Real-time Online Probabilistic Medical Computation using Bayesian Networks

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***Abstract*— Advances in both *computing power* and novel *Bayesian inference algorithms* have enabled Bayesian Networks (BN) to be applied for decision-support in healthcare and other domains. This work presents CardiPro, a flexible, online application for interfacing with non-trivial causal BN models. Designed especially to make BN use easy for less-technical users like patients and clinicians, CardiPro provides near real-time probabilistic computation. CardiPro was developed as part of the PamBayesian research project (www.pambayesian.org) and represents the first of a new generation of online BN-based applications that may benefit adoption of AI-based clinical decision-support.**

Keywords—Bayesian networks, Healthcare, mHealth

I. Introduction

Prior to the 1990's and outside of a small group of dedicated theorists and statisticians, Bayesian methods remained largely ignored [1]. It is only since and arising out of the development of novel inference algorithms [2, 3] for Bayesian networks (BNs) and computer processors capable of mathematically intense calculation that near real-time complicated Bayesian computation has become possible for a large class of significantly complex problems [1, 4]. With the computational frontier attained, there is a growing movement toward bringing Bayesian prediction onto the domain of online and mobile electronic health (mHealth) applications. Issues of complexity, inconvenience, user unfriendliness and the processor-intensive requirements of BNs have made mobilising them difficult, with those online BN solutions that are observed either presenting as an HTML-veneer that does little to mitigate these issues, or limited to very simplistic *single-layer models* only capable of computing a single child node, as shown in [5]. We believe that to be effective, any approach to *real-time online* Bayesian computation should seek to be computationally lightweight, capable of on-the-fly prediction, and accessible to patient and clinician alike using existing common consumer technology. This paper proposes an approach, a practical architecture and functional design for developing online Bayesian-based eHealth applications. It goes on to present CardiPro, an application designed as part of the EPSRC-funded PamBayesian Project [6] that demonstrates and evaluates our approach using two Bayesian models: (1) a simple model for diagnosis of Angina, and (2) a more complex trauma care model for assessing patient condition and coagulopathy.

II. Fundamental Concepts, Terms and Motivation

This section considers the fundamental questions a reader might be expected to ask of the theoretical background behind this work and the solution proposed. It provides background, and in some cases motivation, for each of the highlighted questions.

Why Bayesian?

Absent of theorem, formula, and in many cases even the Bayesian name, hypothesis evaluation through Bayesian reasoning has long been taught to medical students [7]. The classical approach to clinical evaluation and medical reasoning is naturally Bayesian [8]. The process of differential diagnosis sees new knowledge considered as a modifier that updates the clinician's prior belief, which itself was based on assessment of previous knowledge regarding whether the patient has the target disease [8, 9]. Rather than observing new information in isolation, or as absolute, the Bayesian asks: *Given my prior belief and these symptoms and test results, what is the probability that the person actually has the disease?* [8, 9].

Why Computerised Clinical Decision Support?

The quantity of literature proposing novel computer-based clinical decision support system (CDSS) solutions has continued to grow in recent years [10, 11]. At the same time, the number of mobile health (mHealth) apps being proposed as CDSS has also increased [12]. Computerised CDSS can improve the overall practice of medicine and patient outcomes [13, 14]. At their most basic, computerised CDSS support evidence-based decision-making by healthcare professionals [13]. When developed in furtherance of a Learning Health System (LHS), they go beyond evidence-based medicine (EBM) and advance the practice of precision medicine [15].

Why Online?

Increasing patient participation and engagement in monitoring their own health and healthcare is a national goal [16]. Patient engagement has been described as the *blockbuster drug of the century*: capable of reducing hospital and clinician resource use and significantly reducing the impact of chronic disease and therefore improving quality of life [17]. While patient engagement is described in terms of participation in the care process, patient empowerment goes further to elevate the patient's power in their relationship with the healthcare professional [18]. Engagement is necessary to enable empowerment, and it is through empowerment that the patient can attain sufficient power to properly engage in self-care [18]. Availability and use of online eHealth applications significantly increases patient empowerment, promotes collaboration and as a result of their interaction with these tools, patients are more likely to make positive health choices [19, 20]. Computerised CDSS are more successful when they involve both clinician and patient, most likely resulting from empowerment of patients as active participants in their own medical care [14].

III. The Challenge of a Realtime Online Bayesian Solution

Traditionally, the focus of BN tools has been on helping modellers design BNs through a graphical interface and performing efficient inference. These tools never really focused on the concept of making it easy to deploy BNs for the general user. However, recently, several commercial and other BN tool developers have proposed web-based solutions with varying levels of complexity, functionality and efficiency. These include:

- **ShinyBN** by Chen et al [15] This requires several partner applications to function. It adds a Web interface layer to the process of creating BNs and all input requires uploading or declaring a carefully structured table of data for the entire model.
- **BN Webserver (BNW)** by Ziebarth et al [16]. This focuses on learning BN models from data and also using the resulting BN models for predictive tasks.
- **Bayesian Net BBToolbox** In 2001 the developers of (BNT) and OpenBayes set themselves a goal for a future version that could *support online inference and learning* [17]. The latest online BNT application layer still performs these as *offline* or *batch processed* tasks. [18]
- **Genie and SMILE**: Jognsawat et al [5] proposed a model using GeNIe as the base upon which they layer their own tool, SMILE, for online real-time computation. Their approach works with simplistic single-layer models where a number of single parent nodes all feed into a single discrete child node.
- **Netica-Web**: This allows deployment of BNs as an online question-answer system.
- **BayesiaLab WebSimulator**. This allows publication of interactive models online [19].
- **AgenaRisk**: The current enterprise version provides some support for web-deployment.

The work reported in this paper provides a new approach to BN web deployment that supports complex models with near real-time computation, enables non-specialist users both to easily deploy and use the models, and requires only one partner application (AgenaRisk).

Recommendations for consideration by those seeking to develop truly online Bayesian approaches arise out of the work of Martinez-Perez et al [12] who identify that: (1) images are useful and as such, CDSS should avoid using text-only or data-focused interfaces; (2) the time a user requires to interact with the CDSS is a key factor: that to reduce it the CDSS should be integrated with the EHR; (3) there is a need to use incremental forms to reduce the amount of manual input for the user; (4) more interaction with the user is important and interactivity with smartphones is one way to achieve this; (5) developers should develop mHealth apps for underexplored medical conditions that have fewer of these type of CDSS apps. This paper subscribes to these recommendations.

IV. Approach and Design: *Overview of the Proposed Solution*

This section presents the architectural and functional design that would address the challenges presented in the previous section and that is evaluated through the CardiPro system. The section also presents the algorithms used to achieve the major functionality of the system.

A. *Solution Architecture*

Figure 1 provides an overview of the proposed solution architecture for CardiPro. The rest of this subsection describes the core components of this architecture, namely, *the*

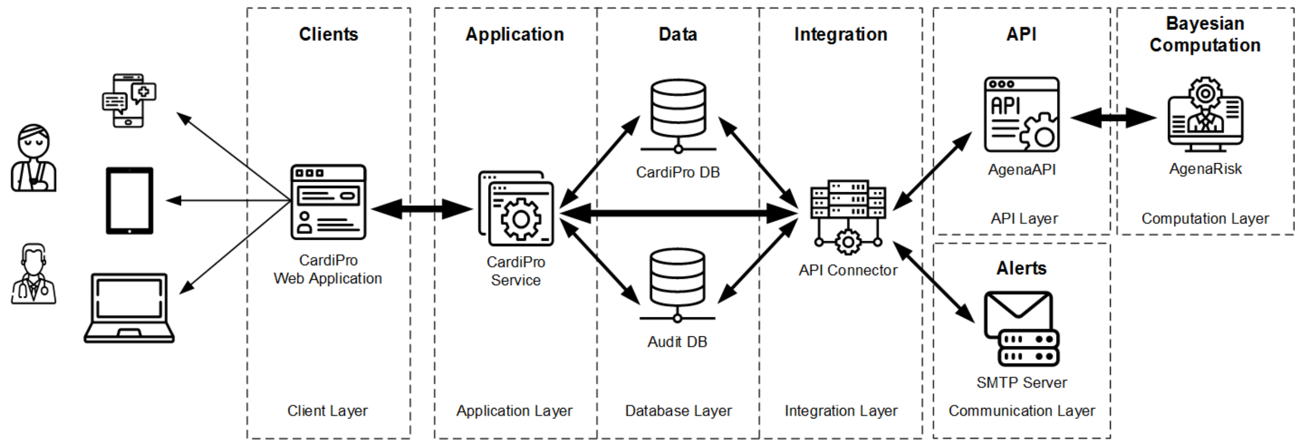

Fig. 1. Overview of the Solution Architecture

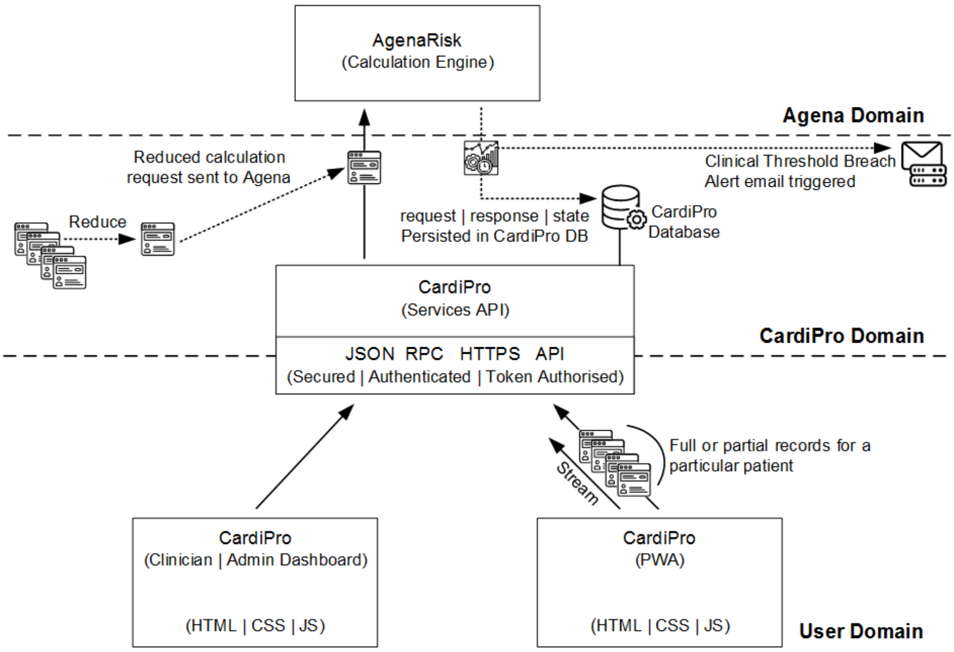

Fig. 2. CardiPro Functional Topology

CardiPro system, *the AgenaRisk Cloud API* (AgenaAPI), and *the Client.*

The CardiPro System: Consists of the front- and back-end systems necessary to host and support the CardiPro solution. Our design for the CardiPro solution presents with five tiers represented as layers within Figure 1. These layers are as follows:

1. *Application Layer* containing the CardiPro application server which hosts the CardiPro Service which performs all of the processing and logical functions of the overall solution.
2. *Database Layer* where information is stored to and retrieved from. All logic functions and computational processes within the overall solution generate data that is recorded against the relevant anonymous patient in the CardiPro database, while all user authentication, access and activities are reported in the audit database.
3. *Integration Layer* that computes a *reduced calculation request* that includes either a full or partial patient record in a predefined JSON format which is passed by the API Connector to the AgenaAPI. It also receives the computed probabilities response from AgenaRisk.
4. *Client Layer* which presents the user interface for CardiPro to user devices, allowing clinicians researchers and patients to provide data to and interact with the complete solution stack.
5. *Communication Layer* which transmits alerts via email to clinicians and patients where a prediction falls outside a clinician-defined threshold.

The AgenaRisk Cloud API: The AgenaRisk component consists of two tiers provided by AgenaRisk Ltd. The AgenaRisk layers fall outside of CardiPro and are accessed over a secure internet connection, represented in the layers on the far right of Figure 1. The *AgenaRisk Cloud API Layer* receives requests for Bayesian computations from CardiPro, and returns the calculated probabilities. The *Computation Layer* incorporates the AgenaRisk Bayesian processing engine that performs the actual computational reasoning.

The Client: Given that the system is intended for use by patients and clinicians and as a mobile eHealth service, the CardiPro solution has been designed to be accessed over the internet by most common client devices. The CardiPro web application in the *Client Layer* provides access to all functions equally, whether the user connects using a tablet or full computer system. It should be noted that a *progressive web app* (PWA) presentation layer for smartphones is also under development.

B. *Functional Topology*

Figure 2 describes the functional topology for the complete CardiPro solution. Interfaces to endpoint services exist at each point where information must be passed between layers.

V. Evaluation of Approach and Design: *Prototype System and Case Studies*

This section evaluates the approach, architectural and functional designs presented in the previous section. Validation is achieved by implementing the designs to create a *prototype system*, the CardiPro solution, and *evaluating* this solution by testing it through implementing two medically-focused case studies: one evaluating the severity of *angina* symptoms, and another that predicts *acute traumatic coagulopathy (ATC)* in the care of trauma patients.

A. *Prototype Implementation*

Figure 3 provides an overview of the Infrastructure Architecture that was implemented for the as-built prototype. The infrastructure is divided into three zones: (i) the CardiPro Solution; (ii) the AgenaRisk Service; and (iii) Users.

The CardiPro Solution: The infrastructure consists of the front and back-end systems necessary to host and publish the

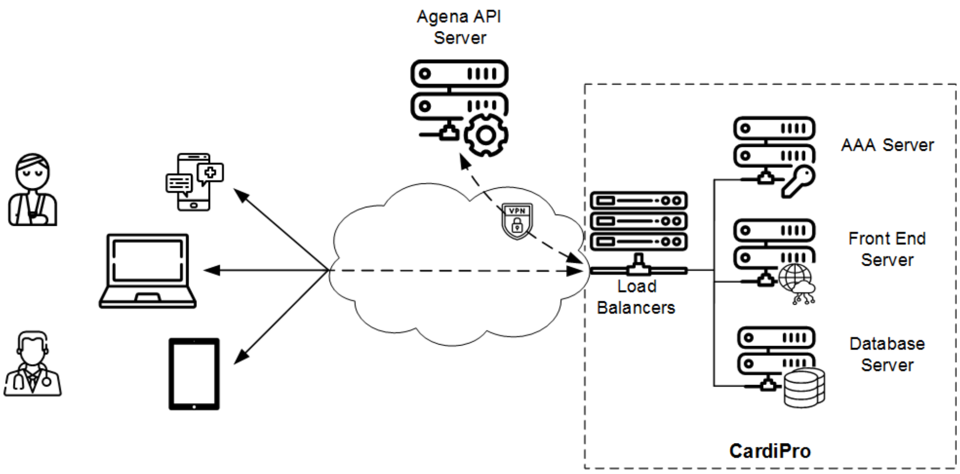

Fig. 3. Overview of the CardiPro Infrastructure Architecture

CardiPro solution. Authentication, Access and Auditing (AAA) servers manage user- and machine-level authentication and access control, and maintains access and usage logs. Users interact with CardiPro through the front-end servers, which present the HTTPS/CSS/JSON application to the internet. Bayesian models may be declared and configured in CardiPro, followed by the creation of patients and recording of relevant observations regarding the patient's history, risk factors and symptomatology. Bayesian computations are referred via the load balancers to a server hosting the AgenaRisk Cloud API for calculation, and the resulting probabilities are returned and presented as updated data visualisations (graphs) for the user. All interactions and data are stored in servers running an industry-standard SQL database platform. These databases separately store: (i) the Bayesian models; (ii) anonymous patient records; (iii) a complete history of all computations requested, and predictions returned for each patient; and (iv) log-shipped systems and security audit logs.

While the entire CardiPro solution is lightweight enough that it could be run on a single dedicated host server, our test implementation ran it on an existing server farm with established web, data and security services provided by clustered or load-balanced teams of host servers with shared access to redundant Storage Attached Network (SAN) disk arrays.

B. Case Studies

Two case studies were implemented to test and evaluate the CardiPro solution.

Case Study 1: Angina

Angina is one of the most common symptoms of coronary artery disease (CAD) and a leading cause of death globally [20, 21]. Around half of all people diagnosed with CAD have angina, with 10-year mortality rates post-diagnosis for higher-risk patients at around 9% [21]. Initially intended as a testing and training model for the CardiPro solution, the angina BN

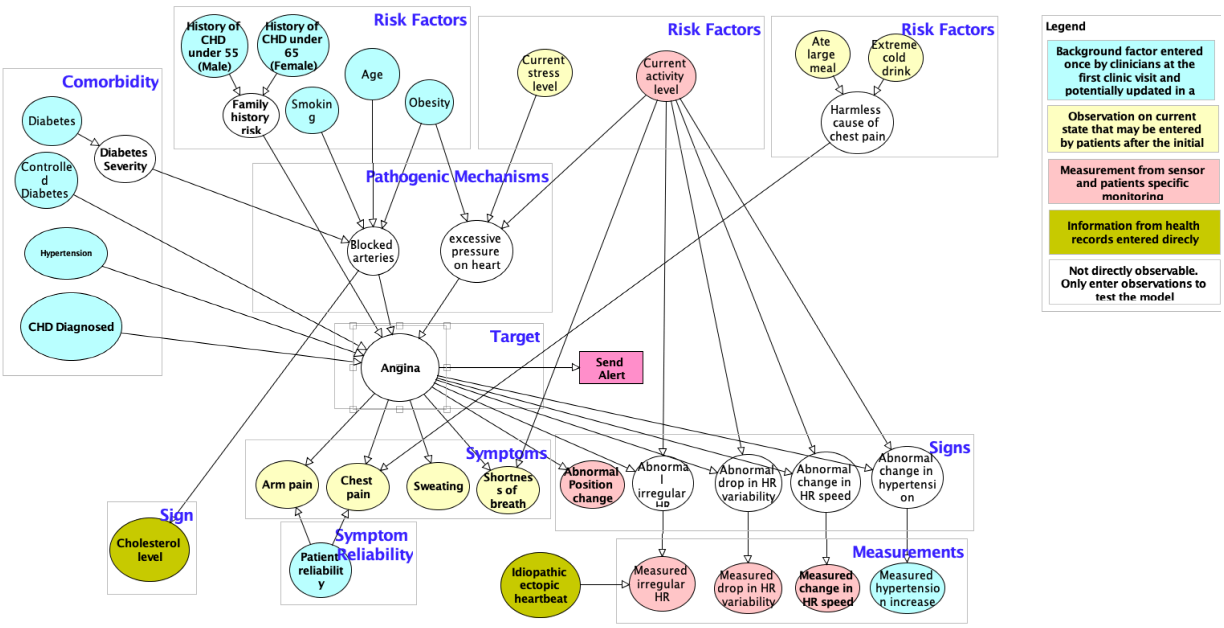

Fig. 4. The BN Prototype Model for Angina

model shown in Figure 4 was developed in AgenaRisk Desktop with minimal input from clinicians, whose input was limited to validating that the model structure and computational output reflected a basic but credible level of application of existing clinical knowledge.

The angina model was exported from AgenaRisk Desktop in JSON format and a project was created in the CardiPro application website. This three-step process entailed: (1) uploading the AgenaRisk JSON file; (2) identifying some of the input and output nodes, which is shown in Figure 5; and (3) setting any threshold output or alert values - in this case, the threshold trigger value for the *Send Alert* node, which is shown in Figure 6.

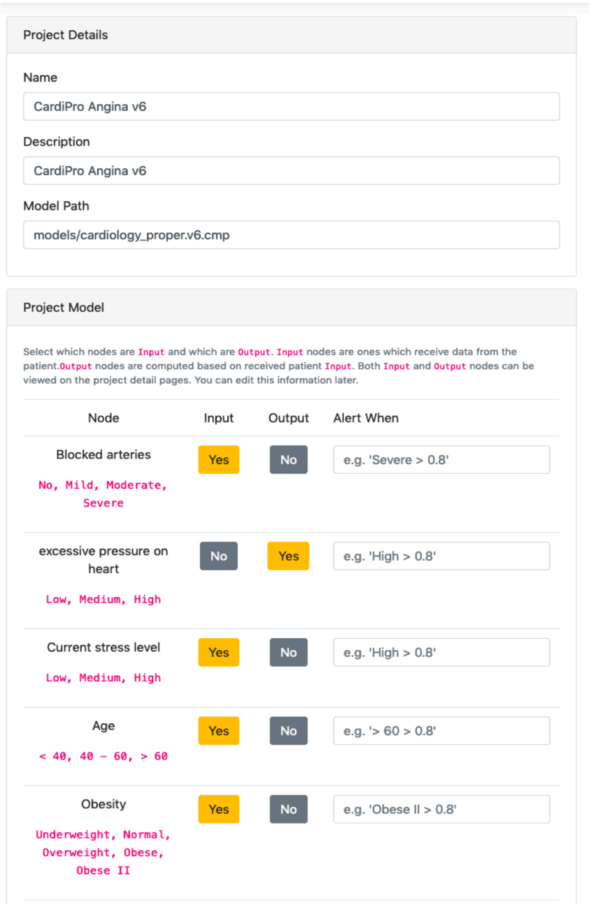

Fig. 5. Declaring the Angina model in CardiPro

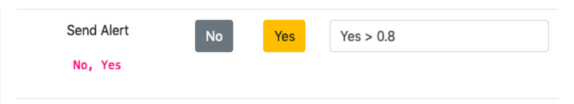

Fig. 6. Customising a node value: Configuring the *Send Alert* threshold

The process of using CardiPro to make predictions entails creating a patient in the application and providing observations regarding the risk factors, signs and symptoms of that patient. Just like AgenaRisk, CardiPro can use pre-defined Boolean, labelled and ranked nodes, while also being capable of handling nodes that accept continuous variables including point-in-time measurements of the patient's heart rate and heart rate variability. As an observation is entered in the CardiPro app, the values of any output nodes are re-calculated in a near real-time computational process that represents the updating of prior belief based on the addition of new information. The output nodes, represented as graphs as seen on the right in Figure 7, are observed by the user to update, while at the same time any diagnostic or treatment threshold alert defined by the clinician is evaluated and, where necessary, an alert is triggered. Alerts can take the form of an email to the clinician and/or patient or may in future result in an audible or visual alert to the patient via the PWA version of the app on their smartphone.

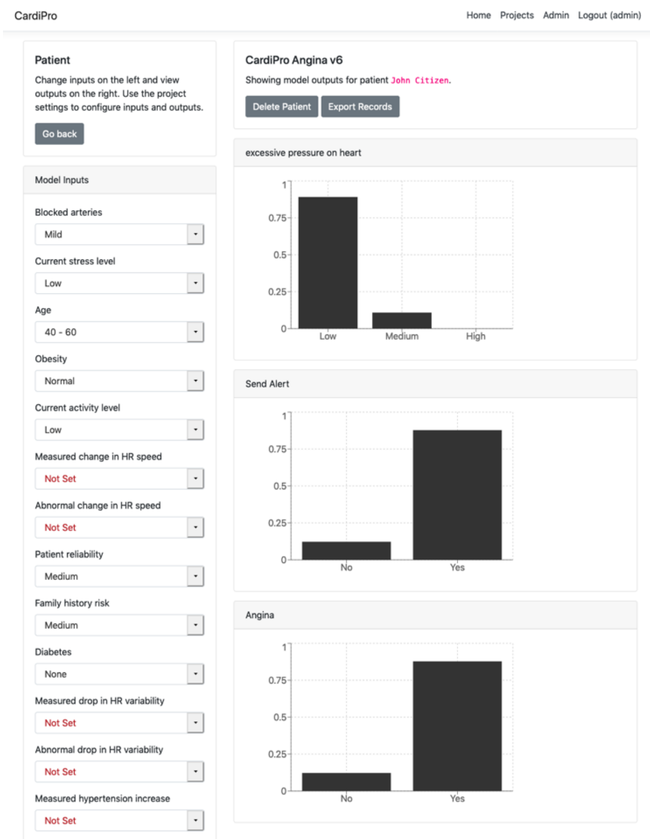

Fig. 7. Example patient inputs and predictions

Case Study 2: Acute Traumatic Coagulopathy

While the previous model was intended only to test the prototype application, the acute traumatic coagulopathy (ATC) model was used to validate the CardiPro solution's operation and accuracy. The development and validation processes for the ATC model shown in Figure 8 are discussed in Yet et al [22] and Perkins [23]: suffice to say that it represents a clinically supported and validated model that makes sound predictions. The clinical benefit and impact of this model are evident in that more recently it was one of three BN models from the same team that were collectively awarded a significant research grant from the United States (US) military to further development of AI solutions using this model for supporting treatment of injured front-line soldiers [24]. The same three-step process described for creating the angina model was used to upload and define the ATC model in CardiPro.

C. Evaluation

What we seek to test is the *near real-time* claim attached in this work to CardiPro through demonstration that the solution consistently provides responses to the user in an acceptable timescale, consistent with the spirit of that claim.

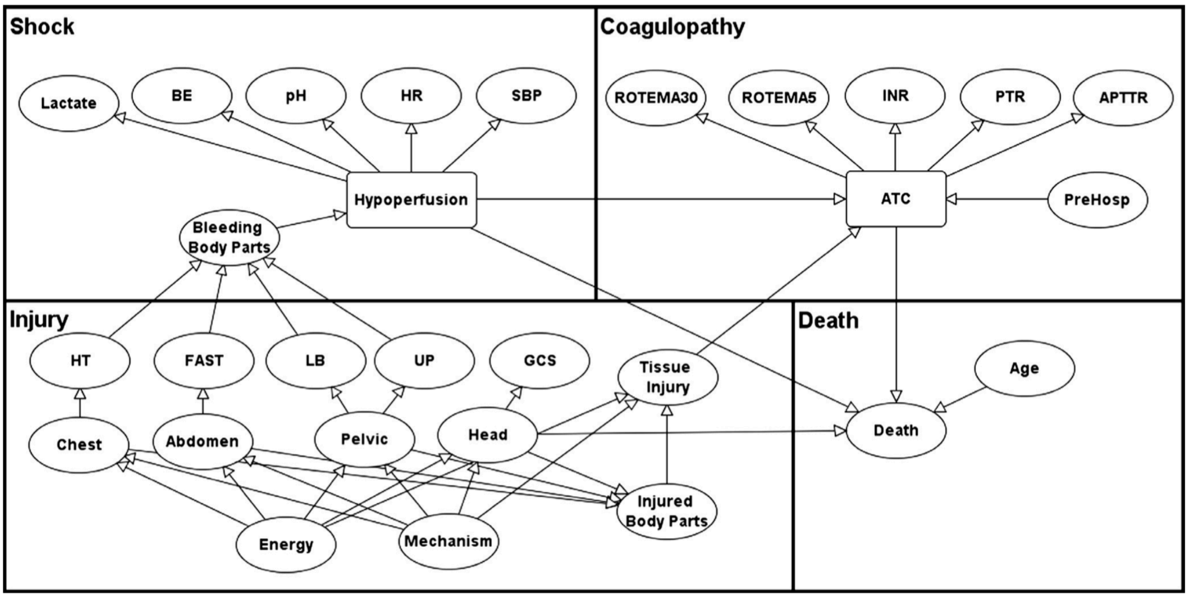

Fig. 8. The ATC BN Structure [29]

We also test *prediction consistency* to demonstrate that even though there is significant difference in the method of performing computation and acquiring responses, the probabilities returned by CardiPro are consistent and accurate to those achieved directly using AgenaRisk.

Three scenarios were devised which are described in Table 1. The *first scenario* presents with a low number of observations regarding a patient in a potentially serious condition. The *second scenario* describes a patient presenting with the same number of observations, and values that would be considerably less concerning. The *third and final scenario* has a higher number of observations that cumulatively describe a patient in critical condition. For each scenario, these identical observations were entered as observations against the BN in both applications and, along with the time taken to perform the Bayesian computation, the predictions for each output node were recorded in Table 2.

TABLE I. ATC TRAUMA SCENARIOS

Scenario	Node	Observation
1	Energy	High
	Mechanism	Blunt
	GCS	3
	Heart Rate	137
2	Energy	Low
	Mechanism	Blunt
	GCS	15
	Heart Rate	87
3	Energy	High
	Mechanism	Blunt
	pH	7.0
	Lactate	6.5
	FAST	Yes
	Temperature	<34

All applications used in the tests computed consistent results with AgenaRisk desktop.

TABLE II. TEST RESULTS

Scenario	ATC (Coag)	Death	Duration (s)
1	Yes: 0.33553	Dead: 0.40597	0.486
2	Yes: 0.03167	Dead: 0.03588	1.009
3	Yes: 0.76399	Dead: 0.53733	0.778

VI. DISCUSSION

CardiPro has a number of key functionalities that arise from its flexibility. CardiPro is not limited to running only a single model. Any number of models can be presented to and used within the CardiPro application. CardiPro is not limited to a single output node, nor to simple two-layer BNs. Nodes can also easily be re-defined as input or output within the web-based application and CardiPro can utilise preferred three-layer causal models. Unlike some applications that can only accept one, or limited, observations contemporaneously, CardiPro accepts any number of observations to update prior probabilities when computing the model. Finally, the BN model is completely abstracted and transparent to the CardiPro interface: the CardiPro user interface is tailored for users who have no knowledge of BNs or Bayesian modelling.

The test results demonstrate that CardiPro: (1) capably performs Bayesian computation and returns results in near real-time; (2) achieves an identical level of accuracy; and (3) is unique in that it flexibly and efficiently performs online inference using three-layer Bayesian networks while also presenting a user-friendly interface.

Benefits from health information technologies (HIT) like CDSS are widely suggested in literature, and while many patients could benefit from their self-management potential the single largest remaining issue preventing successful implementation is a lack of adoption [25 - 28]. For HIT like CardiPro, that are intended for use by both clinician *and* patient, the adoption barrier becomes amplified. This is because these HIT bring together two user groups with disparate roles, motives, needs and expectations and the adoption barrier must be overcome simultaneously for both if the new technology is to succeed [29, 30].

***Information security and personal privacy*:** These issues can be the main barrier to adoption of HIT, and especially mHealth apps [28]. It is usual for mHealth apps to transmit user data outside the app, most often to the app vendor's systems for the purpose of enabling functionality or computation [31, 32]. Recent studies also found alarmingly high rates of mHealth user data being shared with *third parties* [31, 32]. While this is usually in an anonymised and/or disaggregated state, it is recognised that a higher risk to privacy arises when these *third parties* repackage and on-share the data with *fourth parties* who may recombine data from multiple third parties, enabling them to rebuild complete or near-complete copies of patient records [31, 33]. Dramatic headlines like *NHS-approved health apps leaking private data* [34], *Data sharing by popular health apps found to be 'routine'* [33] and *Some apps are sharing your sensitive medical data* [35] draw public attention to this issue, which significantly impacts on patients' ongoing willingness to share health information with mHealth apps [36].

The approach in CardiPro involved a deliberate decision to avoid dependence on third parties that seek shared data, and to avoid technologies in our development stack that were known at the time of development to collect usage, or telemetric, data. All potential patient users of CardiPro will be identified to the application by the clinician using a generated study-ID, with any linking table to identify the real patient maintained in the clinician's secure hospital or clinic computer. Patient devices transmit physiometric data (such as heartbeat and temperature) and observations (patient symptoms) using a SHA-based hash that the clinician inserts into the PWA app on the smart device on installation to identify which study-ID the data from that device relates to. Neither the study-ID or hash are required across the AgenaRisk API when recomputing Bayesian probabilities. IP addresses and device IDs are also not collected. Thus CardiPro, the app developers and the research team are never aware of who the real patient is.

Age and cultural differences: Age persists as a significant barrier to computer use [37]. Applications developed for the general population are not always suitable for elderly users without some modification to account for age-related sensory changes in vision and hearing, physical ability, memory and cognition [37, 38]. Users report greater willingness to engage with apps that provide simple and straight-forward educational materials and self-care recommendations, something many apps lack [39, 28]. Also, the ethnic/racial digital divide means that disparities exist because patients from non-English speaking cultures often lack basic education and self-awareness of their medical condition [39, 40]. These barriers make engagement with mHealth apps even more difficult for older peoples from immigrant populations.

While the CardiPro prototype presents with a *vanilla interface* rendered using React, it is customisable for different audiences using cascading style sheet (CSS) templates. In future versions we will integrate knowledge obtained by the human-computer-interface (HCI) researchers on PamBayesian. They have been working with patients in patient-public-involvement (PPI) groups to develop complex avatar patients and an understanding of patient interface needs that will allow us to create customised CSS interfaces for different patient groups.

VII. Summary and Conclusion

This paper has presented CardiPro, the first of a new generation of online Bayesian network-based applications developed for the PamBayesian research project. CardiPro is capable of hosting complex three-layer BNs and accepting input in the form of observations such as signs and symptoms, and supporting clinical and patient self-management decision-making in near real-time. Engineered to overcome the limitations observed of other BN-based mHealth apps, CardiPro is flexible, accurate and can be adapted to support any number of acute and chronic conditions and user types. Future work will include development of customised interfaces for different patient groups, and development of processes that can integrate and perform contemporaneous decision-making from a number of medical BNs in order to identify health impacts and interactions, and support patients with comorbid conditions.

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