Decision Network for Myocardial Infarction and Chest Pain Related Ambulance Calls

Shai Aarons
University of Cape Town
Cape Town, South Africa
arnsha011@myuct.ac.za

Joshua Rosenthal
University of Cape Town
Cape Town, South Africa
rsnjos005@myuct.ac.za

Jarred Fisher
University of Cape Town
Cape Town, South Africa
JSHJAR002@myuct.ac.za

1 INTRODUCTION

1.0.1 Background. According to the WHO's 2019 global health figures, Ischemic Heart Disease (IHD) has been the primary cause of death worldwide, responsible for 16% of the world's total deaths. In the last twenty years, the increase of deaths due to IHD, has risen from 2 million to 8.9 million deaths [26]. IHD is the precursor to Myocardial Infarction (MI) which can be described as when the blood supply to the muscular tissue of the heart is interrupted, causing irreversible damage to the cells responsible for generating contractile force in the heart [18]. MI, also called a heart attack, can frequently occur in patients with a history of IHD [38].

1.0.2 Objective. The Western Cape's Emergency Medical Services 2020 report on medical services, notes that non-emergency calls (such as head- and toothache) account for up to 70% of calls received at their call centres [10]. Such calls impede on service delivery, straining already limited resources. Our decision network will be employed for determining whether a patient's medical situation warrants the calling of an ambulance. The goal being to better utilize scarce medical resources, whilst still delivering appropriate medical service to patients in a genuine medical emergency.

For the purpose of this work, we restrict the medical emergency to a MI, which has a high mortality rate of 12% [15] and the chance of survival is inextricably linked to the time taken to receive medical treatment, following the onset of symptoms [19] . This, in addition to a worrying proportion of heart attack victims not calling ambulances when they should (53% in one study [14]), motivated our choice in objective.

Secondary objectives include modeling the impact of personal health indicators on the risk of developing IHD and the likelihood of a patient experiencing an MI. This is inferred from our Bayesian network.

1.0.3 User Community. Inferring on our decision network, we propose its use in potentially life-threatening situations to assist the medical emergency call centre operators and the patient in deciding whether to dispatch an ambulance. Additionally, when inferring on our Bayesian network, we envision the potential user community being general practitioners (GP) wanting to better inform on a patient's risk of developing IHD, given the patient's observable risk factors. This could assist in encouraging patients to make better lifestyle choices. Lastly, in an emergency situation, our network could be used to model the likelihood that a patient is having a heart attack, based on observable ECG characteristics (e.g. ST-Segment Elevation), risk factors or symptoms such as severe chest pain.

2 PROBLEM ANALYSIS

The structure of the Bayesian (and Decision) network is entirely informed by relevant literature and datasets. The inception of the network begins at the well-established link between heart disease and MI [5, 24]. We use this established connection and a very common and highly observable symptom of MI, chest pain [12, 35], to develop the conditional probability table for MI (see Table 2d). From this point, we branch out in two directions.

Firstly, we model the probability of the existence of ST Segment Elevation given MI [16] (see Table 2b). ST Segment Elevation is a common feature of an electrocardiogram that is present in cases of STEMI, a variant of MI that is particularly harmful. Secondly, we attempt to model the multi-faceted and well studied nature of heart disease and its associated causes. For this we include several personal health indicators that have been shown to have a strong correlation, and in same cases causation, with IHD. The prior probabilities of these health indicators can be found in Table 2a.

We use the following binary personal health indicators to inform the probability of IHD: smoking [23] (smokes or does not), hypertension [9] (has high blood pressure or does not), low-density lipoprotein (LDL) cholesterol [13] (Has high LDL cholesterol or does not), alcohol abuse [31] (drinks approximately 8 to 15 drinks or more per week or does not), and physical activity [41] (is physically active or is not). To build this complex conditional relationship, we use the Heart Disease Health Indicators Dataset [1], which is a subset of The Behavioral Risk Factor Surveillance System (BRFSS) 2015 dataset provided by the Centers for Disease Control and Prevention (CDC). We further model the joint impact that alcohol abuse and smoking have on hypertension [2, 40, 45] as this relationship is also well-known and studied (see Table 2c). Please refer to Table 1 for a summary of the network as well as the associated sources that justify the links we make.

3 DECISION NETWORK MODEL

For the decision network, we add the actionable node to call an ambulance so as to achieve our goal detailed in section 1. To this, we attach a utility node that is affected by the probabilities of the MI node. This utility function is meant to represent a combination of a patient's health and resources where the goal of the network is return the optimal decision such that the health of the patient is maximized and the waste of resources is minimized, given a set of observations. The overall structure of the decision network can be found in Figure 2. Our decision network is apportioned into three modules. Each will be explained in the following paragraphs.

[1]https://www.kaggle.com/datasets/alexteboul/heart-disease-health-indicators-dataset

Table 1: Summary Table of Network Topology and Justifying Sources

From	To	Source
[Smokes, Alcohol_Abuse]	[Hypertension]	[2, 40, 45]
[Smokes, Hypertension, Cholesterol, Alcohol_Abuse, Physical_Activity]	[Heart_Disease]	[9, 13, 23, 31, 41]
[Chest_Pain,Heart_Disease]	[MI]	[5, 12, 24, 35]
[MI]	[ST_Segment_Elevation]	[16]

Table 2: Conditional Probability Tables and Justifying Sources

(a) Prior Probabilities

Node	Prob(X=Yes)	Source
Chest_Pain	0.300	[30, 34]
Smokes	0.265	[28]
Alcohol_Abuse	0.223	[25, 36]
Physical_Activity	0.725	[11]
Cholesterol	0.390	[27]

(b) Prob(ST_Segment_Elevation | MI)

MI?	Prob(ST_Segment_Elevation=Yes)	Source
No	0.11	[29]
Yes	0.825	[16]

(c) Prob (Hypertension | Smokes, Alcohol_Abuse)

Smokes?	Alcohol_Abuse?	Prob(Hyp=Yes)	Source
No	No	0.299	[45]
No	Yes	0.365	[45]
Yes	No	0.385	[2]
Yes	Yes	0.392	[2]

(d) Prob(MI | Heart_Disease, Chest_Pain)

Heart_Disease?	Chest_Pain?	Prob(MI=Yes)	Source
No	No	0.0004	[24, 35]
No	Yes	0.150	[12]
Yes	No	0.1511	[24, 35]
Yes	Yes	0.720	[12]

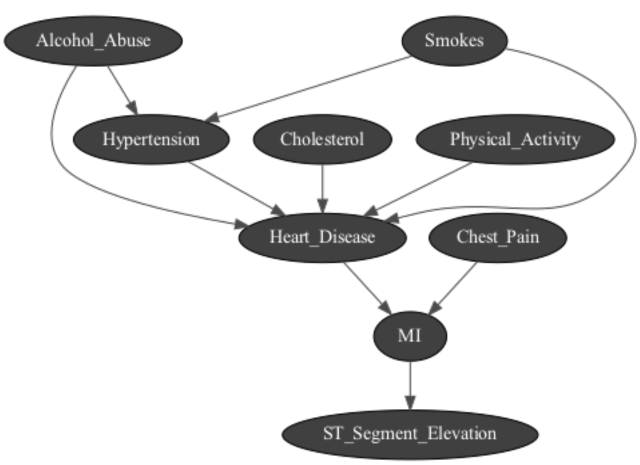

Figure 1: Structure of the Bayesian Network

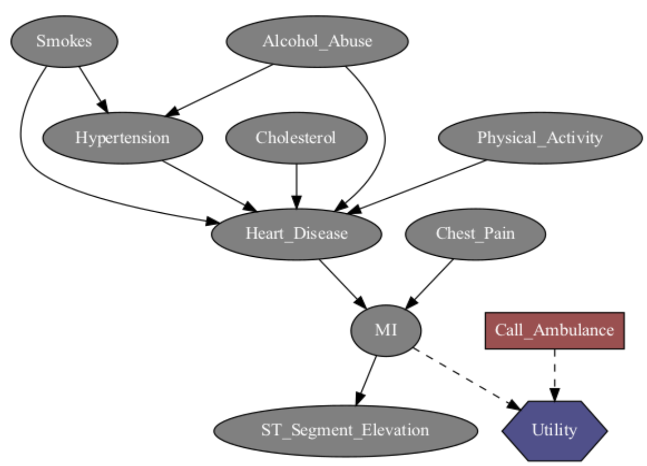

Figure 2: Structure of the Decision Network

3.1 Heart Disease Risk Module

The first module of our decision network is the heart disease risk factoring module (see Figure 3). This module serves to model the risk of heart disease as the ‘introduction‘ and primary steps into making a decision about calling an ambulance. A potential use case for this portion of the model is for situations where patients are not sure if they have heart disease or not, and, using their background health information, can come to a conclusion about the decision of calling an ambulance from the model.

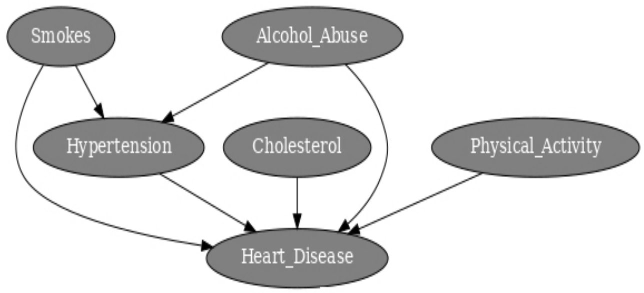

Figure 3: Heart Disease Risk Module

3.2 Heart Attack Risk Modelling

When designing our network, one of our main objectives was to model the likelihood that a person is having a heart attack (MI) given that they are having chest pain. The way in which we have designed our model allows us to encode all the information from module 1 into the 'Heart Disease' node. This allows us to pass that information, along with the information about the patient's chest pain, into the 'MI' module to model the chance that a person is having a heart attack. We also incorporated observing ST-Segment elevation in a patient's ECG. The heart attack risk portion of the decision network can be found in Figure 4.

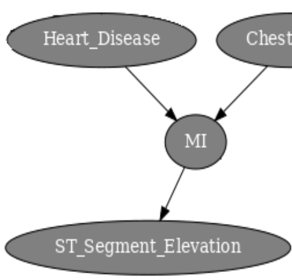

Figure 4: Heart Attack Risk Module

3.3 Utility Module

The final module in our decision network is the utility module. This is the module that will ultimately make the decision regarding calling an ambulance. The utility node makes its decisions based on the decision node 'Call Ambulance' and the MI conditional probability table. This portion of the model can be found in Figure 5. Our given utility values based on each decision, along with the reason for our chosen utility values, are found in Table 3.

4 MODEL TESTING AND EVALUATION

To evaluate whether our presented model makes valuable decisions and inferences we need to assess how evidence influences

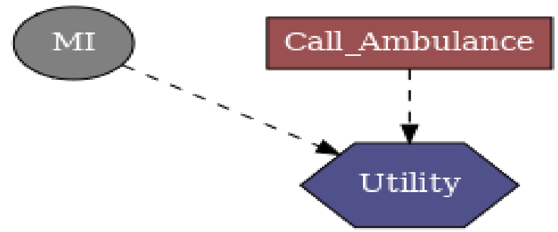

Figure 5: Utility Module

Table 3: Utility Node Values and Reasons

Call Ambulance Decision	MI	Value	Reason
No	No	0	This decision is given a neutral value because a patient will not be waisting their own resources or healthcare resources. The patient is in no immediate danger.
No	Yes	-100	This decision is given the lowest utility. The patient is in immediate life-threatening danger. By not calling an ambulance the patient risks dying. Healthcare and monetary resources are being misused in this case by not being used at all
Yes	No	-50	This decision is given a negative value because a patient will be wasting their own monetary resources as well as healthcare resources in the case of chest pain/heart related issues. This is less of a critical situation than the decision above, hence the more positive value given.
Yes	Yes	100	This is the decision which is given the highest value. Here medical and monetary resources are being used appropriately. The patient's life is at less risk by calling the ambulance.

unobserved variables in the network. The Bayesian Network model allows us to make inferences about MI and heart disease, providing valuable information about which risk factors have the greatest impact on their respective posterior probabilities. Our decision network extends this, by providing patients at home the optimal decision on whether or not to call an ambulance based on their own health standings. Ambulances are expensive for both the consumer and distributors of healthcare resources - the network takes this all into account when suggesting an optimal decision.

4.1 Bayesian Network

The Bayesian network models the posterior probabilities calculated from the conditional probability tables and available evidence, if any. From these posterior distributions, inference can be made on events represented by unobserved random variables. In assessing the Bayesian network, we will make use of the heart disease and heart attack risk modeling modules as outlined in Subsection 3.1 and Subsection 3.2, respectively.

4.1.1 Heart Disease Risk. Without any observations, the posterior probability of developing IHD is 6.52%, as can be seen in Figure 6. A study looking at the epidemiology of IHD notes that the overall prevalence of IHD among those older than 20 years is 6.4% [7]. This places our probability estimate for IHD very near (|0.12%|) to the real-world statistic.

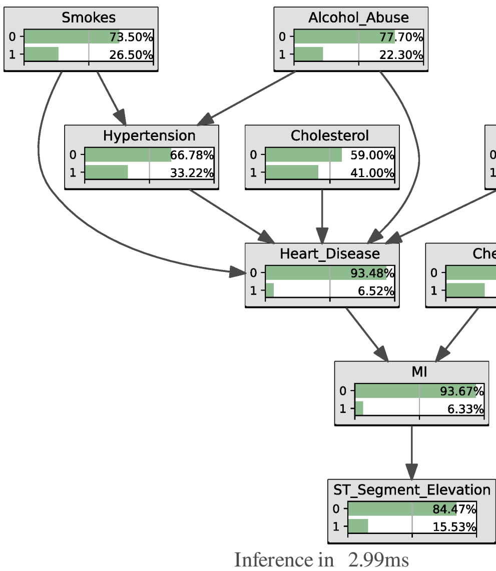

Figure 6: Bayesian Network Given No Evidence

To better assess the usefulness of the Bayesian Network for modeling the likelihood of developing IHD, we envision a scenario wherein a patient is visiting their GP or going onto a medical website with the goal of determining their risk of developing IHD, given their personal health indicators.

Looking at Figure 7, we see a particularly healthy patient, that is, wherein they do not smoke, abuse alcohol, have high LDL cholesterol or high blood pressure and are physically active — has a probability of 1.56% for developing IHD (4.96% less than our baseline). This finding is supported by several studies that show a notable decline in the likelihood of developing IHD, when these key risk factors are not present [1, 3, 22].

A polar opposite patient can be imagined, wherein most of these key risk factors are present. This can be seen in Figure 8. The likelihood here for developing IHD is 26.89%. This shows a significant increase of 25.33% and 20.32% over our healthy patient and baseline scenarios, respectively. Using a IHD probability table developed by Brittain [4] and inputting these risk factors, the probability is 21%, which brings our posterior calculations near to this real-world estimate. It also worth noting the resulting increased risk of a heart attack, which has risen to 11.96% (i.e. 5.63% over the baseline).

4.1.2 Heart Attack Risk. In the presence of a MI, swift and effective medical treatment can mitigate irreversible damage caused to heart tissue [43]. Unfortunately, misdiagnosis is a major concern. In a UK national cohort study, 31% of the 564 412 patients treated for MI were initially misdiagnosed [42]. First responders such as paramedics may lack the proficiency of cardiologists or the hospital

Figure 7: Bayesian Network with most Risk Factors not present (i.e. healthy patient)

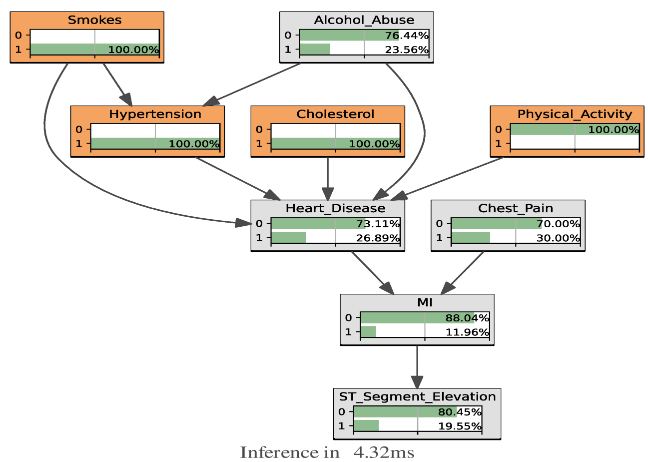

Figure 8: Bayesian Network with most Risk Factors present (i.e. unhealthy patient)

might be short-staffed of such experts [44]. This establishes precedence to develop an automated expert system that can effectively screen patients for potential MI, at a low cost and with relative ease. Looking at Figure 9, we see a person who has observed the absence of IHD, chest pain and ST Segment Elevation. The posterior probability of them experiencing an MI is then 0.01%. Such a low likelihood is supported by the fact that only 5-6% of all heart attacks present without IHD [20]. Additionally, a silent heart attack (i.e. presenting without symptoms, such as chest pain) accounts for just 20% of all heart attacks [39].

Contrary to the above, Figure 10 shows a near-certain risk of a patient experiencing MI (95.07%). This use-case also depicts the most dangerous type of MI, a STEMI, which requires immediate

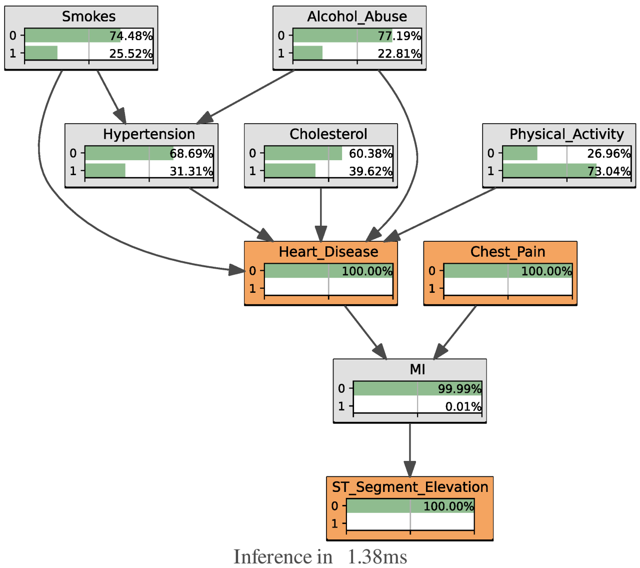

Figure 9: Bayesian Network with primary MI indicators not present

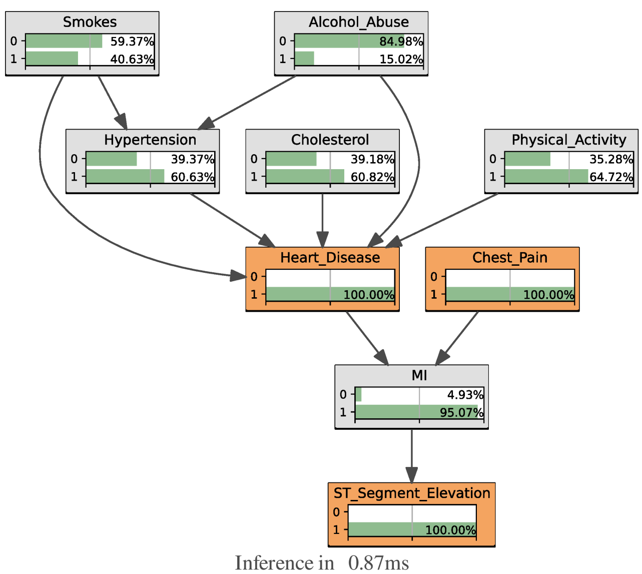

Figure 10: Bayesian Network with primary MI indicators present

medical treatment to prevent further patient deterioration [6]. The diagnosis of STEMI is primarily based on clinical presentation on the 12-lead ECG, which will show ST Segment Elevation if a STEMI is present [43]. This evidence, coupled with observed IHD and severe chest pain is what lead the network to calculate such a high likelihood for MI being present.

A medium-risk model for MI being present is seen in Figure 11. This patient presents with severe chest pain and is known to have IHD, however the ST Segment is not elevated. This is why the

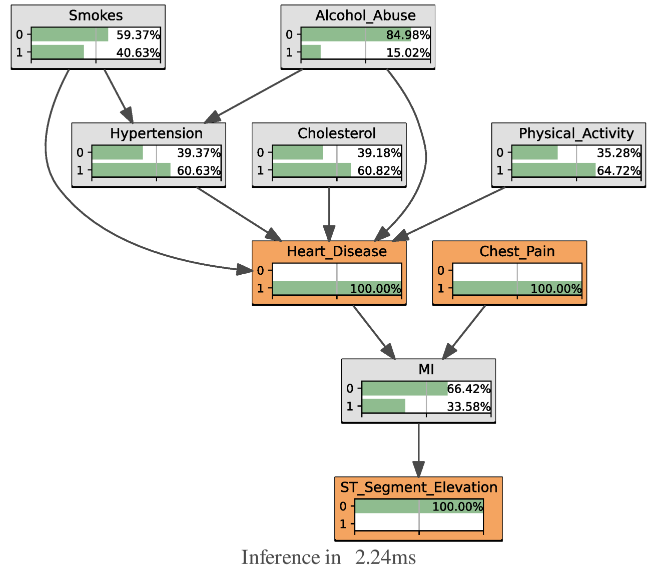

Figure 11: Bayesian Network with no ST_Segment Elevation present

model returns a likelihood for MI of 33.58%. This could be a Non-elevated STEMI (NSTEMI), which is a less dangerous type of MI, but still warrants immediate medical treatment [21]. However, the significant drop in the network's belief that MI is presenting, can be attributed to the variety of other syndromes that can cause non-cardiac chest pain [8]. In a study assessing the proportion of patients visiting the emergency department for chest pain, only 15 to 25% of such patients actually have acute coronary syndrome (ACS)[2] [32, 33]

To confirm a patient is suffering from a NSTEMI would require taking blood samples to measure cardiac biomarkers that are released following severe myocardial necrosis. Elevated levels of enzymes such as myoglobin, troponin and creatine kinase can confirm both NSTEMIs and STEMIs [17].

4.2 Decision Network

The decision network tells us whether or not we should call an ambulance, given certain observations made within the environment. Our decision network is structured in such a way that when no observations are made, the optimal action with the maximum utility, is to *not* call an ambulance. This optimal decision is a sound translation to real-world settings, where given no evidence of causes of heart disease, or indicators of chest pain, then one should most likely not call an ambulance. When there is no evidence, the maximum expected utility has a value of -6.27. This can be seen in Figure 12.

However, this optimal decision varies depending on what observations are made by the network/user. We highlight how the optimal decisions and maximum expected utility deviate depending on what observations are made through our suggested high-level

[2]ACS describes a range of conditions associated with sudden, reduced blood flow to the heart. MI is one such condition [37].

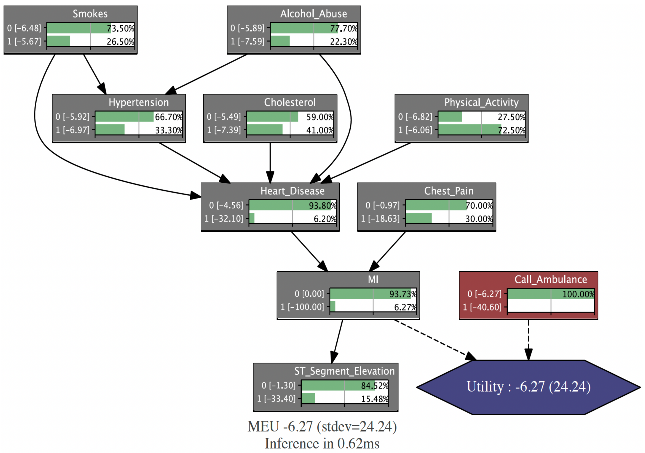

Figure 12: Decision Network Showing Optimal Decision Given No Evidence

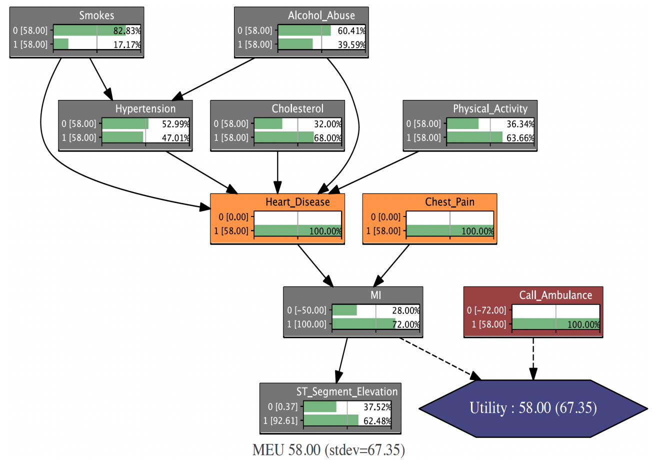

Figure 13: Decision Network Showing Optimal Decision Given Chest Pain and Heart Disease

use-case of the network: A Personal Health Decision-Maker.

4.2.1 The Personal Health Decision-Maker. This use case implies usage from people who suffer from heart diseases or heart-disease comorbidities and are presenting with chest pain. This allows users to gain statistical insight into whether or not they should pursue the costly endeavor of calling an ambulance. The decision network will take into account all the user's known (observed) risk factors and will make a decision for the user.

The first example usage of the decision network is the most simple case. Here a patient is suffering from chest pain, and the patient is aware that they have heart disease. Here, both heart disease and chest pain are observed variables, and no other variables are observed. The resulting network, given these two variables only, can be found in Figure 13. In this case, the user will be notified that the optimal decision is to call an ambulance. The maximum expected utility value corresponding to calling an ambulance is 58.00, which is almost a tenfold increase in expected utility when compared to the optimal decision given no evidence.

This translates to real-world settings, as recommended by the National Health Service of Scotland[3], wherein patients are urged to call an ambulance, given these two symptoms. In this use-case, the chance of having a heart attack increases from 6.27% to 72%. Further, the posterior distribution of observing ST-segment elevation increases from 15.48% to 62.48% when compared to our baseline of no evidence. As noted in Subsection 1.0.2, MI requires immediate medical attention and thus the patient should call an ambulance.

As a second example of this use case, we demonstrate the maximum utility action the network produces when a patient is unaware if they suffer from heart disease or not, given that they are suffering from chest pain. As an illustration of a typically high-risk user, we have a user that is a heavy smoker, abuses alcohol, is not physically active, and has high levels of LDL cholesterol. In this case, again, the optimal decision is to call an ambulance. The maximum expected utility of calling an ambulance was calculated to be -15.05. This is demonstrated in the posterior distributions of the network in Figure 14. This maximum expected utility value of -15.05 is less than that of when the heart disease variable is observed. Also, the risk of heart attack is 23.30% compared to 76.70% when heart disease is observed.

These facts indicate that the model recognizes that while it is still worthwhile calling an ambulance for a high-risk patient, it is less urgent to call an ambulance than for a patient who is aware that they have IHD. The same outcome holds true for when a patient only observes a subset of the risk factors with chest pain. For example, when a patient is inflicted with both hypertension and high LDL cholesterol only as well as having chest pain, the network suggests calling an ambulance. This is demonstrated in Figure 15.

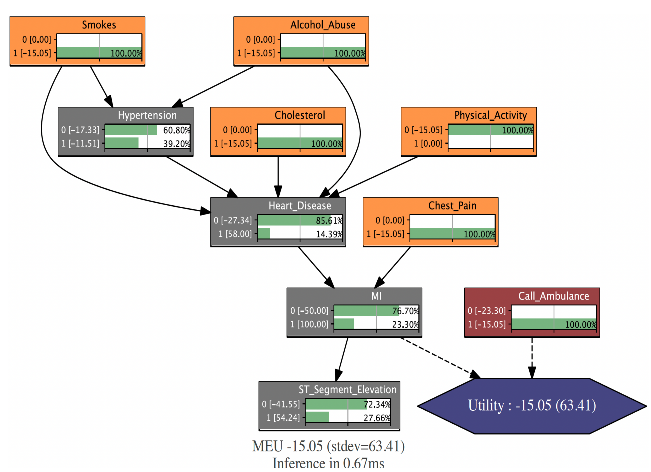

Figure 14: Decision Network Showing Optimal Decision Given Chest Pain and a Patient Who Smokes, Abuses Alcohol, Has High Cholesterol and is not Physically Active

[3]https://www.nhsinform.scot/illnesses-and-conditions/heart-and-blood-vessels/heart-emergencies/what-to-do-in-a-heart-emergency

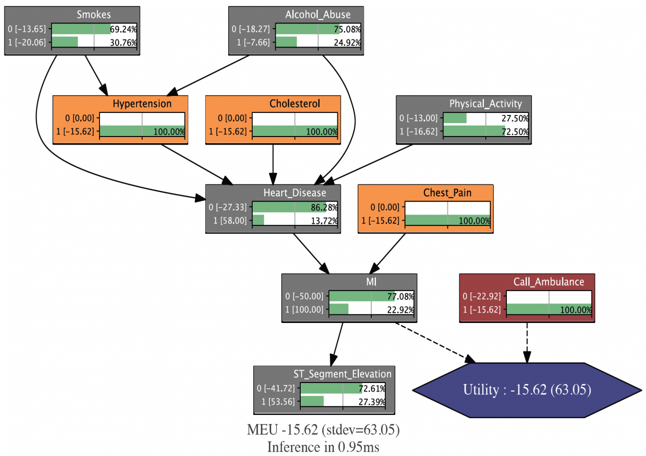

Figure 15: Decision Network Showing Optimal Decision Given Chest Pain and a Patient Who Has High Cholesterol and Has Hypertension

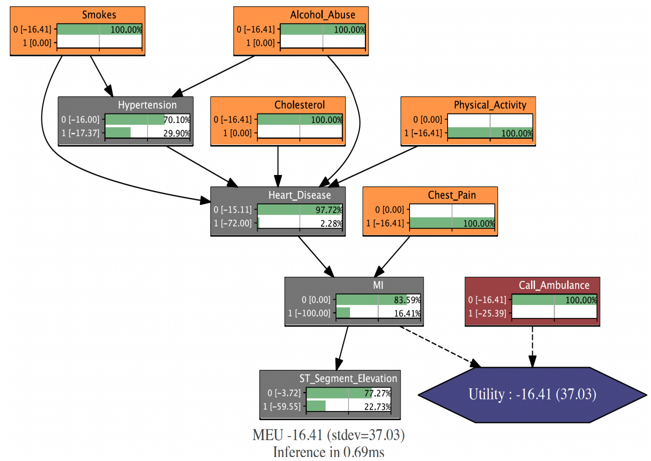

Figure 16: Decision Network Showing Optimal Decision Given Chest Pain and a Patient Who does not Smoke, does not Abuse Alcohol, Has Low Cholesterol and is Physically Active

The opposite of the above can also be observed from the decision network. Here we will observe a generally healthy individual who does not smoke, does not abuse alcohol, does not have high LDL cholesterol, and partakes in physical activity, but is suffering from chest pain. The network suggests the optimal decision is to not call an ambulance. The maximum expected utility associated with not calling an ambulance is -16.41.

This translates to real-world settings where if a patient is not high risk, but is suffering from chest pain, it is worthwhile to save on the ambulance fees and medical healthcare resource usage by not calling an ambulance. This is reflected in the decision network diagram in Figure 16. We note that in this case the percent chance of having a heart disease is only 2.28%, and hence the highest determining factor (heart disease) of calling an ambulance or not, has indicated that the user should not call an ambulance.

5 CONCLUSION

We present a Bayesian and Decision network capable of modelling the risk of IHD, MI and whether or not one should call an ambulance given these risk factors. We use relevant expert knowledge and the Heart Disease Health Indicators Dataset to inform the structure and weights of our network. We design a utility function that is meant to consider both patient health and use of resources when making a decision to call an ambulance. We show the effectiveness of our network through several use cases and we find that it produces logical decisions based on the evidence we provide it.

We acknowledge that this model fails to capture hidden synergistic and antagonistic effects between some of the nodes. This said, we do believe that attempting to model these relationships introduces complexity that falls outside of the scope of this assignment. Future work should attempt to add more completeness to the effect of personal risk factors on heart disease and further explain the relationships that these factors have with each other. Future work could also look to include other possible causes of chest pain so as to offer a more complete representation of the symptom.

REFERENCES

[1] Benjamín Acosta-Cázares and Jorge Escobedo-de la Peña. 2010. High burden of cardiovascular disease risk factors in Mexico: An epidemic of ischemic heart disease that may be on its way? *American Heart Journal* 160, 2 (2010), 230–236.

[2] Amer Aladin, Parag Chevli, Muhammad Imtiaz Ahmad, Shereen Rasool, and David Herrington. 2019. ALCOHOL CONSUMPTION AND RISK OF HYPERTENSION. *Journal of the American College of Cardiology* 73, 9, Supplement 2 (2019), 12. https://doi.org/10.1016/S0735-1097(19)33774-X ACC.19: The American College of Cardiology 68th Annual Scientific Sessions.

[3] Elizabeth Barrett-Connor, Lucina Suarez, Kay-tee Khaw, Michael H Criqui, and Deborah L Wingard. 1984. Ischemic heart disease risk factors after age 50. *Journal of chronic diseases* 37, 12 (1984), 903–908.

[4] ERICA Brittain. 1982. Probability of coronary heart disease developing. *Western Journal of Medicine* 136, 1 (1982), 86.

[5] Andrew R Chapman, Philip D Adamson, and Nicholas L Mills. 2017. Assessment and classification of patients with myocardial injury and infarction in clinical practice. *Heart* 103, 1 (2017), 10–18. https://doi.org/10.1136/heartjnl-2016-309530 arXiv:https://heart.bmj.com/content/103/1/10.full.pdf

[6] Konstantinos Dimopoulos, Dariusz Dudek, Federico Piscione, Waldemar Mielecki, Stefano Savonitto, Francesco Borgia, Ernesto Murena, Antonio Manari, Achille Gaspardone, Andrzej Ochala, et al. 2012. Timing of events in STEMI patients treated with immediate PCI or standard medical therapy: implications on optimisation of timing of treatment from the CARESS-in-AMI trial. *International journal of cardiology* 154, 3 (2012), 275–281.

[7] Ignacio Ferreira-González. 2014. The epidemiology of coronary heart disease. *Revista Española de Cardiología (English Edition)* 67, 2 (2014), 139–144.

[8] Thomas Frieling. 2018. Non-cardiac chest pain. *Visceral medicine* 34, 2 (2018), 92–96.

[9] Flávio D. Fuchs and Paul K. Whelton. 2020. High Blood Pressure and Cardiovascular Disease. *Hypertension* 75, 2 (Feb. 2020), 285–292. https://doi.org/10.1161/hypertensionaha.119.14240

[10] Western Cape Government. 2010. https://www.westerncape.gov.za/general-publication/emergency-medical-care. [Retrieved 03-October-2022].

[11] Regina Guthold, Gretchen A Stevens, Leanne M Riley, and Fiona C Bull. 2018. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1· 9 million participants. *The lancet global health* 6, 10 (2018), e1077–e1086.

[12] Jörg Haasenritter, Damaris Stanze, Grit Widera, Christian Wilimzig, Maren Abu Hani, Andreas C Sönnichsen, Stefan Bösner, Justine Rochon, and Norbert Donner-Banzhoff. 2012. Does the patient with chest pain have a coronary heart disease? Diagnostic value of single symptoms and signs – a meta-analysis. *Croatian Medical Journal* 53, 5 (Oct. 2012), 432–441. https://doi.org/10.3325/cmj.2012.53.432

[13] Su-Min Jeong, Seulggie Choi, Kyuwoong Kim, Sung Min Kim, Gyeongsil Lee, Seong Yong Park, Yeon-Yong Kim, Joung Sik Son, Jae-Moon Yun, and Sang Min Park. 2018. Effect of change in total cholesterol levels on cardiovascular disease among young adults. *J. Am. Heart Assoc.* 7, 12 (June 2018).

[14] Debra Kerr, D Holden, Jennifer Smith, Anne-Maree Kelly, and S Bunker. 2006. Predictors of ambulance use in patients with acute myocardial infarction in Australia. *Emergency medicine journal* 23, 12 (2006), 948–952.

[15] Harlan M Krumholz, Sharon-Lise T Normand, and Yun Wang. 2019. Twenty-year trends in outcomes for older adults with acute myocardial infarction in the United States. *JAMA network open* 2, 3 (2019), e191938–e191938.

[16] Ville Kytö, Jussi Sipilä, and Päivi Rautava. 2014. Likelihood and Predictors of ST-Elevation in Patients Hospitalized for Myocardial Infarction. *PLoS ONE* 9, 9 (Sept. 2014), e108440. https://doi.org/10.1371/journal.pone.0108440

[17] Muhammad Ajmal Malik, Shahzad Alam Khan, Sohail Safdar, et al. 2013. Chest Pain as a presenting complaint in patients with acute myocardial infarction (AMI). *Pakistan journal of medical sciences* 29, 2 (2013), 565.

[18] Waldomiro Carlos Manfroi, Carolina Peukert, Clarissa Bacha Berti, Clarissa Noer, Danielle de Ávila Gutierres, and Felipe Theodoro Bezerra Gaspar Carvalho da Silva. 2002. Acute myocardial infarction: the first manifestation of ischemic heart disease and relation to risk factors. *Arquivos Brasileiros de Cardiologia* 78 (2002), 392–395.

[19] Hendrika Meischke, Mary T Ho, Mickey S Eisenberg, Sharon M Schaeffer, and Mary P Larsen. 1995. Reasons patients with chest pain delay or do not call 911. *Annals of emergency medicine* 25, 2 (1995), 193–197.

[20] Ann Milanowski. 2022. Heart attack without blocked arteries. https://health.clevelandclinic.org/can-you-have-a-heart-attack-without-having-any-blocked-arteries/#:~:text=Is%20this%20possible%3F,more%20likely%20to%20be%20female.. [Retrieved 04-October-2022].

[21] Aleksandra Milosevic, Zorana Vasiljevic-Pokrajcic, Dejan Milasinovic, Jelena Marinkovic, Vladan Vukcevic, Branislav Stefanovic, Milika Asanin, Miodrag Dikic, Sanja Stankovic, and Goran Stankovic. 2016. Immediate versus delayed invasive intervention for non-STEMI patients: the RIDDLE-NSTEMI study. *JACC: Cardiovascular Interventions* 9, 6 (2016), 541–549.

[22] Alexandra N Nowbar, Mauro Gitto, James P Howard, Darrel P Francis, and Rasha Al-Lamee. 2019. Mortality from ischemic heart disease: Analysis of data from the World Health Organization and coronary artery disease risk factors From NCD Risk Factor Collaboration. *Circulation: cardiovascular quality and outcomes* 12, 6 (2019), e005375.

[23] Ira S. Ockene and Nancy Houston Miller. 1997. Cigarette Smoking, Cardiovascular Disease, and Stroke. *Circulation* 96, 9 (Nov. 1997), 3243–3247. https://doi.org/10.1161/01.cir.96.9.3243

[24] Institute of Medicine (US) and National Academies Press (US). 2010. *Cardiovascular Disability: Updating the Social Security Listings.* National Academies Press.

[25] National Institute on Alcohol Abuse and Alcoholism. 2019. Alcohol Facts and Statistics. https://www.niaaa.nih.gov/publications/brochures-and-fact-sheets/alcohol-facts-and-statistics#:~:text=An%20estimated%2095%2C000%20people%20(approximately,death%20in%20the%20United%20States.. [Retrieved 03-October-2022].

[26] World Health Organization. 2019. Global Health Estimates: Life Expectancy and leading causes of death and disability. https://www.who.int/data/gho/data/themes/theme-details/GHO/mortality-and-global-health-estimates. [Retrieved 01-October-2022].

[27] World Health Organization. 2019. Raised cholesterol. https://www.who.int/data/gho/indicator-metadata-registry/imr-details/3236. [Retrieved 01-October-2022].

[28] World Health Organization. 2022. Tobacco. https://www.who.int/news-room/fact-sheets/detail/tobacco#:~:text=Over%2080%25%20of%20the%20world's,7.8%25%20of%20the%20world's%20women.. [Retrieved 02-October-2022].

[29] Laurie A Otto and Tom P Aufderheide. 1994. Evaluation of ST segment elevation criteria for the prehospital electrocardiographic diagnosis of acute myocardial infarction. *Annals of emergency medicine* 23, 1 (1994), 17–24.

[30] Nino Paichadze, Badar Afzal, Nukhba Zia, Rakshinda Mujeeb, Muhammad Mujeeb Khan, and Junaid A Razzak. 2015. Characteristics of chest pain and its acute management in a low-middle income country: analysis of emergency department surveillance data from Pakistan. *BMC Emergency Medicine* 15, 2 (2015), 1–6.

[31] Mariann R Piano. 2017. Alcohol's effects on the cardiovascular system. *Alcohol Res.* 38, 2 (2017), 219–241.

[32] J Hector Pope, Tom P Aufderheide, Robin Ruthazer, Robert H Woolard, James A Feldman, Joni R Beshansky, John L Griffith, and Harry P Selker. 2000. Missed diagnoses of acute cardiac ischemia in the emergency department. *New England Journal of Medicine* 342, 16 (2000), 1163–1170.

[33] Michael W Pozen, Ralph B D'Agostino, Harry P Selker, Pamela A Sytkowski, and William B Hood Jr. 1984. A predictive instrument to improve coronary-care-unit admission practices in acute ischemic heart disease: a prospective multicenter clinical trial. *New England Journal of Medicine* 310, 20 (1984), 1273–1278.

[34] David Railton. 2022. What could cause chest pain? https://www.medicalnewstoday.com/articles/321650 [Retrieved 01-October-2022].

[35] Harmony R. Reynolds. 2012. Myocardial infarction without obstructive coronary artery disease. *Current Opinion in Cardiology* 27, 6 (Nov. 2012), 655–660. https://doi.org/10.1097/hco.0b013e3283583247

[36] SAMHSA, Center for Behavioral Health Statistics and Quality. 2018. 2019 National Survey on Drug Use and Health. https://www.samhsa.gov/data/sites/default/files/reports/rpt29394/NSDUHDetailedTabs2019/NSDUHDetTabsSect2pe2019.htm#tab2-20b. [Retrieved 03-October-2022].

[37] Fabian Sanchis-Gomar, Carme Perez-Quilis, Roman Leischik, and Alejandro Lucia. 2016. Epidemiology of coronary heart disease and acute coronary syndrome. *Annals of translational medicine* 4, 13 (2016).

[38] Jen Hong Tan, Yuki Hagiwara, Winnie Pang, Ivy Lim, Shu Lih Oh, Muhammad Adam, Ru San Tan, Ming Chen, and U Rajendra Acharya. 2018. Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals. *Computers in biology and medicine* 94 (2018), 19–26.

[39] Connie W Tsao, Aaron W Aday, Zaid I Almarzooq, Alvaro Alonso, Andrea Z Beaton, Marcio S Bittencourt, Amelia K Boehme, Alfred E Buxton, April P Carson, Yvonne Commodore-Mensah, et al. 2022. Heart disease and stroke statistics—2022 update: a report from the American Heart Association. *Circulation* 145, 8 (2022), e153–e639.

[40] A. Virdis, C. Giannarelli, M. Fritsch Neves, S. Taddei, and L. Ghiadoni. 2010. Cigarette Smoking and Hypertension. *Current Pharmaceutical Design* 16, 23 (Aug. 2010), 2518–2525. https://doi.org/10.2174/138161210792062920

[41] Ephraim Bernhard Winzer, Felix Woitek, and Axel Linke. 2018. Physical Activity in the Prevention and Treatment of Coronary Artery Disease. *Journal of the American Heart Association* 7, 4 (Feb. 2018). https://doi.org/10.1161/jaha.117.007725

[42] Jianhua Wu, Chris P Gale, Marlous Hall, Tatendashe B Dondo, Elizabeth Metcalfe, Ged Oliver, Phil D Batin, Harry Hemingway, Adam Timmis, and Robert M West. 2018. Editor's Choice-Impact of initial hospital diagnosis on mortality for acute myocardial infarction: A national cohort study. *European Heart Journal: Acute Cardiovascular Care* 7, 2 (2018), 139–148.

[43] Lin Wu, Guifang Huang, Xianguan Yu, Minzhong Ye, Lu Liu, Yesheng Ling, Xiangyu Liu, Dinghui Liu, Bin Zhou, Yong Liu, et al. 2022. Deep Learning

Networks Accurately Detect ST-Segment Elevation Myocardial Infarction and Culprit Vessel. *Frontiers in cardiovascular medicine* 9 (2022).

[44] Ran Xiao, Yuan Xu, Michele M Pelter, David W Mortara, and Xiao Hu. 2018. A deep learning approach to examine ischemic ST changes in ambulatory ECG recordings. *AMIA Summits on Translational Science Proceedings* 2018 (2018), 256.

[45] Jeetendra Yadav, Shaziya Allarakha, Chander Shekhar, and Ganesh Prasad Jena. 2021. Alcohol and tobacco influencing prevalence of hypertension among 15–54 years old Indian men: An application of discriminant analysis using National Family Health Survey (NFHS), 2015–16. *Clinical Epidemiology and Global Health* 12 (2021), 100894. https://doi.org/10.1016/j.cegh.2021.100894