

The role of Bayesian Belief Networks in medical diagnosis applications

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Introduction

Bayesian Belief Networks (BBN) were first described by Julian Pearl in the 1980's based on the work of Rev. Bayes involving conditional probability and expected outcomes based on prior or expert knowledge.

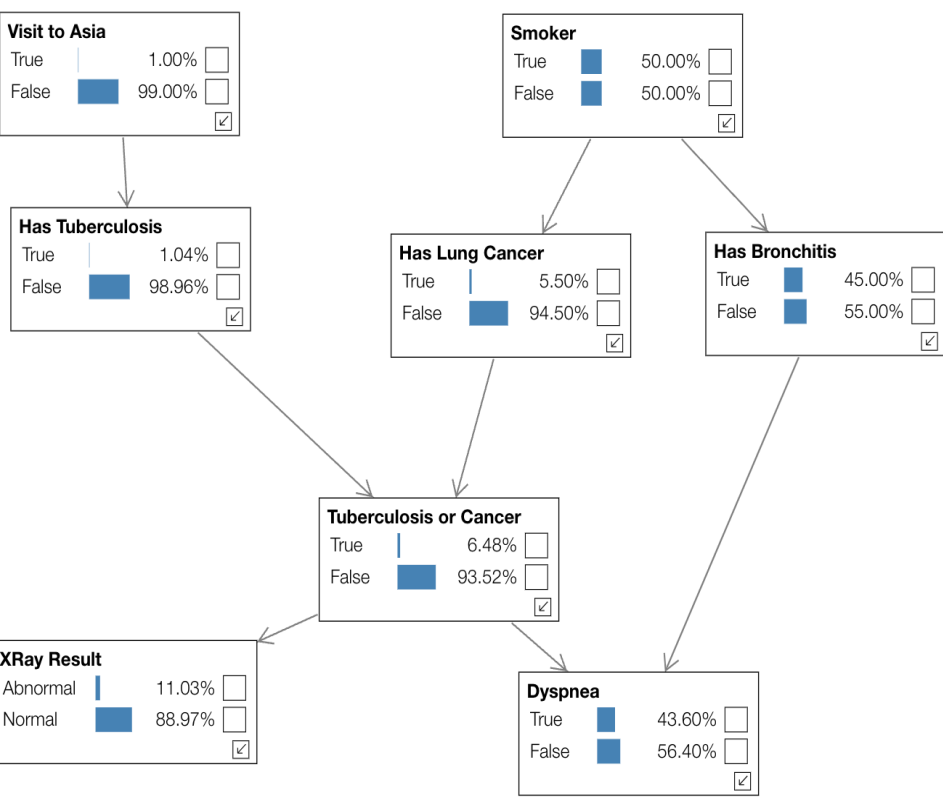
BNN's provide graphical models which represent conditional relationships using the probability between variables of interest, giving the causal relationship between the two variables. Broadly speaking BNN's consist of two key elements:

Qualitative – the links (arcs) drawn between variables of interest (nodes)

Quantitative – inference of the impact one variable has on another based on its state

When finished this gives a direct acyclic graph (DAG) with nodes and arcs (Figure One)

Each node has an attached probability distribution table, which is dependent on the parent node and can be based on previous study data, expert knowledge or hybrid (Gadewadikar et al. 2010)



Bayesian Statistics

In a clinical application of Bayesian statistics:

$$P(\text{disease} \mid \text{finding}) = \frac{P(\text{finding} \mid \text{disease}) P(\text{disease})}{P(\text{finding})}$$

Probability a disease is present in a finding - $P(\text{disease} \mid \text{finding})$
Probability of finding a given disease - $P(\text{finding} \mid \text{disease})$
Probability of disease - $P(\text{disease})$
Probability of a finding - $P(\text{finding})$

Example (Gadewadikar et al. (2010):
Probability of Smallpox if spots are present,
 $P(\text{smallpox} \mid \text{spots})$

Probability of spots a given Smallpox -
 $P(\text{finding} \mid \text{disease}) = 0.9$
Probability of Smallpox (general pop.) -
 $P(\text{disease}) = 0.001$
Probability of spots (general pop.) -
 $P(\text{finding}) = 0.081$

$$P(\text{smallpox} \mid \text{spots}) = \frac{(0.9 * 0.001)}{0.081} = 0.011$$

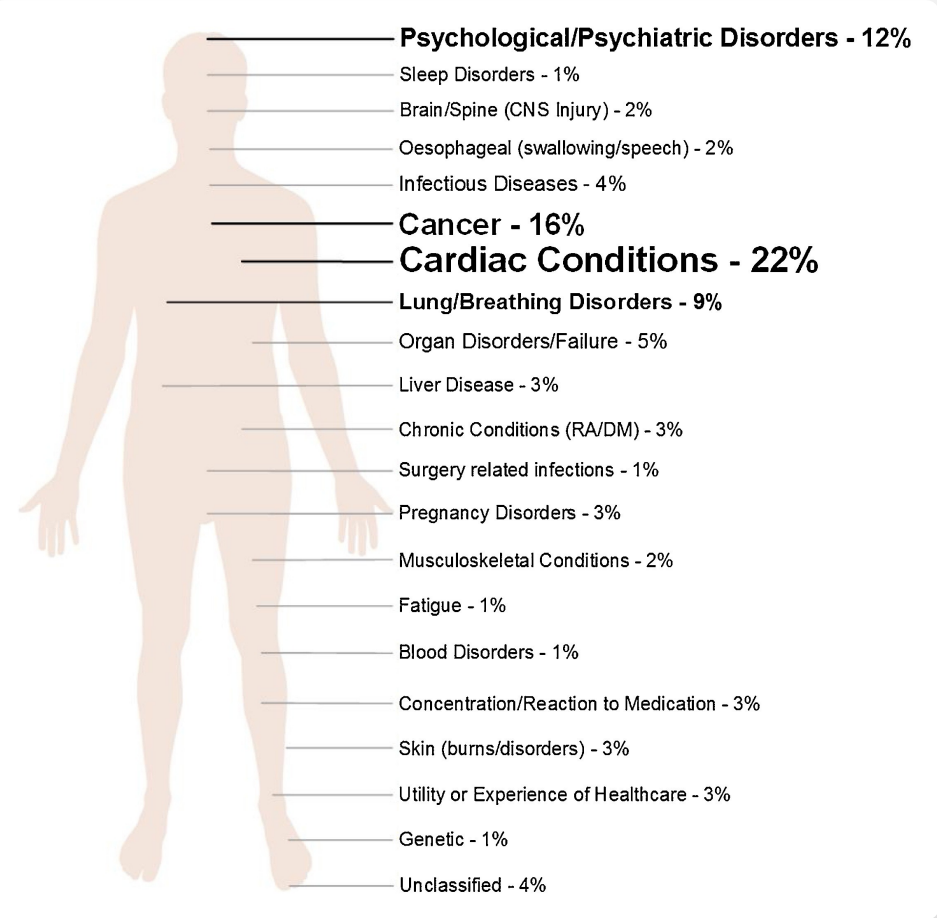
Medical Industry adoption of BBN's

A systematic review by McLachlan et al. 2020 reviewed the literature to assess the distribution by medical condition of published BBN's. Following filtering to only include:

- Post 2012
- Written in English
- Those which did not provide a BBN

After the exclusion process 123 papers were included. The top themes include cancer, lung psychological, and cardiac diseases (Figure 2).

When compared to Zemouri et al. 2019 reviewing Deep Learning (DL) in medical applications who found that in 2019 alone 8000 papers were published which included DL, though it is not clear if the same exclusion / inclusion criteria was employed. Though this does offer support to the conclusion by McLachlan et al 2020 that BBN's are 'drowned out' in the literature and consideration within the medical artificial intelligence arena.



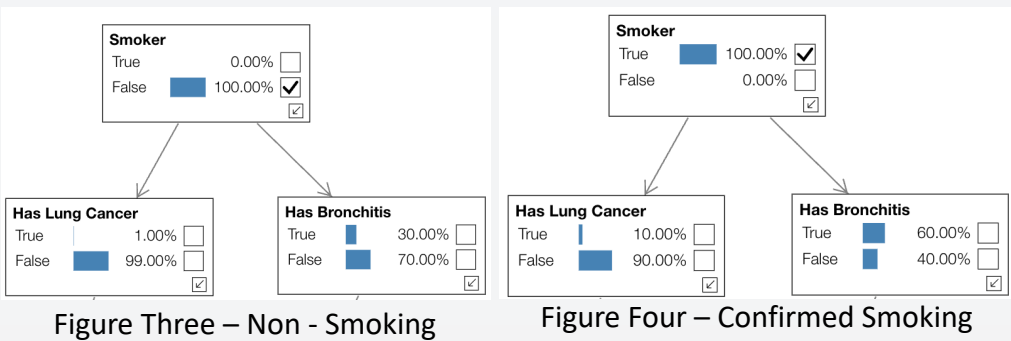
Utilising BBN's for patient education

BNN's show promise to facilitate patient education when having to consider complicated information regarding health choice options and probabilities of expected outcomes. Fagerlin et al. 2011 published a ten step guide to help clinicians improve patient understanding of complex issues concerning their health and likelihood of the available options.

Using the Lauritzen and Spiegelhalter (1988) Asian Bayesian network for lung disease. Demonstrated in Figures 1,3,4:

Smoking status unknown – Lung Cancer Risk - 5.5%
Known no smoking status – Lung Cancer Risk - 1%
Known smoking status – Lung Cancer Risk – 10%

This demonstrates an example of patient education regarding their possible smoking status. Using the format described by Fagerlin et al. 2011, patient education could be enhanced by using a BBN DAG which can quickly show the conditional probabilities of different smoking status's to the patient and the likelihood of outcomes to their future health.



Conclusion

BBN's are often under utilised and 'drowned out' by Machine Learning and Deep Learning. BBN's demonstrate clear causal inference, produce easy to understand graphical models and show potential in the patient educational setting.

References

- Fagerlin, A., Zikmund-Fisher, B.J. and Ubel, P.A. (2011). Helping Patients Decide: Ten Steps to Better Risk Communication. JNCI Journal of the National Cancer Institute, [online] 103(19), pp.1436–1443
- Gadewadikar, J., Kuljaca, O., Agyepong, K., Sarigul, E., Zheng, Y. and Zhang, P. (2010). Exploring Bayesian networks for medical decision support in breast cancer detection. African Journal of Mathematics and Computer Science Research, 3(10), pp.225–231.
- Lauritzen, S. and Spiegelhalter, D. (1988) Local Computations with probabilities on graphical structures and their application to expert systems. Journal of the Royal Statistical Society: Series B (Methodological). 50 (2)
- McLachlan, S., Dube, K., A Hitman, G., Fenton, N. and Kyrimi, E. (2020). Bayesian Networks in Healthcare: Distribution by Medical Condition. Artificial Intelligence in Medicine
- Zemouri, R., Zerhouni, N. and Racocceani, D. (2019). Deep Learning in the Biomedical Applications: Recent and Future Status. Applied Sciences, 9(8), p.1526.