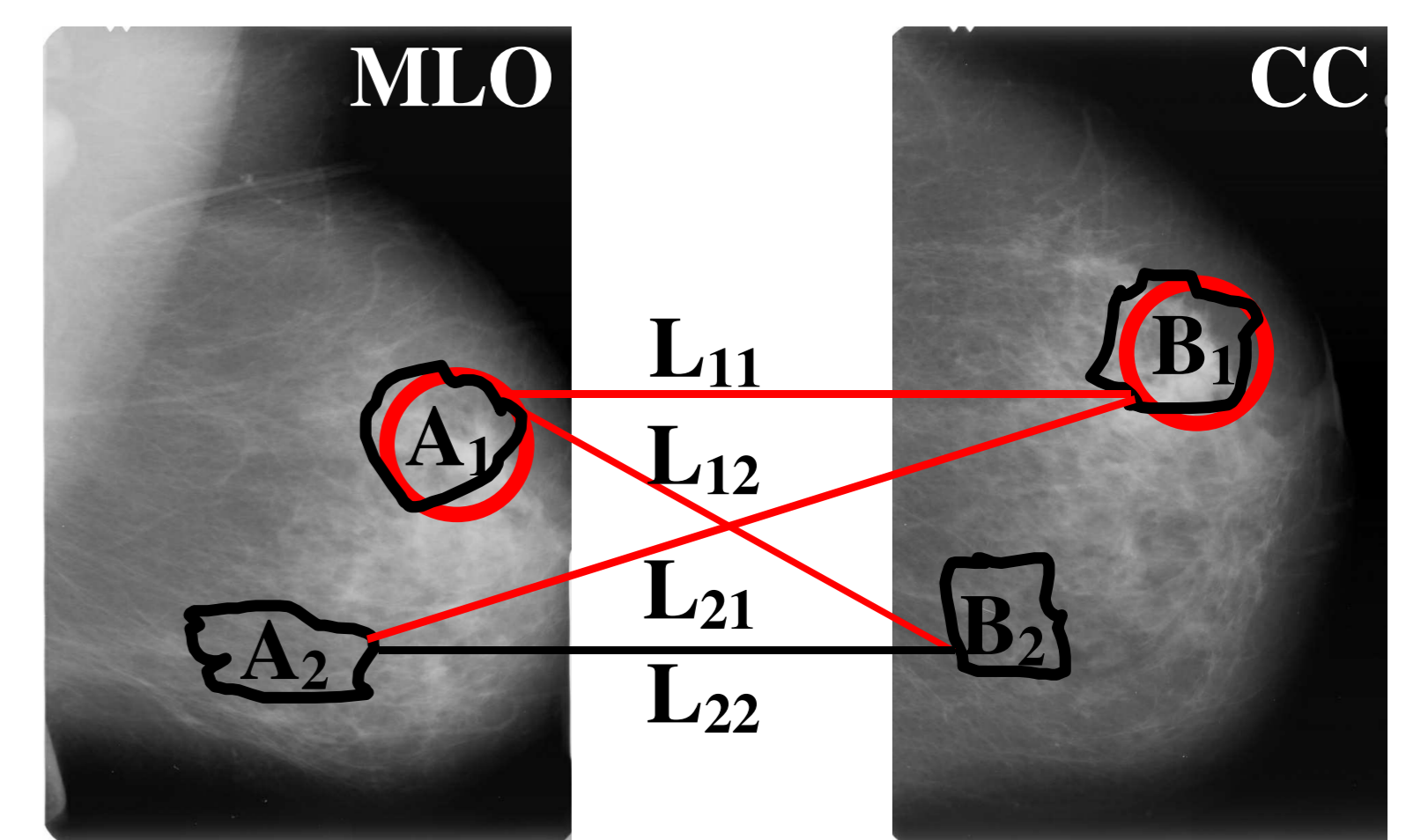
Conclusions

The experimental results demonstrated the superiority of the Bayesian network multi-view framework over the single-view CAD system in terms of a better breast cancer detection rate. This is due to the incorporation of expert knowledge which is done by: (1) defining links between the regions detected by the single-view CAD system in MLO and CC views and (2) building a probabilistic causal model where all detected regions with their feature vectors and the established region links are considered simultaneously.

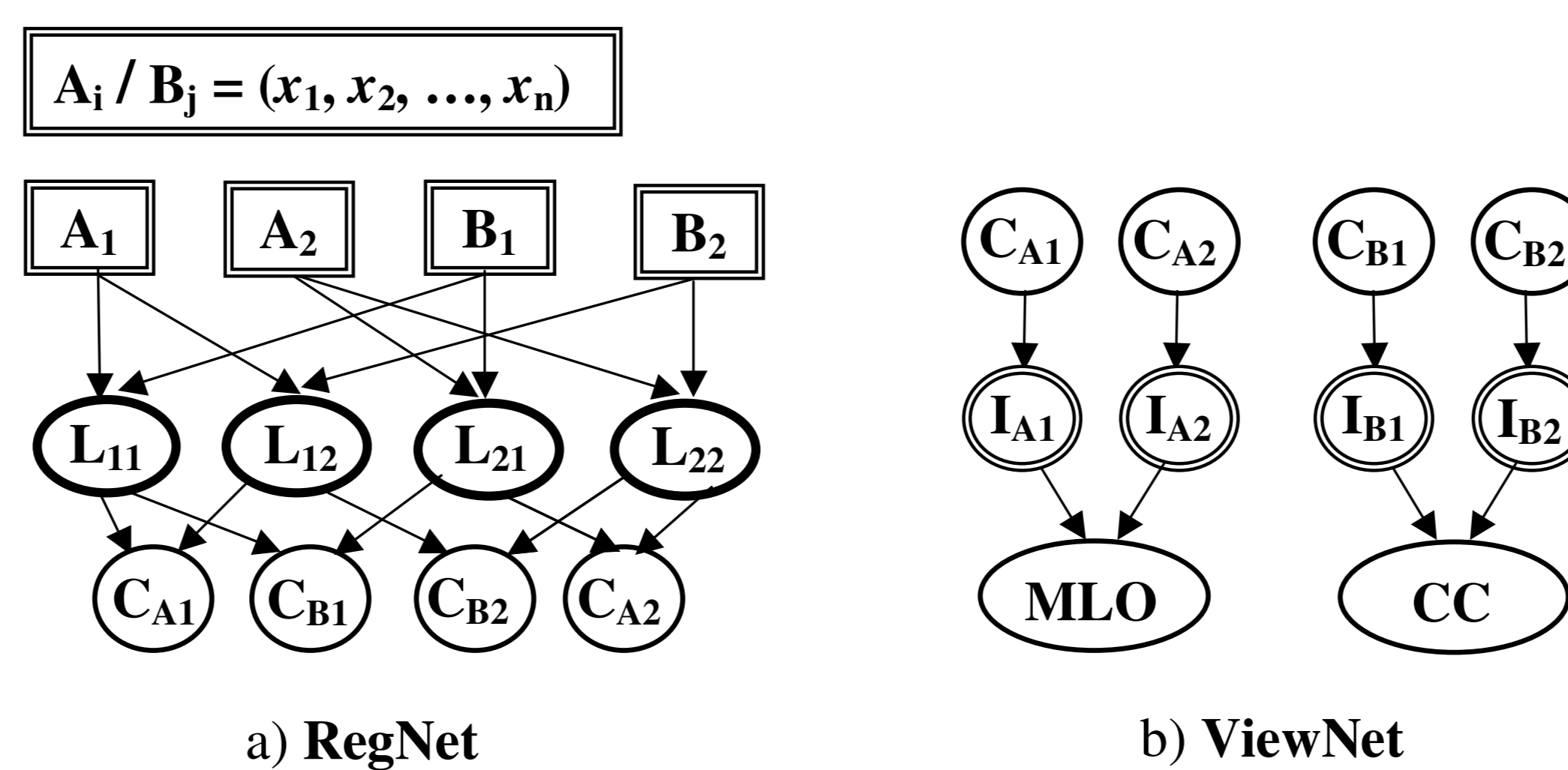
Bayesian multi-view analysis

Automatic multi-view analysis scheme. In both views a single-view CAD system detects potential cancerous regions: A_1 and B_1 are correct detections of the cancer, i.e., true positive (TP) regions whereas A_2 and B_2 are false positive (FP) regions. A lesion (represented by the red circles in both projections) is present in the breast and thus, the whole breast is cancerous. We introduce links (L_{ij}) between A_i and B_j to model view dependencies. Every link has a binary class $L_{ij} = \ell_{ij}$ with

$$\ell_{ij} = \begin{cases} true & \text{if } A_i \text{ OR } B_j \text{ are TP,} \\ false & \text{otherwise.} \end{cases} \quad (1)$$



Bayesian network multi-view framework (MultiView)



RegNet: A_i/B_j are vectors of real-valued features x_n extracted from the single-view CAD system. Logistic regression is used to compute $P(L_{ij} = true|A_i, B_j)$. Given (1), we use the logical OR to compute $P(C_{Ai} = true|L_{ij} = \ell_{ij})$ and $P(C_{Bj} = true|L_{ij} = \ell_{ij})$, where C_{Ai}/C_{Bj} is the class of A_i/B_j .

ViewNet: The computed region probabilities from RegNet are combined for each view through the logical OR to obtain the probability of the view being true.

Breast probability $P(Br = true|MLO, CC)$:

- Average(MLO, CC) (Avg)
- Logistic regression(MLO, CC) (LR)

Case (patient) probability $P(Case = true|LeftBr, RightBr)$:

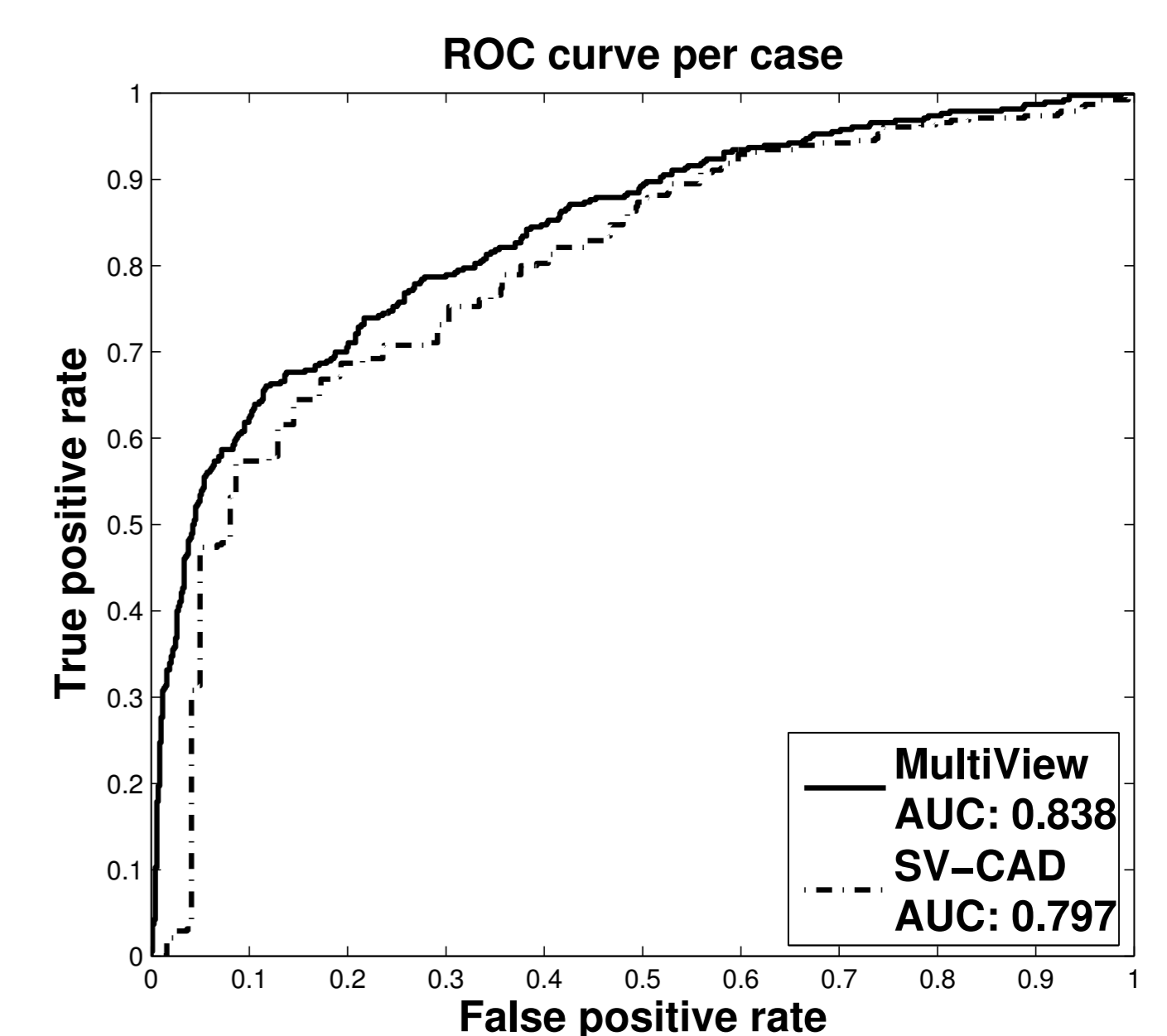
- $\max(LeftBr, RightBr)$ (Max)
- $|LeftBr - RightBr|$ (Diff)

Application

Breast cancer data. The dataset contains 1063 mammographic exams (cases) from which 383 are cancerous. For each mammogram the 5 most suspicious regions obtained from the single-view CAD system are selected. Every region is described by a set of 11 real-valued features (e.g., contrast, size, location).

Results. The evaluation is done in comparison to the single-view CAD system (SV-CAD) ([2]) using the Area Under the Curve (AUC).

Method	Breast	p -value	Case	p -value
SV-CAD	0.850	–	0.797	–
MultiViewAvg-Max	0.864	0.123	0.827	0.135
MutliViewLR-Max	0.875	0.001	0.832	0.014
MultiViewLR-Diff	0.875	0.001	0.838	0.006



References

- [1] P.J.F. Lucas. Bayesian network modelling through qualitative patterns. *Artificial Intelligence*, vol. 163, pp. 233–263, 2005
- [2] S. Van Engeland, S. Timp, N. Karssemeijer. Finding corresponding regions of interest in mediolateral oblique and craniocaudal mammographic views. *Medical Physics* 33(9), pp. 3203–3212, 2006

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