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Research paper

A fuzzy analytic hierarchy attribute weighting and deep learning for improving CHD prediction of optimized semi parametric extended dynamic bayesian network

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Abstract

Several Data mining techniques have been developed to enhance the prediction accuracy and analyze several events in Coronary Heart Disease (CHD). One among them was Extended Dynamic Bayesian Network (EDBN) which integrates temporal abstractions with DBN. Then EDBN was extended as Optimized Semi parametric Extended Dynamic Bayesian Network (OSEDBN) to handle Complex temporal abstractions in irregular interval time series data. The deep learning network is generated the various time points in the next level to improve the analysis and prediction of CHD. In this paper, Optimized Semi parametric Extended Deep Dynamic Bayesian Network (OSEDDBN) is proposed by integrating deep learning architecture with OSEDBN to improve the ability of extracting more important data and support complex structures from various types of input sources. Additionally the Fuzzy Analytic Hierarchy Process (FAHP) approach is used to compute the global weights for the attributes based on their individual contribution. The global weights of the attributes obtained by FAHP are utilized for training OSEDDBN to further improve the prediction of Coronary Heart Disease (CHD) risks. The performance of EDBN, OSEDBN, OSEDDBN, and OSEDDBN-FAHP are evaluated in terms of Precision, Recall and F-Measure.

Keywords: *Coronary Heart Disease (CHD), Fuzzy Analytic Hierarchy Process (FAHP), Extended Dynamic Bayesian Network (EDBN) and Deep Dynamic Bayesian Network (DDBN)*

1. Introduction

Data mining [1] is essential technology for generating application in medical informatics. The more number of data mining algorithms were iteratively increase to realize medical data more clearly by differentiating pathological data from normal data to manage decision-making as well as visualization and identification of hidden complex relationships between diagnostic features of different patient groups.

Now a day the Coronary Heart Disease (CHD) is common disease which is affected the heart and causes for occurring premature death. it is world known fact because heart is the most essential part in the human body if that heart gets affected then also suffered the other parts of the body. So that it is necessary for people to go for a heart disease diagnosis. Coronary Heart Disease (CHD) [2] is a major cause of disability in adults.

CHD includes hyperlipidemia, myocardial infarction, and angina pectoris. The early diagnose of the CHDs very critical task, but for effective treatment, its early diagnosis is important. So the prediction of CHD [3] is needed to minimize the management costs of CHD and for promoting health. CHD [4] is very dangerous because it is closely associated with the patient’s life. Hence prevent is crucial. However, diagnoses [5] are depend upon medical expert’s personal experiences and understanding of the disease which increases the risks of errors, delay appropriate treatment and taken more time for treatment.

The one of the machine learning technique like Neural Networks (NN) are used to find the CHD and also improve the performance. The NN is very efficient to generalize the data without the prior knowledge of CHD to training. Additionally the NN is easily explored the new patterns and information of complex data which are related with the CHD. In this paper Deep Dynamic Bayesian Network (DDBN) and Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) presented to improve prognosis of Coronary Heart Disease (CHD).

The remaining section of the paper is scheduled as follows: Section 2 investigates about the various methods data mining methods to detect Coronary Heart Disease. Section 3 explains the methodology of proposed system. Section 4 illustrates the experimental results by various performance metrics. Section 5 concludes and discusses about the proposed work.

2. Literature survey

Dynamic Bayesian Network (DBN) [6] presented to construct the realistic prognostic models with temporal and decision making characteristics. The result shows that the DBN provides detailed predictions which includes not only patient survival but also contains disease progression, the effect of treatment and the development of complications. The DBN perform better than traditional approaches. Since the interpretation of DBN Network increase complexity.

Integration of Temporal Abstraction and Dynamic Bayesian Network (DBN) [7] presented to improve the diagnosis of coronary heart disease (CHD). The hypothesis analysis plan the effective temporal abstraction methods is incorporated with

DBNs. The aim of this research is examine how the DBN represents the abstracted data to build the prognostic model. Since this approach does not perform well in high dimensional datasets.

Bayesian Network [8] presented to enhance the performance of prediction of heart diseases in early stages. This research was mainly focused to generate the knowledge based inference with Bayesian network for early diagnose of heart disease. Finally implemented the web based system for the patient to get the early diagnose of heart disease. However the Bayesian network require significant amount of probability data to construct the knowledge base.

Genetics and Genomics [9] presented to focus the current methods and overall advance techniques of cardiovascular disease and offering some of the mechanism to reduce the complexity of disease. This research was related with the coronary artery disease (CAD) in the context of GWAS, transcriptomic profiling, probing of in the vivo protein- DNS interactions, regulatory and higher order chromatin structure. Finally found the most advantages of this mechanism and applying CRISPR/Cas0 technology which was inducible and specific gene cell deletions and given priority to unravel the complex web of gene and disease interactions. Since this model require large amounts of probability data.

Intelligent Postoperative Morbidity [10] presented to prediction of heart disease. This analysis demonstrates the development of an informative ensemble prediction model consists of Bayesian Networks, Artificial Neural Networks and Support Vector Machines for the prediction of Postoperative Morbidity and the descriptions of casual effects between preoperative variables. However the Bayesian Networks has high computational overhead.

Integration of Dynamic Bayesian Network (DBN) and Temporal Abstractions (TAs) [11] presented for assessing the intricacy of coronary heart disease (CHD) event. The conventional TAs and DBNs were analyzed to enhance the model to a longitudinal CHD dataset. The risk factors of CHD are chosen based on the expert domain knowledge and efficiently handled class imbalance in the training. However the DBN has high time complexity issue.

Dynamic Bayesian Network [12] methodology presented for diagnosing coronary arteries disease. In this mechanism collect the patient details based on baseline study. The goal of this research was analyzed the entire source of data like Demographic, Clinical, Biochemical profile and Treatment characteristics to possible manifestations of the disease. Furthermore, this research was predicted the key factors that represent the progression of atherosclerosis and build a model to predict the progression of atherosclerosis for the specific patient. Since the DBN network has require to increase the accuracy.

Fuzzy Expert System [13] presented for heart disease diagnosis. This system was used to investigate the 13 input fields and more output fields. The input field was included chest pain type, blood pressure, cholesterol, resting blood sugar, maximum heart rate, maximum heart rate, resting electrocardiography (ECG), Exercise, Old peak, thallium scan, sex and age. The output field was referred the presence of heart disease in the patient. The output system utilizes the Mamdani inference method. The result shows that the proposed mechanisms are perform better than the traditional approaches. Since the Fuzzy rules are more complex.

Analyze the impact of coronary heart disease [14] presented to diagnosis in early stages. The traditional approached does not perform well in high dimensional data and complex data types. This analysis was efficiently analyze to know the impact of interventions in a real clinical setting which leads to obtain new way for the researches of integrative medicine in coronary heart disease. Since these mechanisms has high computational overhead.

Artificial Neural Network (ANN) [15] presented to found the heart disease in early stages. This mechanism was found the following two diseases such as nephritis disease the data are the disease symptoms and heart disease, the data in on Cardiac Single Proton Emission Computed Tomography (SPECT) images. According to this mechanism the patient was categorized into two well known categories like infected and non-infected. The experimental result was provided the ANNs methodology perform acute nephritis diagnosis depends on the specified symptoms shows the efficiency of network to analyze the pattern for the specified patients. However the ANN was required high processing time is the network is large.

3. Proposed methodology

In proposed methodology the Deep Dynamic Bayesian Network (DDBN) and Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) technique presented to diagnosis of risk for coronary heart disease (CHD).

3.1. Optimized semi parametric Extended Deep Dynamic Bayesian Network (OSEDDBN)

The construction of Optimized Semi parametric Extended Deep Dynamic Bayesian Network (OSEDDBN) contains following criteria such as Deep Learning, Dynamic component. The proposed Deep Dynamic Bayesian Network (DDBN) is used to improve the prognosis of risk for coronary heart disease (CHD). The DDBN consists of two steps such as (i) Deep Learning and (ii) Dynamic Component.

3.1.1. Deep learning

The Deep learning is also referred as the new subset of machine learning and which is provided the shallow architecture i.e., a system is included only one layers to point out the hidden attributes of a system. This hidden layer is permitted for the components of system which are not directly observed for the analysis. These types of architecture were not always applicable the real world dynamical systems. The deep learning techniques are mainly implemented to focus the extraction of most required data and complex structures from various input resources.

3.1.2. Deep belief networks

The Deep belief network is probabilistic generative models and which is constructed by multiple layers of stochastic variables. The hidden variables are relied upon part of the system. The deep Belief network is focused how the structure of the network is designed by stack of restricted Boltzmann machines (RBMs). The RMBs is one of the types of the Markov random filed which included two stochastic layers.

3.1.3. Dynamic component

The dynamic components is integrated a temporal or dynamic components into deep learning with deep belief networks. The development of DBN-HMM (Deep Belief Network Hidden Markov Model) has started to make significant contribution in the field of area. The deep dynamic component contains several benefits and which can efficiently modeled a dynamic system which involves sequential time dependent data. The efficient construction of this model is used the time dependent data access for better analysis with multiple levels of abstraction as current deep networks assume a static domain.

3.1.4. Dynamic bayesian network

The dynamic Bayesian networks (DBNs) is explored how the inclusion of dynamic components access the network to model the real world system. The Bayesian Networks (BNs) are the probabilistic graphical model which is focused the relationships between a group of random variable where the probabilistic nature of model permits uncertainty in a system to be modeled appropriately. These attributes are make them appropriate model for the analysis of multiple domain areas. The DBNs are the

extended model for traditional Bayesian network which integrated temporal dimensions.
The proposed model is mainly concentrate how to model a Deep Dynamic Bayesian Network (DDBN) framework to describe a novel learning model incorporating DBN temporal component into a network containing multiple hidden layers. This research work is fully integrated system to focus the hidden layers and how they performed throughout the dynamic process to be modeled. The new network is referred as the deep dynamic Bayesian network (DDBN).

3.2 Optimized semi parametric extended deep dynamic bayesian network with fuzzy analytic hierarchy process (OSEDDBN-FAHP) for the prediction the risk factor of coronary heart disease

The fuzzy analytic hierarchy process (Fuzzy-AHP) technique presented to compute the global weights for the attributes based on the individual contributions. Then the global weights represents the contributions of the attributes were apply to train the Deep Dynamic Bayesian Network for prediction of Coronary Heart Disease (CHD) risk prediction in patients.
The proposed hybrid method based on DDBN and Fuzzy AHP techniques for CHD risk prediction had two sequential stages. In the first stage, the 19 CHD attributes considered in this research as shown in Table 1 were evaluated and ranked in order of their importance through Heart Disease risk using Fuzzy-AHP technique. The application of the fuzzy-AHP technique was achieved in the following three steps.
Step 1: The problem was represented using a hierarchical structure that shows the relationship between goals (CHD diagnosis), attributes (CHD attributes) that contribute to the goal and attributes alternatives in the decision process (Figure 1).
Step 2: Having decomposed the problem into goal, attributes and alternatives a pair wise comparison of each attribute with respect to the others was carried out based on experience and judgments of medical practitioners. The each attribute’s alternatives were represented by using fuzzy triangular membership function prior to the pair wise comparison. The results obtain from the pair wise comparison were afterwards expressed on semantic judgments and converted to numerical values based on saaty fundamental scale, quantification of judgments ranges from 1 to 9 (Table 2).

Table 1: Coronary Heart Disease (CHD) Diagnosis Attributes: Description and Grading of the Attributes Alternatives

S.No	Attribute Description	Attribute Code	Alternatives	Range
1	Smoking	Smoking	Non Smoker, Current Smoker	1 0
2	Medicines for Reducing Cholesterol	medCH	Taken, Not Taken	1 0
3	Medicines for Reducing Blood Pressure	medBP	Taken, Not Taken	1 0
4	Systolic Blood Pressure	SystBP	Normal Prehypertension High Blood Pressure	<120 [120-140] >140
5	Diastolic Blood Pressure	DiastBP	Normal Prehypertension High Blood Pressure	<80 [80-90] >90
6	Dyslipidemia	Dyslipidemia	Absent Present	0 1
7	Disease	CurrentEvent	Absent Present	0 1
8	Predict Coronary Heart Disease	Class Variable	Pred_Event Absent Present	0 1 2
9	Diabetes	Diabetes	Absent Present	0 1
10	Family History	FH	Absent Present	0 1
11	History of Coronary Heart Disease	HHD	Absent Present	0 1
12	Body Mass Index	BMI	Normal Weight Overweight Obesity	<25 [25-30] >30
13	Low density lipoprotein cholesterol	LDL	Normal High Very High	<100mg [100-160]mg >160mg
14	Triglycerides	TRIG	Normal High Very High	<150mg [150-200]mg >200mg
15	High density lipoprotein cholesterol	HDL	Normal High Very High	<40mg [40-60]mg >60mg
16	Total Cholesterol	TCH	Normal High Very High	<200mg [200-240]mg >240mg
17	Age	AGE	Young Old Very old	<50years [50-60] years >60 years
18	Diet	DIET	Following a Diet Not Following a Diet	1 0
19	Exercise	Exercise	Exercising Not Exercising	1 0

Table 2: The AHP Fundamental Preference Scale [16]

S.NO	AHP Scale of Importance for comparison pair	Numeric Rating	Reciprocal (Decimal)
1	Extreme Importance	9	1/9 (0.111)
2	Very Strong to Extreme Importance	8	1/8 (0.125)
3	Very Strong Importance	7	1/7 (0.143)
4	Strongly to Very Strong	6	1/6 (0.167)
5	Strong Importance	5	1/5 (0.200)
6	Moderately to Strong	4	1/4 (0.250)
7	Moderately Importance	3	1/3 (0.333)
8	Equally to Moderately	2	1/2 (0.500)
9	Equal Importance	1	1 (1.000)

The procedure was represented by using a square matrix of preferences, where the number in row i and column j of the matrix gives the priority of a certain attribute C_i in comparison to another C_j and the square matrix is shown in equation (1).

$$X=[x_{i,j}]=\begin{bmatrix} 1 & x_{12} & x_{13} & \dots & x_{1j} \\ \frac{1}{x_{12}} & 1 & x_{23} & \dots & x_{2j} \\ \frac{1}{x_{13}} & \frac{1}{x_{23}} & 1 & \dots & x_{3j} \\ \dots & \dots & \dots & 1 & \dots \\ \frac{1}{x_{1j}} & \frac{1}{x_{2j}} & \frac{1}{x_{3j}} & \dots & 1 \end{bmatrix} \quad (1)$$

Let X=$[x_{i,j}]$ (i, j=1, 2 ...n) represents a square pair wise matrix, where $x_{i,j}$ gives the relative importance of the elements in row i and column j. Also, $x_{i,j}$ is represented by a quantified value of judgment based on experiential knowledge of medical practitioners. This descriptions is constrained by the conditions in equation (2)

$$\begin{cases} if\ x_{i,j} = x, then\ x_{j,i} = \frac{1}{x}, x \neq 0; \\ if\ C_i\ is\ considered\ equally\ relevant\ as\ C_j \\ Then\ x_{i,j} = 1, x_{j,i} = 1\ and\ x_{i,i} = 1, \forall i \end{cases} \quad (2)$$

Step 3: Thus far, the matrices of comparison have been obtained and then weights for individual criterion across the hierarchical levels in relation to the alternatives under consideration were coupled by using the eigenvector which is represent in equation (3).

$$W_i=[\prod_{i=1}^{n} x_{ij}]^{\frac{1}{n}} \quad (3)$$

Where W_i denote the weight of the ith criteria and n is is the number of criterion.In this research work the standardization process was carried out by computing the proportion of each attribute related to the sum of all attributes based on equation (4).

$$Y = \frac{W_i}{\sum_{i=1}^{n} W_i} \quad (4)$$

Where Y is represented the normalized eigenvector and W_i is the weight of the ith attribute (i=1, 2... n).

This procedure is leads to the ordering of the eigenvector with respect to the priorities of the attributes and repeated till the difference between the normalized results of the last and current computation is negligible. Furthermore, the rank of the attributes depends on the individual importance towards CHD diagnosis was obtained. Thereafter, the weights of the attributes alternatives were find and arranges in a matrix form and the values in each column of the matrix were multiplied by the rank of the related attributes to predicts the weight that were later used to train an Deep Dynamic Bayesian Network (DDBN) predictor for CHD risk prediction.

The second stage of the proposed hybrid method involved the development of the DDBN predictor whose architecture was conceptualized as shown in figure 2. The typical feed forward network model depends on back propagation learning algorithm and scale conjugate gradient technique was constructed for the prediction of CHD risks. The network model is contained input, hidden and output layer (Figure 2). The input layer is contained the 19 nodes related to the CHD attributes that were fully connected to the nodes in the hidden layer. The 19 CHD attributes were included in to the network via the input layer and then transferred on to the hidden layer by multiplying the value of each attribute with their corresponding weight. The hidden layers were constructed to process the input information by measuring the weighted sum and adding a bias (θ_j) as represent in equation (5).

$$Net_j = \sum_{i}^{m} x_i * w_{ij} + \theta_j \quad (5)$$

Where x_i is the input data, θ_j is the bias and w_{ij} is the weighted link between the nodes. Thereafter, Net_j is transformed by using sigmoid transfer function represent in the equation (6) and the processed information is transferred to the output nodes to find the status of the patients with respect to CHD risk.

$$f(Net_j) = \frac{1}{1+e^{-Net_j}} \quad (6)$$

The nodes in the output layer represent the two possible classes of CHD risk prediction; CHD presence and CHD absence. And the network training process began with the initialization of the connection weights by choosing the set of random variable.

The back propagation algorithm is chosen because it permit the network to analyse and allocates high volume of input and output mapping relations and also manage the networks weight as well as threshold values in order to find minimum error. While training the network, the calculated error was propagated backward and the weights were adjusted by using equation (7).

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \quad (7)$$

When η represent the positive constant called the learning rate and E denotes the error. Based on the training error, all the weights were recomputed and updated and then the output values of the nodes in the output layer were re evaluated. The process repeated continuously till the network converged to a point where the error finds out between the actual and target output was relatively minimal. Additionally, the error is finding by using cross entropy measure whose formula is shown in equation (8). The cross entropy measure is adopted because it is previously identified as a better means of measuring the networks performance in terms of error, especially when using DDBN method for classification tasks.

$$CE = -t * \log(y) - (i - t) * \log(1 - y) \quad (8)$$

Where CE is the cross entropy, t and y represent the target output and the actual output.

4. Result & discussion

The Proposed method Optimized Semi Parametric Extended Deep Dynamic Bayesian Network (OSEDDBN), Optimized Semi Parametric Extended Deep Dynamic Bayesian Network with fuzzy analytic hierarchy process (OSEDDBN-FAHP) and Existing Method Extended Dynamic Bayesian Network (EDBN), Optimized Semi Parametric Extended Dynamic Bayesian Network (OSEDBN) compared in terms of precision, recall, F1-score.

A. Description of the dataset

The STULONG dataset is collected from the longitudinal analysis of atherosclerosis primary prevention. The target group is coupled with 1417 middle age men. The initial examination of the every single patient has measurements of the blood pressures, basic anthropometric measurements like weight and height then the analysis of ECG. Furthermore the each patient explored the information about the diet, physical activity, smoking and alcohol drinking habits, social behavior which may suffer the job responsibilities as well as family and personal history about the medical which captured about the cardiovascular diseases. The each value of the 244 attributes is surveyed in the initial examination of each patient whereas the following examinations then the values of the 66 attributes are evaluated via physical and biomedical investigations to find out the disease predictions.

B. Precision

Precision value is measured based on the feature classification at true positive prediction; false positive.It is calculated as:

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}}$$

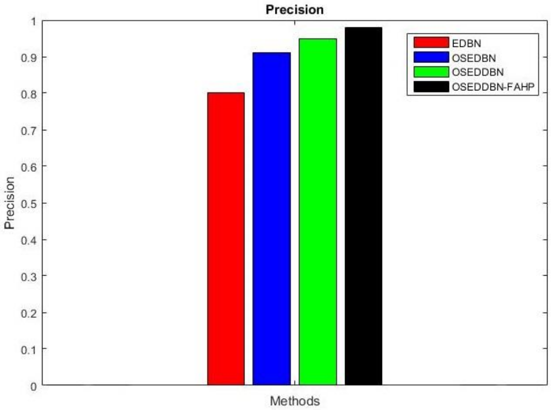

Figure 3: Comparison of precision

The figure 3 shows that comparison of precision values between the Existing Method Extended Dynamic Bayesian Network (EDBN), Optimized Semi Parametric Extended Dynamic Bayesian Network (OSEDBN) and Proposed Method Optimized Semi Parametric Extended Deep Dynamic Bayesian Network (OSEDDBN), Optimized Semi Parametric Extended Deep Dynamic Bayesian Network with fuzzy analytic hierarchy process (OSEDDBN-FAHP). The result shows the proposed methods such as OSEDDBN, OSEDDBN-FAHP provides better results compare to existing methods such as EDBN, OSEDBN in terms of precision values.

C. Recall

Recall value is calculated based on the feature classification at true positive prediction, false negative. It is given as,

$$\text{Recall} = \frac{\text{Truepositive}}{(\text{Truepositive} + \text{Falsenegative})}$$

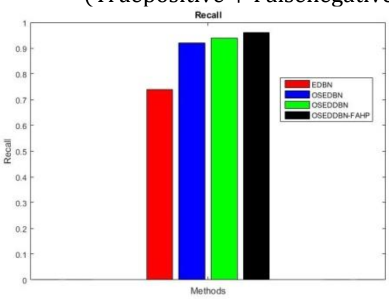

Figure 4: Comparison of recall

The figure 4 shows that comparison of Recall values between the Existing Method Extended Dynamic Bayesian Network (EDBN), Optimized Semi Parametric Extended Dynamic Bayesian Network (OSEDBN) and Proposed Method Optimized Semi Parametric Extended Deep Dynamic Bayesian Network (OSEDDBN), Optimized Semi Parametric Extended Deep Dynamic Bayesian Network with fuzzy analytic hierarchy process (OSEDDBN-FAHP). The result shows the proposed methods such as OSEDDBN, OSEDDBN-FAHP provides better results compare to existing methods such as EDBN, OSEDBN in terms of Recall values.

D. F-Measure

F-measure is measured through precision and recall value. It is defined as:

$$\text{f} - \text{measure} = 2 \times \left(\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}\right)$$

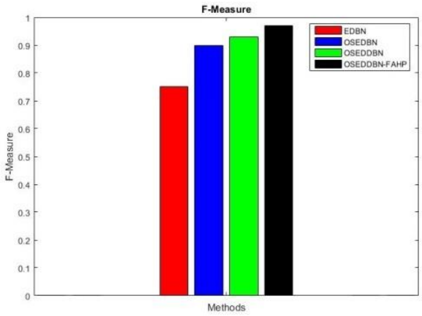

Figure 5: Comparison of F-Measure

The figure 5 shows that comparison of F-Measure values between the Existing Method Extended Dynamic Bayesian Network (EDBN), Optimized Semi Parametric Extended Dynamic Bayesian Network (OSEDBN) and Proposed Method Optimized Semi Parametric Extended Deep Dynamic Bayesian Network (OSEDDBN), Optimized Semi Parametric Extended Deep Dynamic Bayesian Network with fuzzy analytic hierarchy process (OSEDDBN-FAHP). The result shows the proposed methods such as OSEDDBN, OSEDDBN-FAHP provides better results compare to existing methods such as EDBN, OSEDBN in terms of F-Measures values.

Table 3: Shows the Comparison of EDBN, OSEDBN, OSEDDBN and OSEDDBN-FAHP

	Precision	Recall	F-Measure
EDBN	0.80	0.74	0.75
OSEDBN	0.91	0.92	0.90
OSEDDBN	0.95	0.94	0.93
OSEDDBN-FAHP	0.98	0.96	0.97

5. Conclusion

The proposed Optimized Semi Parametric Extended Deep Dynamic Bayesian Network (OSEDDBN) is used to incorporating a temporal component to the Optimized Semi Parametric Extended Dynamic Bayesian Network (OSEDBN) for prognosis of coronary heart disease (CHD). The Optimized Semi Parametric Extended Deep Dynamic Bayesian Network is integrated with the Fuzzy Analytic Hierarchy Process approach (OSEDDBN-FAHP) to compute the global weights for the attributes based on their individual contribution. Then these optimized attributes are applied to train the proposed OSEDDBN classifier to detect Coronary Heart Disease (CHD) risks in patients. The experimental result shows that the proposed methodology improves than earlier approaches through Precision, Recall and F-Measure.

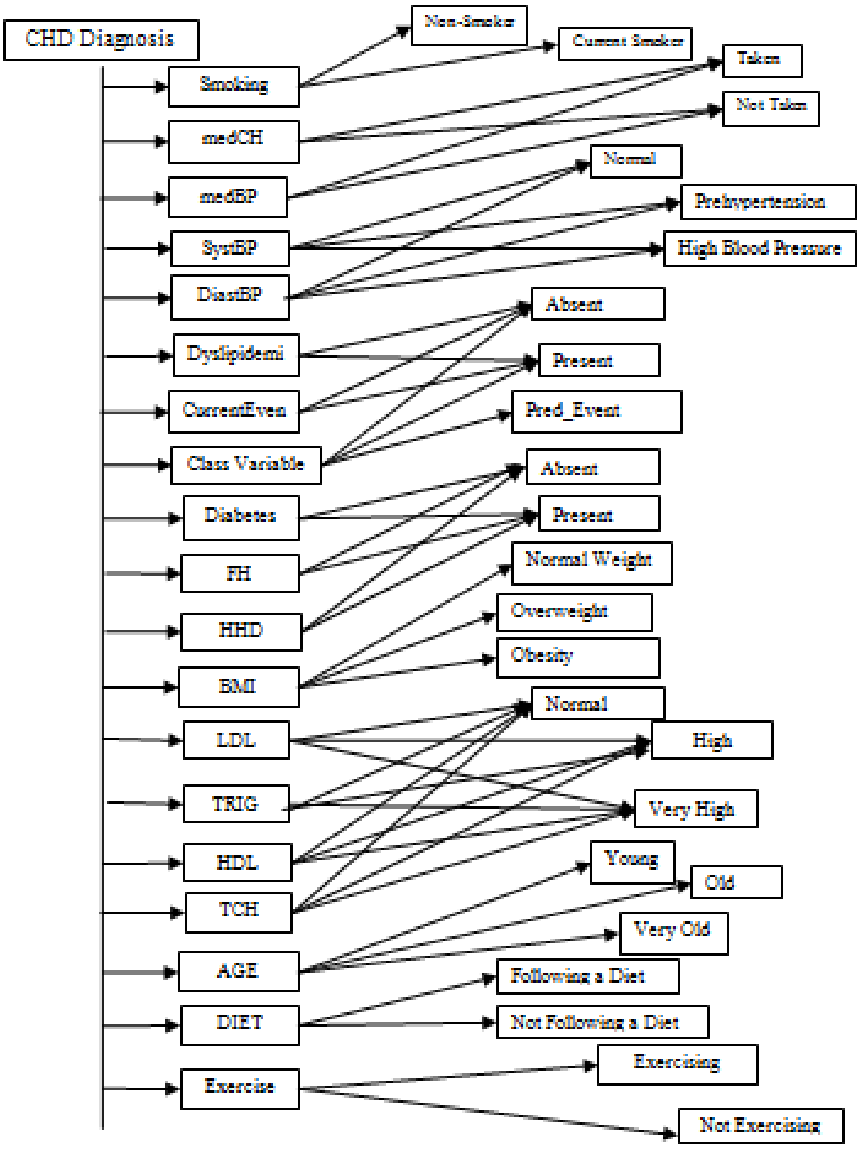

Figure 1: Hierarchical structure showing the goal (Level 1) attributes (Level 2) and attributes alternatives (Level 3)

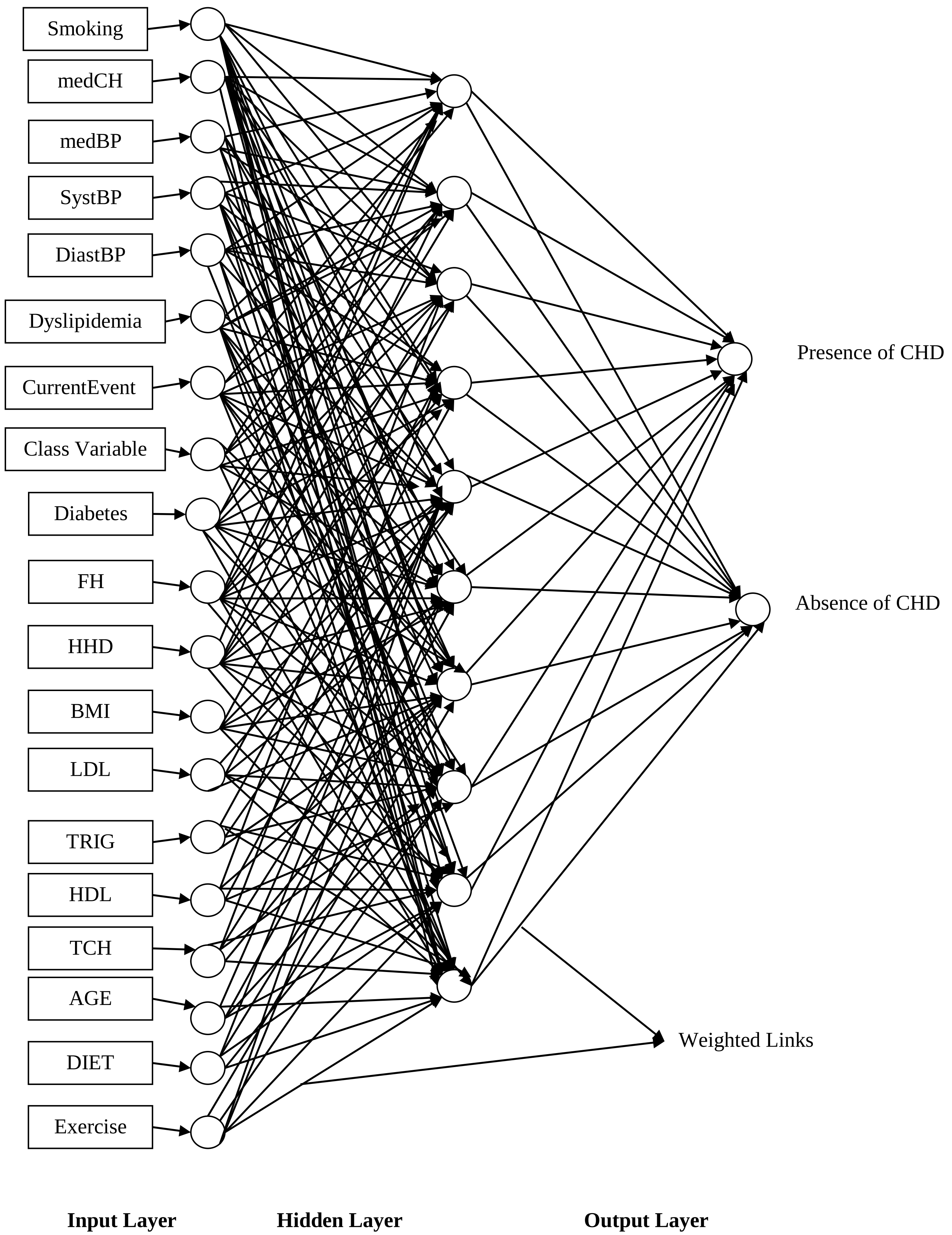

Figure 2: Architecture for the DDBN predictor for CHD risk prediction

References

[1] Methaila A, Kansal P, Arya H & Kumar P, “Early heart disease prediction using data mining techniques”, *Computer Science & Information Technology Journal*, (2014), pp.53-59.

[2] Karaolis MA, Moutiris JA, Hadjipanayi D & Pattichis CS, “Assessment of the risk factors of coronary heart events based on data mining with decision trees”, *IEEE Transactions on information technology in biomedicine*, Vol.14, No.3, (2010), pp.559-566.

[3] Kim J, Lee J & Lee Y, “Data-mining-based coronary heart disease risk prediction model using fuzzy logic and decision tree”, *Healthcare informatics research*, Vol.21, No.3, (2015), pp.167-174.

[4] Chaurasia V & Pal S, “Early prediction of heart diseases using data mining techniques”, *Caribbean Journal of Science and Technology*, Vol.1, (2013), pp.208-217.

[5] Rajkumar A & Reena GS, “Diagnosis of heart disease using datamining algorithm”, *Global journal of computer science and technology*, Vol.10, No.10, (2010), pp.38-43.

[6] Van Gerven MA, Taal BG & Lucas PJ, “Dynamic Bayesian networks as prognostic models for clinical patient management”, *Journal of biomedical informatics*, Vol.41, No.4, (2008), pp.515-529.

[7] Orphanou K, Keravnou E & Moutiris J, “Integration of Temporal Abstraction and Dynamic Bayesian Networks in Clinical Systems” A preliminary approach”, *OASIcs-OpenAccess Series in Informatics, Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik*, (2012).

[8] Sawa MSA, Naba A & Dachlan HS, “Bayesian Network Expert System for Early Diagnosis of Heart Diseases”, *Journal EECCIS*, Vol.7, No.2, (2014), pp.171-178.

[9] Pjanic M, Miller CL, Wirka R, Kim JB, DiRenzo DM & Quertermous T, “Genetics and genomics of coronary artery disease”, *Current cardiology reports*, Vol.18, No.10, (2016).

[10] Hsieh NC, Hung LP, Shih CC, Keh HC & Chan CH, “Intelligent postoperative morbidity prediction of heart disease using artificial intelligence techniques”, *Journal of medical systems*, Vol.36, No.3, (2012), pp.1809-1820.

[11] Orphanou K, Stassopoulou A & Keravnou E, “Risk assessment for primary coronary heart disease event using dynamic Bayesian networks”, *Conference on Artificial Intelligence in Medicine in Europe*, (2015), 161-165.

[12] Surendar, A., M. Kavitha, and V. Saravanakumar. "Proactive model based testing and evaluation for component-based systems." International Journal of Engineering & Technology 8.1.1 (2018): 74-77.

[13] Adeli A & Neshat M, “A fuzzy expert system for heart disease diagnosis”, *Proceedings of International Multi Conference of Engineers and Computer Scientists*, (2010).

[14] Feng Y, Wang Y, Guo F & Xu H, “Applications of data mining methods in the integrative medical studies of coronary heart disease: progress and prospect”, *Evidence-Based Complementary and Alternative Medicine*, (2014).

[15] Khan IY, Zope PH & Suralkar SR, “Importance of Artificial Neural Network in Medical Diagnosis disease like acute nephritis disease and heart disease”, *International Journal of Engineering Science and Innovative Technology (IJESIT)*, Vol.2, No.2, (2013), pp.210-217.

[16] Saaty TL, “How to make a decision: The analytic hierarchy process”, *European Journal of Operational Research*, Vol.48, No.1, (1990), pp.9-26.