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ORIGINAL PAPER

Prediction Models for Early Risk Detection of Cardiovascular Event

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Abstract Cardiovascular disease (CVD) is the major cause of death globally. More people die of CVDs each year than from any other disease. Over 80% of CVD deaths occur in low and middle income countries and occur almost equally in male and female. In this paper, different computational models based on Bayesian Networks, Multilayer Perceptron, Radial Basis Function and Logistic Regression methods are presented to predict early risk detection of the cardiovascular event. A total of 929 (626 male and 303 female) heart attack data are used to construct the models. The models are tested using combined as well as separate male and female data. Among the models used, it is found that the Multilayer Perceptron model yields the best accuracy result.

Keywords Cardiovascular disease · Prediction models · Bayesian Networks · Multilayer Perceptron · Radial Basis Function · Logistic Regression · Heart attack

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Introduction

According to World Health Organization (WHO) report, cardiovascular disease (CVD) forms the major cause of death globally. More people die of CVDs each year than from any other disease. CVD represents a group of disorders relating to heart and blood vessels. CVDs include: Coronary heart disease (CHD) (disease of the blood vessels supplying the heart muscle), Cerebrovascular disease (disease of the blood vessels supplying the brain), Peripheral arterial disease (disease of blood vessels supplying the arms and legs), Rheumatic heart disease (damage to the heart muscle and heart valves from rheumatic fever, caused by streptococcal bacteria), Congenital heart disease (malformations of heart structure existing at birth). Heart attacks and strokes are usually acute events and are mainly caused by a blockage that prevents blood from flowing to the heart or brain. As many as 17.5 million people died due to CVDs in 2005, representing 30% of all global deaths. Over 80 percent of CVD deaths take place in low and middle income countries and occur almost equally in male and female [1].

The number of CVD cases in Malaysia has increased to 14 percent in five years from 96,000 in 1995 to 110,000 in 2000. Approximately 20% of all deaths at the Ministry of Heath hospitals were due to heart attacks and strokes. Two thirds of these deaths were due to heart diseases and the rest due to strokes. It is estimated that 40,000 new stroke cases are recorded annually in Malaysia [2].

Risk analysis (RA) models for early detection of CVDs will not only improve the quality of life of patients but will also be very cost-effective, particularly for developing countries. These models serve as decision support systems (DSS) for physicians and can also be used by the healthcare personnel in remote rural hospitals for quick risk assessment. The prediction for early detection of risk of cardiovascular events using mass spectrometry data and statistical and geostatistical linear prediction models have been reported in [3]. The prediction of risk for first age-related cardiovascular events in an elderly population can be found in [4] where the authors use variables such as age, male gender, diabetes mellitus, systemic hypertension, LV ejection fraction etc. Prediction of cardiovascular disease risk with and without knowledge of genetic variation at Chromosome 9p21.3 is reported in [5].

In this paper, we present models such as Bayesian Networks, Multilayer Perceptron (MLP) networks, Radial Basis Function (RBF) networks and Logistic Regression model for risk prediction of cardiovascular events. These models are used to predict heart attack based on 11 cardiovascular risk factors: (1) Age, (2) Sex, (3) Body Mass Index (BMI), (4) Systolic blood pressure, (5) Diastolic blood pressure, (6) Smoke, (7) Blood Sugar taken at fasting state, (8) Blood Cholesterol, (9) Triglyceride, (10) High density lipo protein (HDL), and (11) Low Density Lipo Protein (LDL). The data used in this paper were collected in Malaysia under a research project supported by Malaysian Government.

Bayesian networks represent knowledge in domains where large sets of interrelated data are available. They are based on a combination of probability, which deals with uncertainty, and graph theory, which deals with complexity. These networks serve as important tools in the design and analysis of machine learning algorithms and are based on the idea of modularity, whereby a complex system is built by combining simpler parts.

Neural Networks such as MLP and RBF are increasingly used for solving a wide variety of problems in areas such as pattern recognition, signal processing, process control and prediction. This paper aims to show that Bayesian Networks, MLP, RBF and Logistic Regression method can prove their potential as prediction models, especially for heart attack. The contribution or novelty of this paper is in showing that among the various models considered, the MLP yields the best accuracy rate for predicting the cardiovascular event.

The paper is organized as follows. In "Prediction models used", we review the prediction models used, namely Bayesian Networks, Multi-layer Perceptron, Radial Basis Function and Logistic Regression models. The performance accuracies result obtained are reported in "Results". "Conclusion" contains the concluding remarks.

Prediction models used

This section describes the basic concepts of Bayesian Networks, Multilayer Perceptron, Radial Basis Functions and Logistic Regression models.

Bayesian networks

Bayesian Network (BN) is a directed acyclic graph (probabilistic expert system) in which every node represents a random variable with a discrete or continuous state [6, 7]. The relationships among variables, indicated by arcs, are interpreted in terms of conditional probabilities according to Bayes' theorem [6]:

$$P(h|e) = \frac{P(e|h)P(h)}{P(e)} \tag{1}$$

where h represents a hypothesis and e an evidence.

Under its usual Bayesian interpretation, it asserts that the probability of a hypothesis h conditioned upon some evidence e is equal to its likelihood $P(e|h)$ times its probability prior to any evidence $P(h)$, normalized by dividing by $P(e)$. $P(e)$ is considered in the equation as the normalization factor:

$$P(e) = P(e|h).P(h) + P(e|\neg h).P(\neg h) \tag{2}$$

Bayesian Network implements the concept of conditional independence that allows the factorization of the joint probability, through the Markov property, in a series of local terms that describe the relationships among variables:

$$f(x_i, x_2, \ldots, x_n) = \prod_{i=1}^{n} f(x_i|pa(x_i)) \tag{3}$$

where $pa(x_i)$ denotes the states of the parents of the variable x_i (child) [7, 8]. Figure 1.

Bayesian Networks are built for specific application domains and represent a broadly specialized knowledge about domains. Bayesian Networks offer an inference system to acquire new relationships from the existing ones which are denoted by the network topology.

Representation of Bayesian Network comprises two parts [9]: (a). The qualitative part of Bayesian Networks is a graphical description of variables the showing distribution and the relationship. This part takes the form of an acyclic directed graph in which each vertex represents the statistical variable that can take one value of a finite set. The arcs represent a direct influential or causal relationship among the variables. (b) The uantitative part of Bayesian Networks

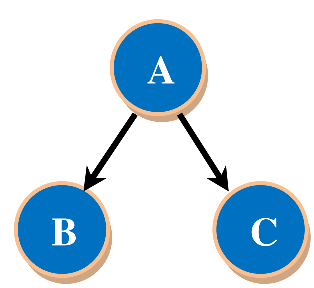


Fig. 1 A Bayesian Network Topology. The node A is parent and nodes B and C are children

is defined representing numerical quantities of probability distribution over domain variables. Each vertex of the directed graph has an associated probability assessment function that describes the influence of each vertex's predecessors to it. The probability assessment functions together constitute the quantitative part of the Bayesian Network.

Neural networks

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use [10].

The neural network model consists of different layers, which are connected to each other by connection weights. The hidden layers occur between the input layer and the output layer. Nodes in the each layer are connected by flexible parameters or weights, which are adjusted based on the error or bias. This process of changing the connection weights is called training.

The motivation for using neural networks is based on the fact that these models are capable of handling non-linear relationships.

Multi-layer perceptron

Multi-Layer Perceptron (MLP) is the most commonly used neural networks architecture in engineering applications. MLP can be seen as a flexible class of nonlinear functions. This model works by receiving a vector of inputs X and computes a response or output Y(X) by propagating X through the interconnected processing elements. Each the layer, the inputs to the layer are nonlinearly transformed by the processing elements and propagated to the next layer. The outputs are computed at the output layer Y(X), which can be scalar valued. Figure 2 shows the architecture of multilayer backpropagation neural networks [11].

$$Y(X) = \beta_0 + \sum_{j=1}^{n} \beta_j \psi\left(\gamma_{j0} + \sum_{i=1}^{I} \gamma_{ji} X_i\right) \tag{4}$$

where (β_0, β_1, ..., β_n, γ_{10},..., γ_{nI}) are the weights or parameters of the MLP. The non-linearity enters into the function Y(X) through the so-called activation function ψ. In this paper, we used the Hyperbolic Tangent [12] given below:

$$\psi(x_j) = \tanh(x_j) = \frac{e^{x_j} - e^{-x_j}}{e^{x_j} + e^{-x_j}} \tag{5}$$

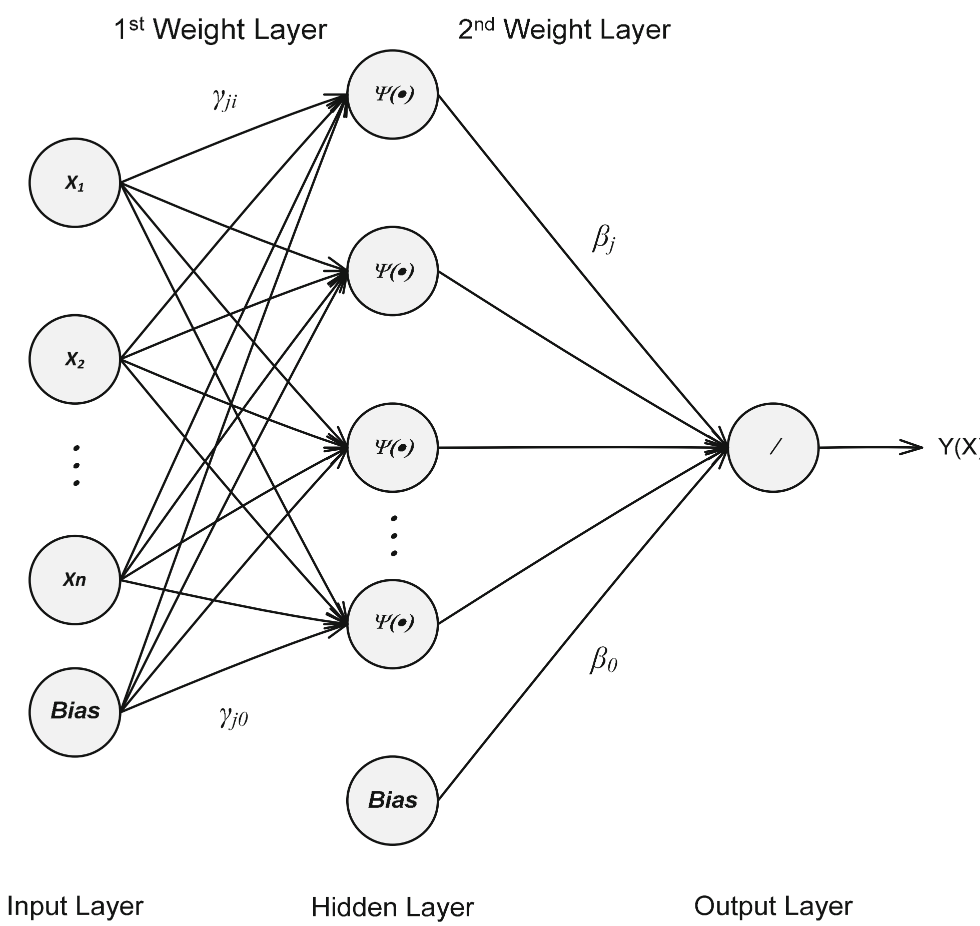


Fig. 2 A general Multilayer Backpropagation Neural Network

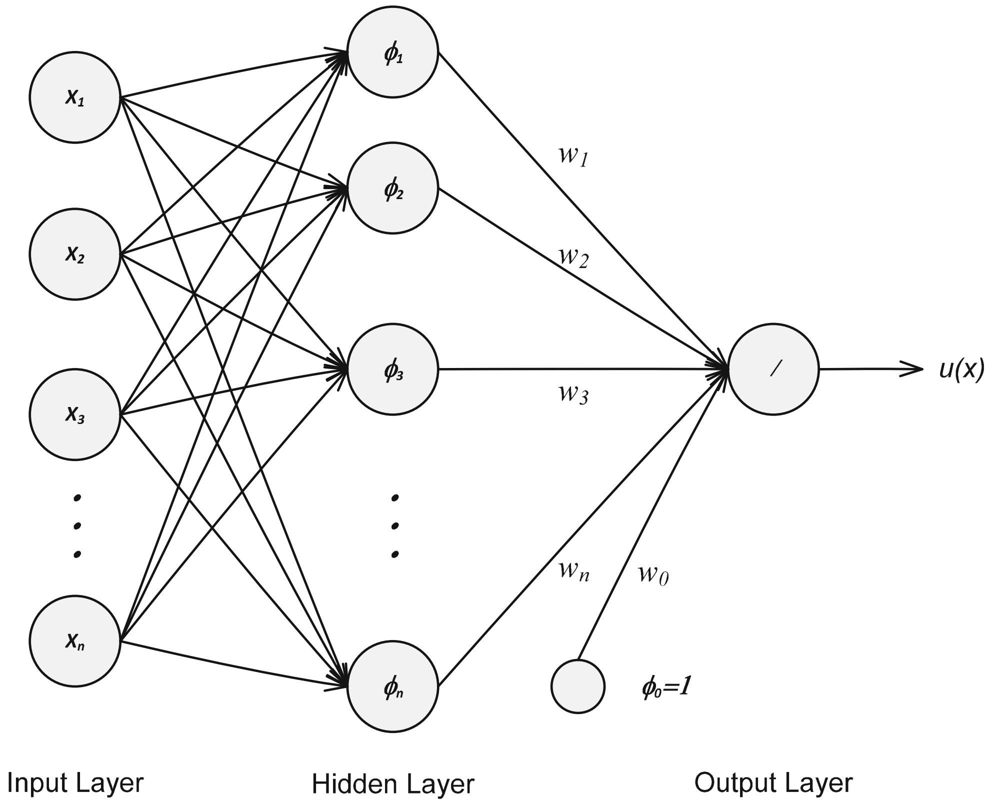


Fig. 3 Radial Basis Function Neural Network

and Softmax [12] as given below:

$$\psi(x_j) = \frac{e^{x_j}}{\sum e^{x_k}} \quad (6)$$

Radial basis functions

The Radial Basis Function (RBF) network makes use of the radial basis or Gaussian density function as the activation function, but the structure of the network is different from the feed-forward or MLP network [10]. Radial Basis Function network has basis functions as typified by Gauss function. Basis function $\phi_j(x)$, commonly a Gaussian is given by:

$$\phi_j(x) = \exp\left(-\frac{\sum_{i=1}^{d}(x_i - c_{ij})^2}{2\sigma_j^2}\right) \quad (7)$$

where c_{ij} is the center vector, σ^2 is a parameter which decides function width.

Mathematically, Radial Basis Function network is constructed as:

$$u(x) = \sum_{j=1}^{m} w_j\phi_j(x) + w_0 \quad (8)$$

where m is the number of hidden units, w_0 is the bias value, w_j is the weights on each basic function, and x is the input data.

A schematic diagram of single output Radial Basis Function is presented in Fig. 3.

Logistic regression method

Independent variables can be denoted as X_1, X_2, ..., X_k where k is the number of variables being considered. In the analysis of such a problem, some kind of mathematical

Table 1 Descriptive statistics of heart attack

Variables	Min.	Max.	Mean	Std. Dev.
Age	23.00	96.00	50.15	14.47
Sex	0.00	1.00	0.67	0.47
Body Mass Index	13.10	38.87	22.37	4.21
Systolic Blood Pressure	90.00	210.00	126.71	19.09
Diastolic Blood Pressure	50.00	130.00	77.96	10.82
Blood Sugar	2.16	12.80	5.15	1.06
Smoke	0.00	1.00	0.26	0.44
Blood Cholesterol	2.91	10.31	5.49	1.13
Triglyseride	0.43	6.53	1.52	0.88
High Density Lipo Protein	0.25	2.67	1.00	0.28
Low Density Lipo Protein	1.18	8.92	3.79	1.09
Heart Attack	0.00	1.00	0.48	0.50

model is typically used to deal with the complex inter-relationships among many variables.

Logistic Regression is a mathematical modeling approach that can be used to describe the relationship between independent variables and a dichotomous dependent variable (Y) [13].

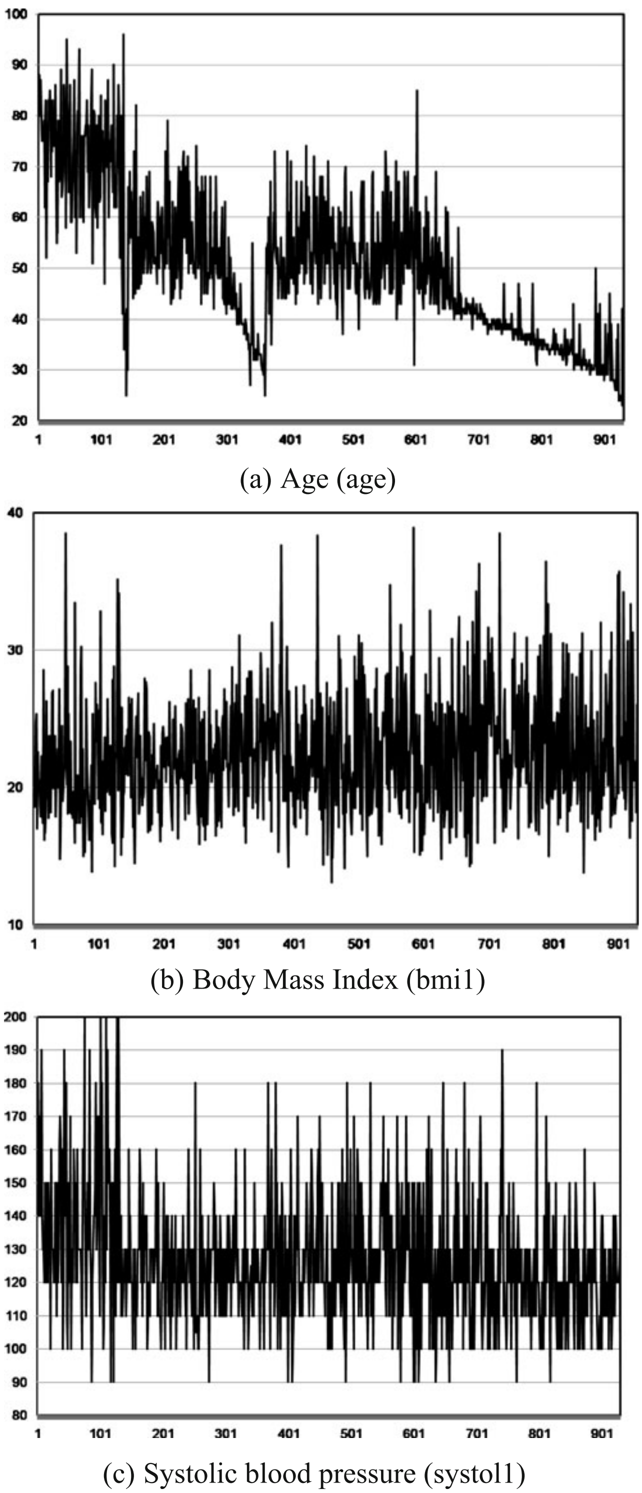


Fig. 4 Distribution of heart attack data for the test subjects

Table 2 Variables on heart attack

No	Var	Meaning	Level	Description
1	age	Age	< 40	
			40–45	
			45–50	
			50–55	
			55–60	
			60–65	
			65–70	
			70–75	
			75–80	
			>= 80	
2	Sex	Sex	1	Male
			0	Female
3	bmi1	Body Mass Index	< 18.5	Underweight
			18.5–24.9	Healthy Range
			25.0–29.9	Overweight
			>= 30	Obese
4	systol1	Systolic blood pressure-upper part	< 120	Normal
			120–139	Pre Hypertension
			140–159	Stage 1 hypertension
			>= 160	Stage 2 hypertension
5	diastol1	Diastol blood pressure-lower part	< 80	Normal
			80–89	Pre Hypertension
			90–99	Stage 1 hypertension
			>= 100	Stage 2 hypertension
6	bs0	Blood sugar	< 5.6	
			5.6–11.0	
			>= 11.1	
7	smoke1	Smoking	1	Yes
			0	No
8	chol1	High Blood Cholesterol	< 5.17	Desirable
			5.17–6.19	Borderline-high
			>= 6.20	High
9	tg1	Triglyceride	< 1.7	Normal
			1.7–2.3	borderline-high
			2.3–5.6	High
			> 5.6	very high
10	hdl1	High density lipo protein	< 1.04	Low
			1.04–1.7	Acceptable
			>= 1.7	Desirable
11	ldl1	Low density lipo protein	< 2.6	Optimal
			2.6–3.4	near optimal
			3.4–4.1	borderline-high
			4.1–4.9	High
			> 4.9	very high
12	Heart Attack	Heart Attack	1	Yes
			0	No

Equation 8 shows the logistic function which describes the mathematical form on which the logistic model is based.

$$f(z) = \frac{1}{1 + e^{-z}} \tag{9}$$

Note that the logistic function $f(z)$ ranges between 0 and 1 and the logistic model is designed to describe a probability, which is always some number between 0 and 1. To obtain the logistic model from the logistic function, we write z as:

$$\left.\begin{aligned} z &= \alpha + \beta_1 X_1 + \ldots + \beta_k X_k \\ z &= \alpha + \sum_{i=1}^{k} \beta_i X_i \end{aligned}\right\} \tag{10}$$

where X_1, X_2, ..., X_k are independent variables and α and the β_i are constant terms representing unknown parameters, $i=1...k$

The probability being modeled can be denoted by the conditional probability statement:

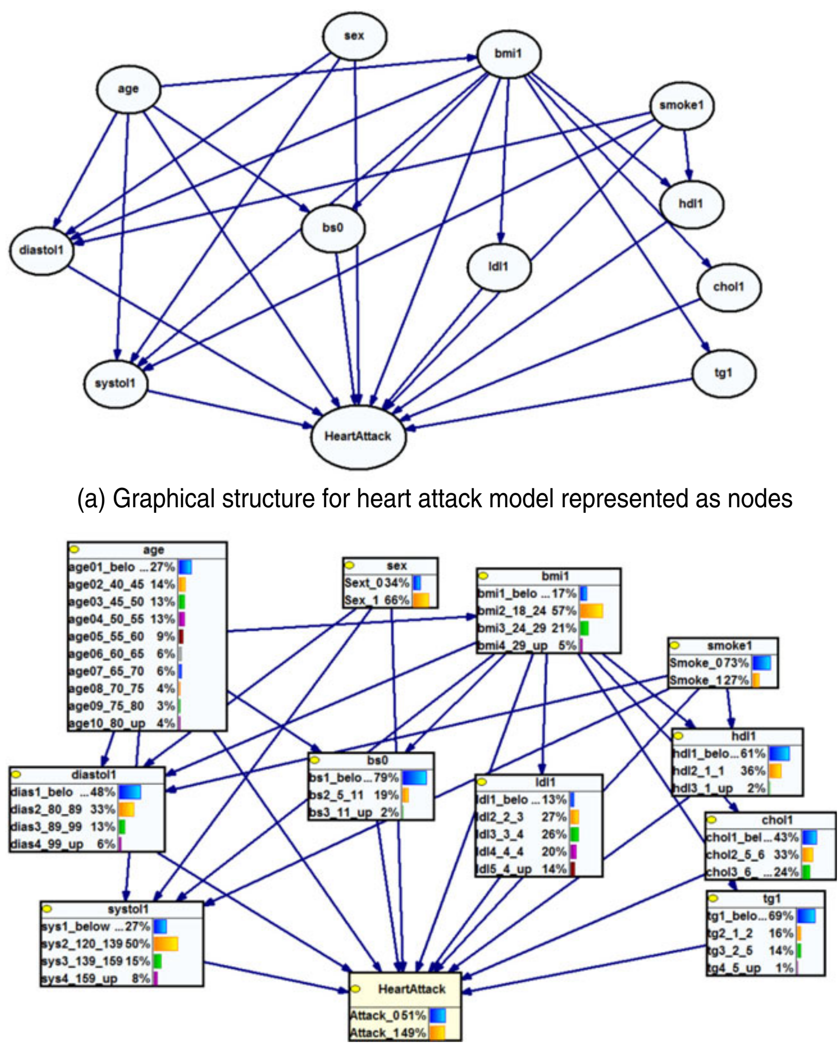
$$P(Y = 1|X_1, X_2, \ldots, X_k) = P(X) = \frac{1}{1 + e^{-\left(\alpha + \sum_{i=1}^{k} \beta_i X_i\right)}} \tag{11}$$

The model is defined as a logistic model.

Data

The Heart Attack data used in this work were collected by a research team in Malaysia under IRPA grant 305/PPSP/6112227, RM8(PR). The data pertain to Age, Sex, Body Mass Index (BMI), Systolic blood pressure, Diastolic blood pressure, Blood sugar level taken at fasting state (BS), Smoking, Blood Cholesterol level, Triglyceride, High density

Fig. 5 Graphical representations of the implemented Bayesian Network



(a) Graphical structure for heart attack model represented as nodes

(b) Graphical structure for heart attack model represented as bar charts

Table 3 MLP architecture and classification

Data	Layer	No. nodes	Activation	Prediction accuracy(%)
Male and Female	Input	13	–	64.0
	Hidden	3	Hyperbolic Tangent	
	Output	2	Softmax	
Male	Input	11	–	69.8
	Hidden	9	Hyperbolic Tangent	
	Output	2	Softmax	
Female	Input	11	–	75.8
	Hidden	8	Hyperbolic Tangent	
	Output	2	Softmax	

lipo protein (HDL), Low density lipo protein (LDL) and Heart Attack. Table 1 displays the statistical features of the data.

A total of 929 heart attack data pertaining to 626 male and 303 female were used. The variables for heart attack detection were based on the 11 cardiovascular risk factors shown in Table 1. The minimum, maximum, mean and standard deviation of the data, are given in Table 1.

Figure 4 shows plots of typical examples of heart attack data, where the horizontal axis represents the patient (subject) i, where i=1, 2, ..., 929 and the vertical axis is the value of variables (Age, Body Mass Index (BMI), Systolic blood pressure) as is observed. The plots show a wide spread of data with respect different test subjects.

Table 4 MLP parameter estimates for male and female

Layer		Weights		
		Hidden layer neurons		
		H1	H2	H3
	(Bias)	−0.206	−0.083	0.105
	[sex=0]	0.322	0.07	−0.005
	[sex=1]	0.172	0.439	0.337
	[smoke1=0]	0.181	0.372	0.202
	[smoke1=1]	0.286	0.226	0.38
	age	−0.167	−0.368	0.335
	bmi1	−0.053	0.763	−0.09
	systol1	0.219	−0.323	0.133
	diastol1	−0.651	−0.061	0.499
	bs0	−0.282	0.084	0.18
	chol1	−0.598	−0.756	−0.323
	tg1	0.269	−0.47	−0.156
	hdl1	1.064	0.885	0.284
	ldl1	0.574	−0.44	−0.166
Output	[HeartAttack=0]	0.769	0.275	0.329
	[HeartAttack=1]	0.033	−0.25	0.05

Results

In this work, we compare four prediction models. The models are based on Bayesian Network, MLP, RBF and Logistic

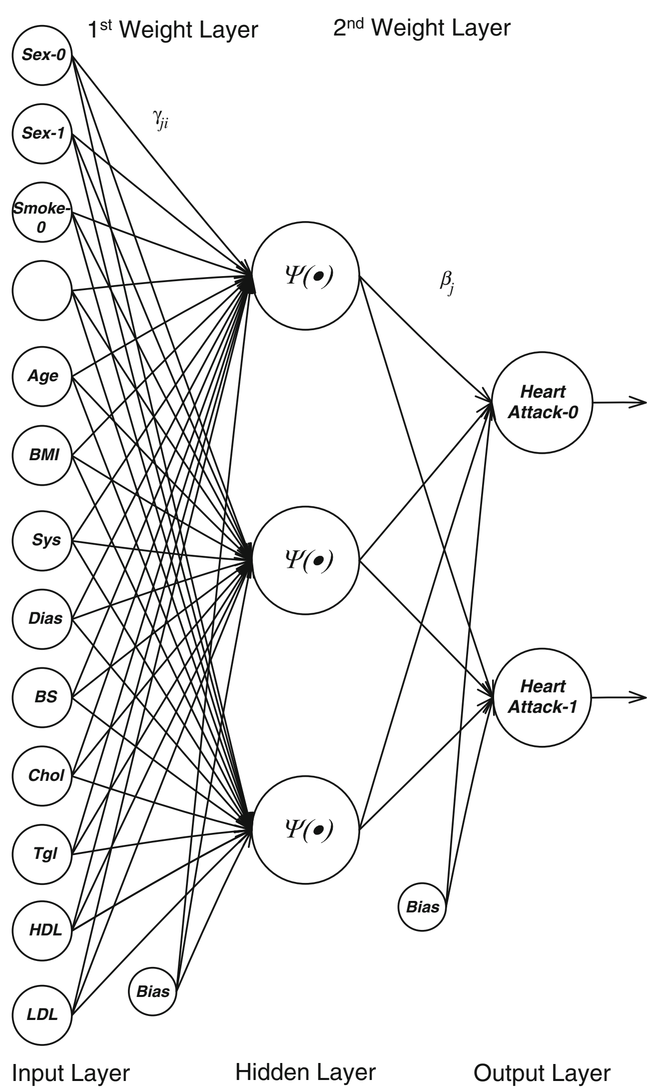


Fig. 6 MLP model architecture for the combined male and female data

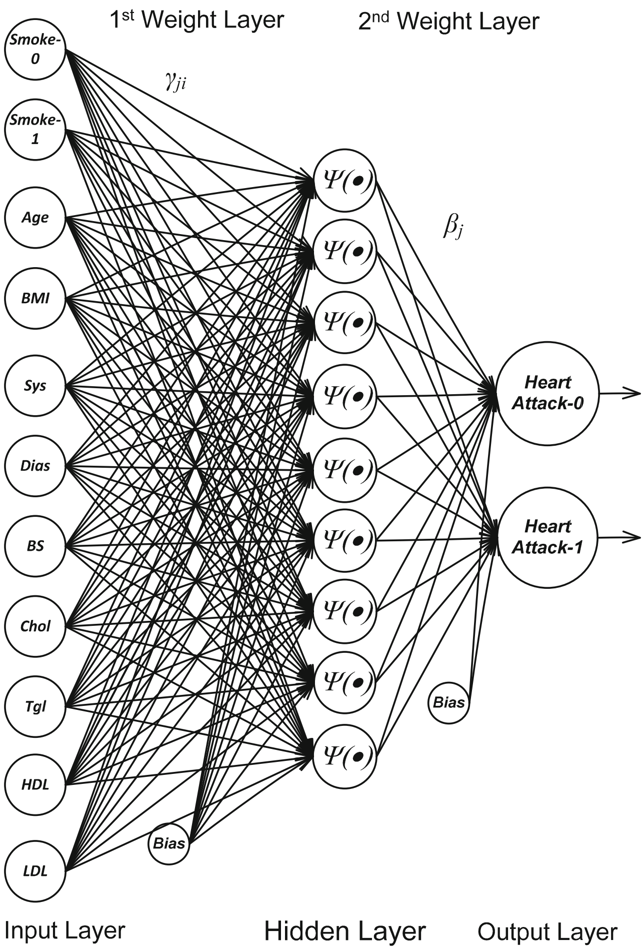


Fig. 7 MLP model architecture for male data only

Regression. The results achieved by each implemented model are discussed below.

Bayesian network

Out of the tested variables, Sex, Smoke and Heart Attack have discrete values and the other variables have continuous values. The continuous variables are discretized as shown in Table 2 for Bayesian network implementation.

The graphical and probability structure of the Bayesian Model can be explored using the Genie tools [14]. Figure 5 (a) illustrates the graphical structure for the Bayesian Network model where the variables are represented as nodes. Figure 5(b) shows the same model with nodes represented as bar charts for heart attack prediction using the combined data (male and female).

The Bayesian Network model was implemented using the combined heart attack data (male and female), as well as individual male and female data. This model describes the relationships between the dependent and independent variables.

The model was developed using the Genie® software platform. The probability values for all the nodes are given at the bottom of the bar chart in Fig. 5(b). The prediction accuracy for heart attack with the combined male and female data is obtained as 51%. The prediction accuracy values obtained using male and female data separately are 53% and 51% respectively.

Neural networks

Multi layer perceptron

The MLP model simulation is applied to the combined as well as separate male and female data. The MLP architecture and the classification results obtained with the combined as well as separate male and female data are shown in Table 3.

The optimum MLP architecture for the case of combined data (Male and Female) comprises 13 input units, single hidden layer with 3 neurons as shown in Table 4. The hidden layer and output layer neurons use hyperbolic tangent and Softmax activation functions respectively.

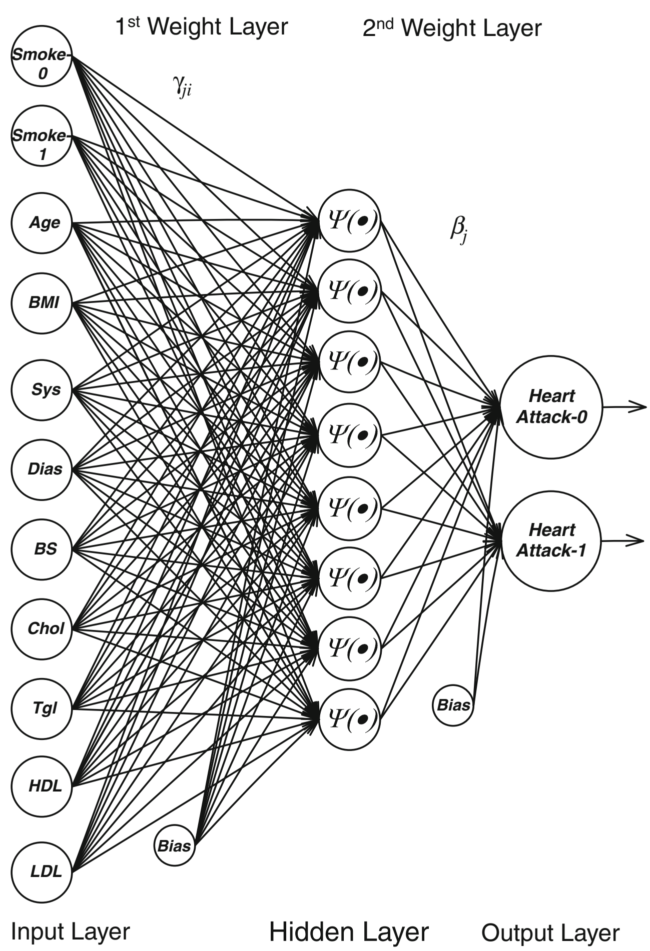


Fig. 8 MLP model architecture for female data only

Table 5 Neural Network (RBF) architecture and classification

Data	Layer	No. nodes	Activation	Prediction accuracy(%)
Male and Female	Input	13	–	62.8
	Hidden	2	Exponential	
	Output	2	Identity	
Male	Input	11	–	60.3
	Hidden	4	Exponential	
	Output	2	Identity	
Female	Input	11	–	75.0
	Hidden	4	Exponential	
	Output	2	Identity	

Figure 6 shows the Multilayer Perceptron architecture used for the combined male and female data. Figures 7 and 8 show the MLP architectures used for male data and female data, respectively.

The values of the parameters or weights estimates in the MLP model (after training) were identified as in Table 4.

The optimum of MLP architecture for male data only is obtained as follows: 11 input units (without sex [0, 1] variables), single hidden layer containing 9 hidden units with Hyperbolic Tangent activation function and 2 output units (heart attack [0, 1]) with Softmax activation function. The optimum MLP architecture for female data only is obtained as follows: 11 input units (without sex [0, 1] variables), single hidden layer containing 8 hidden units with Hyperbolic Tangent activation function, and 2 output units (heart attack [0, 1]) with Softmax activation function.

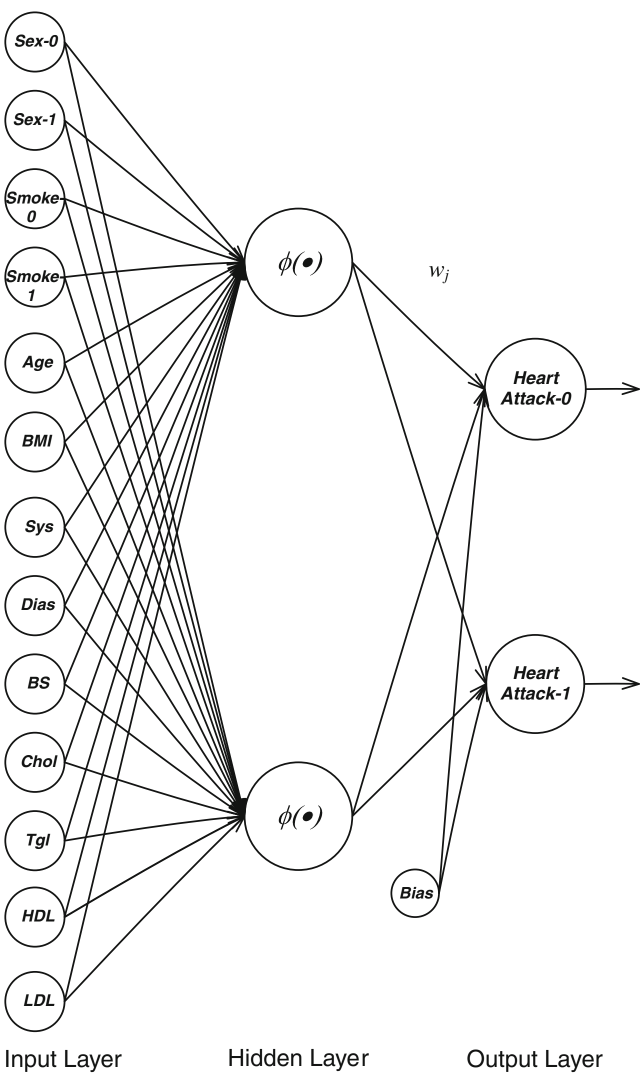


Fig. 9 RBF-model architecture for the combined data

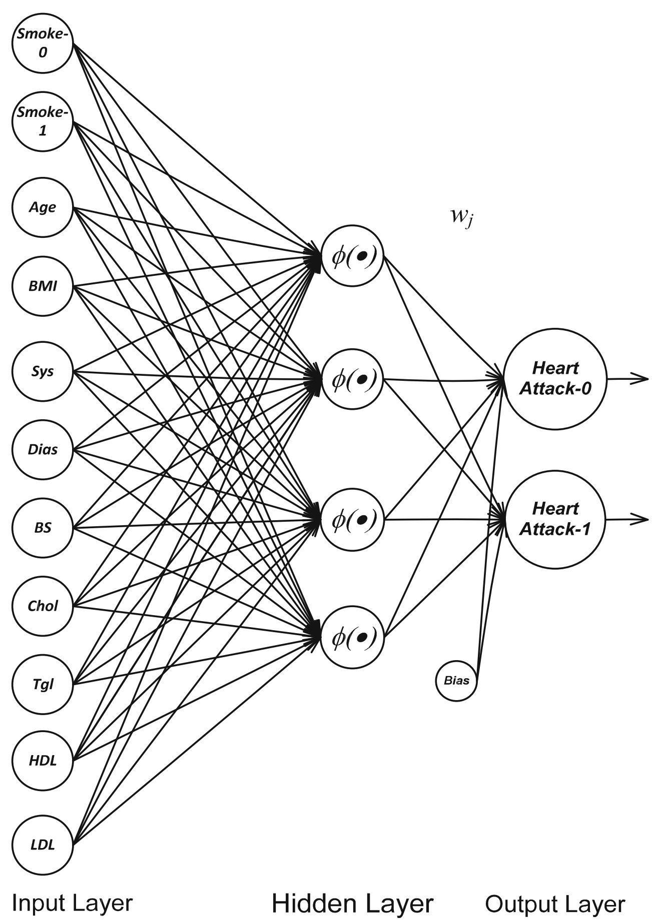


Fig. 10 RBF model architecture for the male as well as female data

Table 6 RBF parameter estimates for male and female

Layer		Weights	
		Hidden layer neurons	
		H1	H2
Input	[sex=0]	0.000	0.862
	[sex=1]	1.000	0.138
	[smoke1=0]	1.000	0.300
	[smoke1=1]	0.000	0.700
	Age	0.322	0.450
	bmi1	0.377	0.330
	systol1	0.306	0.301
	diastol1	0.354	0.336
	bs0	0.244	0.251
	chol1	0.351	0.338
	tg1	0.159	0.211
	hdl1	0.335	0.271
	ldl1	0.338	0.333
Output	[HeartAttack=0]	0.543	0.489
	[HeartAttack=1]	0.457	0.511

Radial basis function

The classification results obtained using RBF model is shown in Table 5.

For the complete data (male and female), the optimum RBF architecture was obtained as follows: 13 input units, Single hidden layer with 2 hidden units and Exponential activation function, and 2 output units (heart attack [0, 1]) with Identity activation function.

Figure 9 shows the Radial Basis Function architecture used for the combined male and female data. Figure 10 shows the RBF architecture used for the male as well as female data.

The values of the parameters or weights estimates in RBF model (after training) were obtained as shown in Table 6.

The optimum architecture for male data only was obtained as: 11 input units (without sex [0, 1] variables), single hidden layer with 4 hidden units using Exponential activation function, and 2 output units (heart attack [0, 1]) with Identity activation function. The optimum RBF architecture for female data only was obtained as: 11 input units (without sex [0, 1] variables), a single hidden layer with 4 hidden units using Exponential activation function, and 2 output units (heart attack [0, 1]) with Identity activation function.

Logistic regression

The Logistic Regression model for the combined data (male and female) was obtained as follows:

$$\begin{aligned} Heart\ Attack = & -0.509 + 0.00{*}age - 0.032{*}sex \\ & +0.00{*}bmi\ 1 + 0.003{*}systol\ 1 \\ & -0.001{*}diastol\ 1 + 0.052{*}bs0 \\ & +0.168{*}smoke\ 1 + 0.101{*}chol\ 1 \\ & -0.071{*}tg\ 1 - 0.426{*}hdl\ 1 \\ & -0.025{*}ldl\ 1 \end{aligned} \tag{12}$$

The prediction accuracy obtained with this model was 56.0%.

For male data only, the Logistic Regression model was obtained as:

$$\begin{aligned} Heart\ Attack = & -0.059 + 0.03{*}age - 0.013{*}bmi\ 1 \\ & +0.005{*}systol\ 1 + 0.000{*}diastol\ 1 \\ & +0.015{*}bs0 + 0.591{*}smoke\ 1 \\ & +0.005{*}chol\ 1 + 0.003{*}tg\ l - 0.550 \\ & {*}hdl\ 1 - 0.033{*}ldl\ 1 \end{aligned} \tag{13}$$

The prediction accuracy obtained with this model was 55.9%.

For female data, the Logistic Regression model was obtained as:

$$\begin{aligned} Heart\ Attack = & -2.065 + 0.03{*}age + 0.054{*}bmi\ 1 \\ & +0.000{*}systol\ 1 + 0.005{*}diastol\ 1 \\ & +0.091{*}bs0 - 0.028{*}smoke\ 1 \\ & +0.233{*}chol\ 1 - 0.248{*}tg\ l \\ & +0.212{*}hdl\ 1 + 0.008{*}ldl\ 1 \end{aligned} \tag{14}$$

The prediction accuracy obtained with this model was 60.1%.

Table 7 Percentage correct for male and female, male and female

No	Models	Prediction accuracy (%)					
		Male and Female		Male		Female	
		Training	Testing	Training	Testing	Training	Testing
1	Bayesian Network	51.0	51.0	53.0	53.0	51.0	51.0
2	MLP	52.0	64.0	54.0	69.8	58.1	75.8
3	RBF	53.1	62.8	57.2	60.3	58.9	75.0
4	Logistic Regression	56.0		55.9		60.1	

Comparison of models

Table 7 shows the comparison of prediction results obtained with Bayesian Network, Multilayer Perceptron, Radial Basis Function and Logistic Regression models.

From Table 7, it is seen that the best model for the combined as well as separate male, female data is MLP with prediction accuracy values of 64.0% 69.4% and 75.8% respectively.

From Table 7, it is seen that the best model for the combined as well as separate male, female data is MLP with prediction accuracy values of 64.0% 69.4% and 75.8% respectively.

Conclusion

The main contribution of this paper is to show the performance capabilities of the various models for cardiovascular event prediction. Specifically, the superior performance of the MLP for health prediction with heterogeneous database pertaining to Malaysian population is highlighted.

The prediction was done using Bayesian Network, Multilayer Perceptron (MLP) network, Radial Basis Function (RBF) network and Logistic Regression model. A total of 929 (626 male and 303 female) heart attack data were used in this study. The models were tested with the combined data as well as with separate male and female data. From the comparison of the four models, it was found that the MLP model performs the best, yielding an accuracy of 64.0% for the combined data (Male and Female), 69.8% for Male data only and 75.8% for Female data only.

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