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Generalized Bayesian Inference Nets Model and Diagnosis of Cardiovascular Diseases

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Abstract. A generalized Bayesian inference nets model (GBINM) is proposed to aid researchers to construct Bayesian inference nets for various applications. The benefit of such a model is well demonstrated by applying GBINM in constructing a hierarchical Bayesian fuzzy inference nets (HBFIN) to diagnose five important types of cardiovascular diseases (CVD). The patients' medical records with doctors' confirmed diagnostic results obtained from two hospitals in China are used to design and verify HBFIN. Bayesian theorem is used to calculate the propagation of probability and address the uncertainties involved in each sequential stage of inference nets to deduce the disease(s). The validity and effectiveness of proposed approach is witnessed clearly from testing results obtained.

Keywords. Generalized Bayesian inference nets model, statistical parameters, diagnosis of cardiovascular disease.

2010 Mathematics Subject Classification. 62F15, 62P10, 68T30, 68T37.

1 Introduction

Bayesian inference nets have emerged as one of the most successful intelligent tools for various applications such as document classification [5], bioinformatics [3], information retrieval [20], etc. Especially, it has established a long history in medicine [1, 6, 12–14, 16, 17] by focusing to develop clinical decision support systems (CDSS) for physicians. Some successful CDSS include MYCIN – designed to diagnose and recommend treatment of blood infections diseases [16], MUMIN – an expert assistant for electromyography analysis [1], ONCOCIN – designed to assist physicians in the treatment of cancer [17], etc. With various advantages such as the ability to reflect experts' knowledge, handle incomplete/uncertain data, facilitate use of prior knowledge, prevent over fitting of data and belief updating when new information is included, the Bayesian inference nets models have been highly successful in various engineering and medical applications. However, it is critical to note that construction of such nets requires defining of compound propositional logic and proper connection of several hundred inference nodes. Though useful, such extremely large networks are difficult to construct, understand

and maintain. Thus in recent years for some specific applications, researchers have developed algorithms for constructing Bayesian inference nets [10, 11, 18]. In this paper we take one step further and propose a GBINM to help researchers construct the hierarchical multistage Bayesian inference nets for handling various applications such as fault detection/diagnosis of electrical machine, defect inspection of bridge and circuit board etc. For validation, the proposed model is specifically applied to construct the HBFIN to diagnose CVD.

CVD is the leading cause of death and a substantial source of chronic disability and health costs worldwide. Thus in past decades R&D of different CVD diagnostic methods have been one of the key areas of interest. However, due to complicated nature of diagnostic decision-making process, there are yet pressing demands to develop the highly reliable and powerful medical diagnostic methods. Literatures show that the diagnostic methods developed so far, are either limited with the diagnosis of one specific type of CVD [2] or mainly designed as physicians' tools for recording pathophysiological signals such as electrocardiogram (ECG) [7], heart rate variability (HRV) [22], magneto cardiogram (MCG) [19] etc. Instead, in this paper an intelligent diagnostic system developed using GBINM is proposed for e-home healthcare usage. The system uses physiological attributes and hemodynamic parameters (HDPs), obtained through a non-invasive sphygmogram (SPG) analysis, as input symptoms to diagnose the five important and most common types of CVD.

2 Generalized Bayesian Inference Nets Model

The proposed GBINM shown in Figure 1 is a generalized branch in q-th stage of inference nets, which can be easily used to construct the hierarchical multistage Bayesian inference nets for various applications. To express the functional or rule node for generating the k-th hypothesis on q-th stage using the symptoms on 0-th stage and the hypotheses deduced in $(q-t)$-th, $q = 1, 2, \ldots, n$; $t = 0, 1, 2, \ldots q-1$ stages briefly and more clearly, the Backus–Naur form (BNF) is adapted.

GBINM illustrates the combination of all possible factors needed to generate hypothesis through functional node. As expressed, the definition of functional node depends on many factors, such as evidences (certain/uncertain), hypotheses deduced from other nodes on previous or same stage, logic junction operations which form the formula to express compound proposition and prove its tautology, statistical parameters such as prior probability, likelihood of sufficiency (LS), likelihood of necessity (LN) of symptoms and hypotheses, etc. In more complicated applications, the generation of hypothesis might also depend on meta-knowledge and execution of procedures stored in procedural repository. Here the

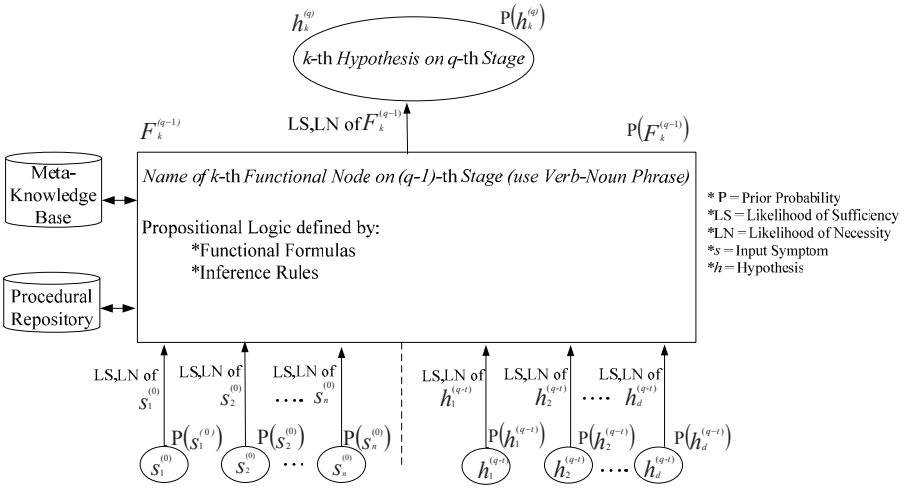

Figure 1. Generalized Bayesian inference nets model.

BNF notation:

<hypothesis> :: = <propositional logic deduced result>;

<propositional logic> :: = <functional formula> with <inference rule>;

<functional formula> :: = <evidence with statistical parameters>
<logic junction or mathematical operator>
<evidence with statistical parameter>
with <meta knowledge> <procedural repository> |
<mathematical formula> with <meta knowledge>
<procedural repository>;

<inference rule> :: = IF <function formula> THEN <function formula>;

<evidence> → symptom on 0-th stage | hypothesis on $(q-t)$-th,
$q = 1, 2, \ldots, n; t = 0, 1, 2, \ldots, q-1$ stages;

<statistical parameter> → prior probability | LS | LN | blank;

<logic junction operators> → ( ) | ¬ | ∧ | ∨ | → | ↔ | blank;

<meta-knowledge> → knowledge for adding/using knowledge into/from knowledge base (KB);

<procedural repository> → procedure | procedural knowledge.

meta-knowledge base and procedural repository are globally used by whole inference nets, but not specifically by one or two branches only. In the paper, the advantage of GBINM is well exemplified in constructing HBFIN using physiological attributes and HDPs to diagnose CVD.

3 Use of GBINM to Construct Inference Nets for Diagnosing Cardiovascular Disease

3.1 Input Symptom Selection and Preprocessing

The on-site measured medical data consist of different sample's medical records, including each patient's physiological attributes, original SPG data, HDPs and doctor's clinical diagnostic results. Denote the medical symptom space as $\mathrm{MSS} \in \mathbb{R}^N$. In this research $N = 38$, including 6 physiological attributes and 32 HDPs [9]. Totally, 165 patients' 2267 medical records were collected from two hospitals of China, where the patient's SPG data and HDPs were measured 12 to 15 times at different time interval within 5 weeks, and their physiological attributes such as age, sex, height, weight, systolic and diastolic blood pressures (SBP and DBP) were recorded too. Plus, 850 healthy records were randomly collected. The doctors' confirmed diagnostic reports indicate that these patients have one or more CVD among coronary heart disease (CHD), hypertension (HT), arrhythmia (AR), pulmonary heart disease (PHD) and cerebral infarction (CIN). To select the most important and eliminate the least significant symptoms (in the sense of their influence on discriminating diseases) from 38 parameters, one-way analysis of variance (ANOVA) [8] is used. Choosing 1190 medical records and 700 healthy records as training data set, the quasi-Gaussian membership functions [21] for all m diseases vs. n symptoms are defined and subjectively analyzed to identify the symptoms with ascendant discriminating capability. As a result, 17 parameters are selected as the prior input symptoms for HBFIN to diagnose the aforementioned 5 CVD.

3.2 Construction of Hierarchical Bayesian Fuzzy Inference Nets

Inference nets formally mimic expert's reasoning procedure of tackling the problem from evidences to intermediate hypothesis or final conclusion. GBINM can be viewed as a generalized network branch of k-th node on q-th stage of inference nets, which shows connections or relations between evidences and hypotheses. First, based on medical specialty knowledge and diagnostic experience, the functional formulas are defined. Then GBINM is used as a guide to construct an inference branch properly and connect it to other formed braches stage by stage.

Taking recorded physiological attributes as evidences, based on medical knowledge and diagnostic experience, the formulas for functional node '*Judge Obesity*' is delineated as Equations (1)–(2) and the relevant rules $1 - N$ are defined. First, body mass index (BMI) is calculated by Equation (1).

$$\text{BMI} = \text{Weight (kg)}/[\text{Height (m)}]^2. \tag{1}$$

According to medical knowledge, for children and teens below age 20, BMI is both age and sex specific, so index X is calculated by Equation (2):

$$X = M \cdot (1 + L \cdot S \cdot Z)^{1/L}, \tag{2}$$

where

L – power in the Box–Cox transformation,
M– median,
S – standard deviation,
Z – z-score, according to current obese condition, normally let $Z = 1.645$.

Corresponding to person's age, the L, M, and S are obtained from Table 1 for male and Table 2 for female.

For adults above age 20, BMI is neither age nor sex specific, standard weight status categories are used which indicate that BMI should be above 30 to conclude the person as obese.

Now from above equations as well as medical knowledge and statistical analysis of patients' records, following rules can be defined, where coefficients α, β are pre-defined and assigned with positive integer values.

Rule 1: IF sex = male $\wedge$ age $\leq 20 \wedge$ BMI $\geq X$
THEN prior probability $= 0.4$, LS $= \alpha \cdot 0.4$;
Rule 2: IF sex = male $\wedge$ age $\geq 20 \wedge$ BMI ≥ 30
THEN prior probability $= 0.8$, LS $= \alpha \cdot 0.8$;
Rule 3: IF sex = male $\wedge$ age $\geq 20 \wedge$ BMI ≤ 30
THEN prior probability $= 0.1$, LN $= \beta \cdot 0.1$;
$\vdots$
Rule N: ...

Now by referring to GBINM, the propositional logic described by Equations (1)–(2) and rules $1 - N$ would guide one to link the relevant evidence nodes $s_1^{(0)}$ '*Height*', $s_2^{(0)}$ '*Weight*', $s_3^{(0)}$ '*Sex*' and $s_4^{(0)}$ '*Age*' to the functional node $F_1^{(0)}$ '*Judge*

Age (yrs)	*L*	*M*	*S*
2	−2.0118	16.57503	0.080592
3	−1.98237	16.54777	0.080127
4	−1.9241	16.49443	0.079234
5	−1.8655	16.4426	0.078389
–	–	–	–
–	–	–	–
–	–	–	–
–	–	–	–
20	−1.84358	23.04138	0.134675

Table 1. L, M, S parameters for male.

Age (yrs)	*L*	*M*	*S*
2	−0.98661	16.4234	0.085452
3	−1.0245	16.38804	0.085026
4	−1.1027	16.31897	0.084214
5	−1.18397	16.25208	0.083455
–	–	–	–
–	–	–	–
–	–	–	–
–	–	–	–
20	−2.3428	21.72191	0.153241

Table 2. L, M, S parameters for female.

Obesity' to generate intermediate hypothesis node $h_1^{(1)}$ '*Influence Degree of Obesity*' as shown in Figure 2. Here, the knowledge for adding new knowledge in KB, instructions on how to use knowledge or select rule among rules etc., will be called from meta-knowledge base. Coefficients α, β and the required Tables 1 and 2 as well as their searching and matching procedures will be called from procedural repository.

Next, the functional formulas required for generating the intermediate hypothesis '*Influence Degree of Age*' are delineated and the relevant inference rules are defined. Based on them and using GBINM another branch of HBFIN is constructed.

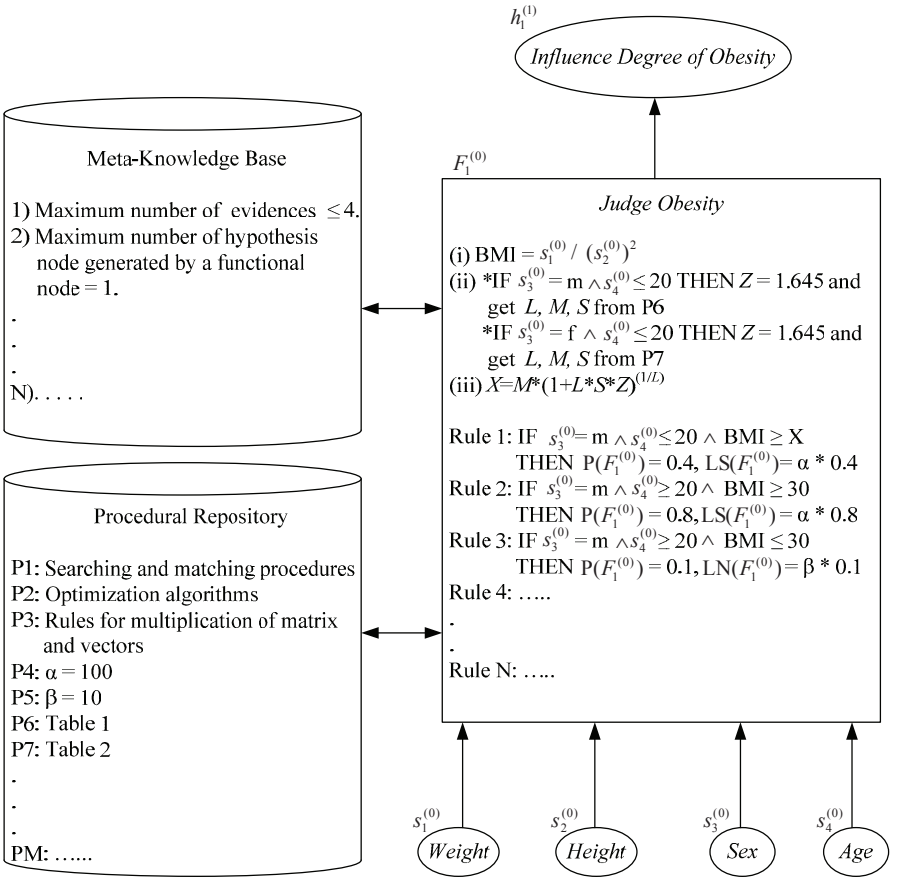

Figure 2. Branch 1 of HBFIN constructed by using GBINM.

First quasi-Gaussian membership functions for physiological attribute '*Age*' is defined by using Equation (3).

$$f_i(s_j) = e^{-\left(\frac{s_j - a_i(s_j)}{2d_i(s_j)}\right)^2}, \tag{3}$$

where $a_i(s_j)$ is the maximum membership grade in the i-th membership function f_i vs. j-th symptom s_j, and $2d_i(s_j)$ is the bandwidth of that function. After matching the curve of Gaussian function to plot of pair (s_j, grade of having 5 typical CVD), the parameters in Equation (3) are fixed as $a_i(s_j) = 60$ and $2d_i(s_j) = 12.33$.

Afterwards, when any patient's '*Age*' is recorded, it is mapped to such a defined membership function and the corresponding membership grade $f_i(s_j)$ is obtained. With $f_i(s_j)$, the following rules 1–2 can be defined.

Rule 1: IF $f_i(s_j) \geq 0.1$ THEN prior probability $= f_i(s_j)$, LS $= \alpha \cdot f_i(s_j)$

Rule 2: IF $f_i(s_j) < 0.1$ THEN prior probability $= f_i(s_j)$, LN $= \beta \cdot f_i(s_j)$

In propositional logic of this functional node, the functional formula Equation (3) with assigned values of parameters is used to calculate the membership grade $f_i(s_j)$ for the input symptom s_j , and the inference rules are further used to define and assign the statistical parameters (prior probability, LS and LN). Note that the dynamic values are assigned to statistical parameters of nodes through mapping input symptoms to membership grades on individual well defined membership functions. The detailed description of this novel approach is elucidated in our paper [15].

Again with the propositional logic defined, GBINM would guide in linking the evidence node $s_4^{(0)}$ '*Age*' to the functional node $F_2^{(0)}$ '*Analyze Age Criteria*' to generate the intermediate hypothesis node $h_2^{(1)}$ '*Influence Degree of Age*' as shown in Figure 3. Here Table 3 in procedural repository is called, which provides the corresponding pre-specified $a_i(s_j)$ and $2d_i(s_j)$ values for input symptoms.

Now, the generated hypotheses nodes $h_1^{(1)}$ and $h_2^{1)}$ will be further used to deduce the indication showing the likelihood of abnormal lipid level. Thus GBINM guides in linking $h_1^{(1)}$ and $h_2^{(1)}$ as evidences to a new functional node $F_1^{(1)}$ '*Carryout Conjunction*', which performs conjunction operation and generates a hypothesis node $h_1^{(2)}$ as shown in Figure 4.

At this stage of HBFIN, the propositional logic for a new functional node $F_2^{(1)}$ '*Estimate BP Level*', which will use physiological attributes '*Sex*', '*Age*', '*SBP*' and '*DBP*' as evidences, is defined, and with GBINM, one more branch of HBFIN is constructed to generate intermediate hypothesis node $h_2^{(2)}$ '*Likelihood of Abnormal BP Level*' as shown in Figure 5. The generated $h_2^{(2)}$ together with $h_1^{(2)}$ are then linked using disjunction operation through the functional node $F_1^{(2)}$ '*Carryout Disjunction*' to generate the intermediate hypothesis $h_1^{(3)}$ '*Favorable Condition for CVD*' as shown in Figure 5.

To construct the next stage of inference nets, HDPs '*CI*' and '*FEK*' are analyzed through the Functional nodes $F_1^{(3)}$'*Analyze CI Criteria*' and $F_2^{(3)}$'*Analyze FEK Criteria*'. Similar to node $F_2^{(0)}$'*Analyze Age Criteria*' as shown in Figure 3, the formulas for functional nodes $F_1^{(3)}$and $F_2^{(3)}$ are defined using Equation (3), with the parameters $a_i(s_j) = 4.5$ and $2d_i(s_j) = 1.16$ fixed for $F_1^{(3)}$ and $a_i(s_j) = 0.25$

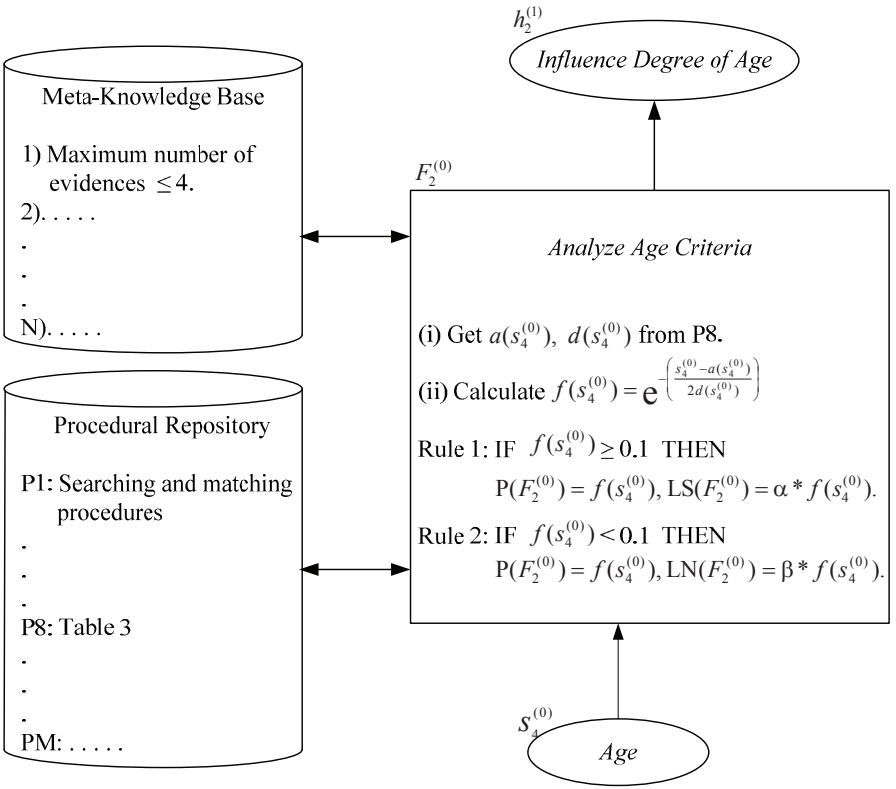

Figure 3. Branch 2 of HBFIN constructed by using GBINM.

Input Symptoms	$a_i(s_j)$	$2d_i(s_j)$
Age (s_1)	60	12.33
CI (s_2)	4.5	1.16
FEK (s_3)	0.25	0.258
…	…	…
…	…	…
PAWP (s_n)	15	8.3

Table 3. Pre-specified $a_i(s_j)$ and $2d_i(s_j)$ values for input symptoms.

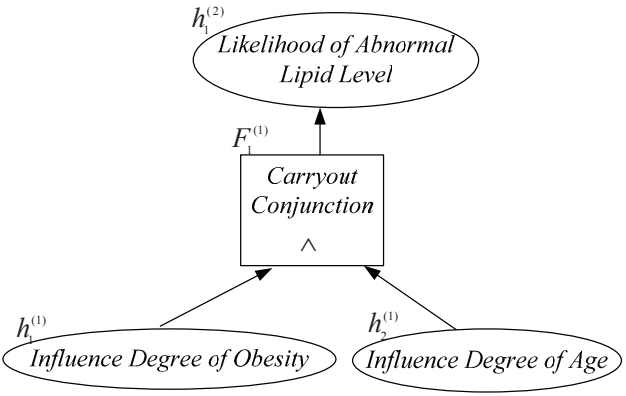

Figure 4. GBINM guides in linking the output of branches.

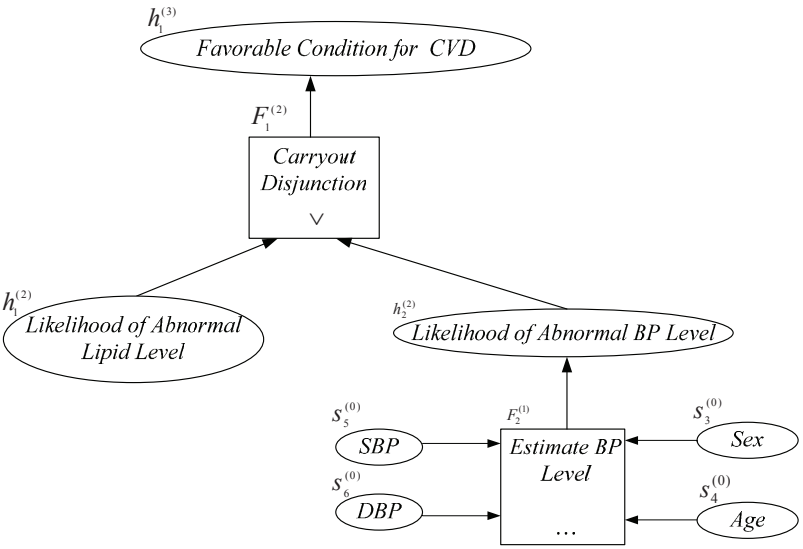

Figure 5. GBINM guides constructing branch 3 and linking it to HBFIN.

and $2d_i(s_j) = 0.258$ fixed for $F_2^{(3)}$, which are called from Table 3 in procedural repository. In practical usage, when HDPs '*CI*', '*FEK*' are tested and recorded, they will be mapped to respective pre-defined quasi-Gaussian membership function to obtain the corresponding membership grade $f_i(s_j)$. With $f_i(s_j)$ the relevant inference rules 1–2 as in node $F_2^{(0)}$ are defined for functional nodes $F_1^{(3)}$ and $F_2^{(3)}$.

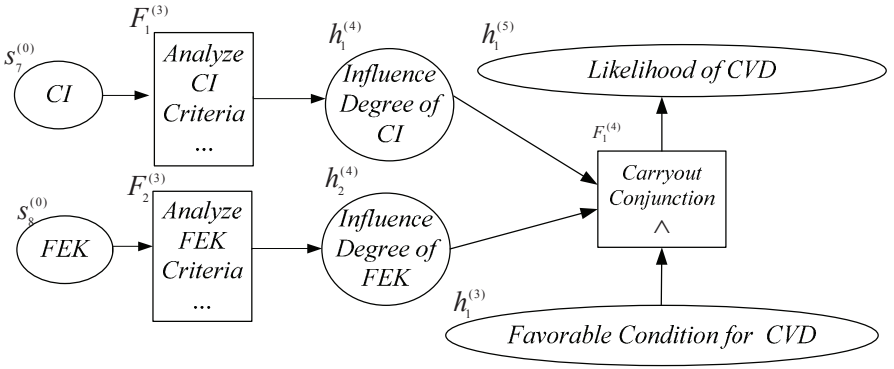

Figure 6. GBINM guides constructing branches 4 and 5 and linking them to HBFIN.

Based on such defined functional formulas and rules, GBINM guides in constructing two more branches of inference nets to generate the intermediate hypothesis nodes $h_1^{(4)}$'*Influence Degree of CI*' and $h_2^{(4)}$'*Influence Degree of FEK*' as shown in Figure 6. These hypothesis nodes are further combined with the previously generated hypothesis node $h_1^{(3)}$ through functional node $F_1^{(4)}$ '*Carryout Conjunction*' to generate the intermediate hypothesis node $h_1^{(5)}$ '*Likelihood of CVD*' as shown in Figure 6.

Likewise, GBINM is further utilized to construct HBFIN stage by stage so as to accumulate evidences in each stage The inference propagates and indicates from plausible, to possible, to probable, and finally confirms the probability of having certain CVD. The partially constructed HBFIN for diagnosing CVD is shown in Figure 7.

It is worth mentioning here that doctors generally use both invasive and non-invasive methods such as blood test, ECG, ultrasound, X-ray, 2-D imaging etc. to get symptoms from patients for diagnosing CVD, whereas in the proposed approach the physiological attributes and HDPs are used as symptoms, to predict the possibility of having certain CVD and generate the warning message to home user. The further confirmation of CVD should be done only by doctors in hospital.

4 Testing Results

The HBFIN forms a static knowledge structure, in which the probability associated with each hypothesis node consequently changes when the evidence is certain or uncertain. This change in probability is propagated up stage by stage through

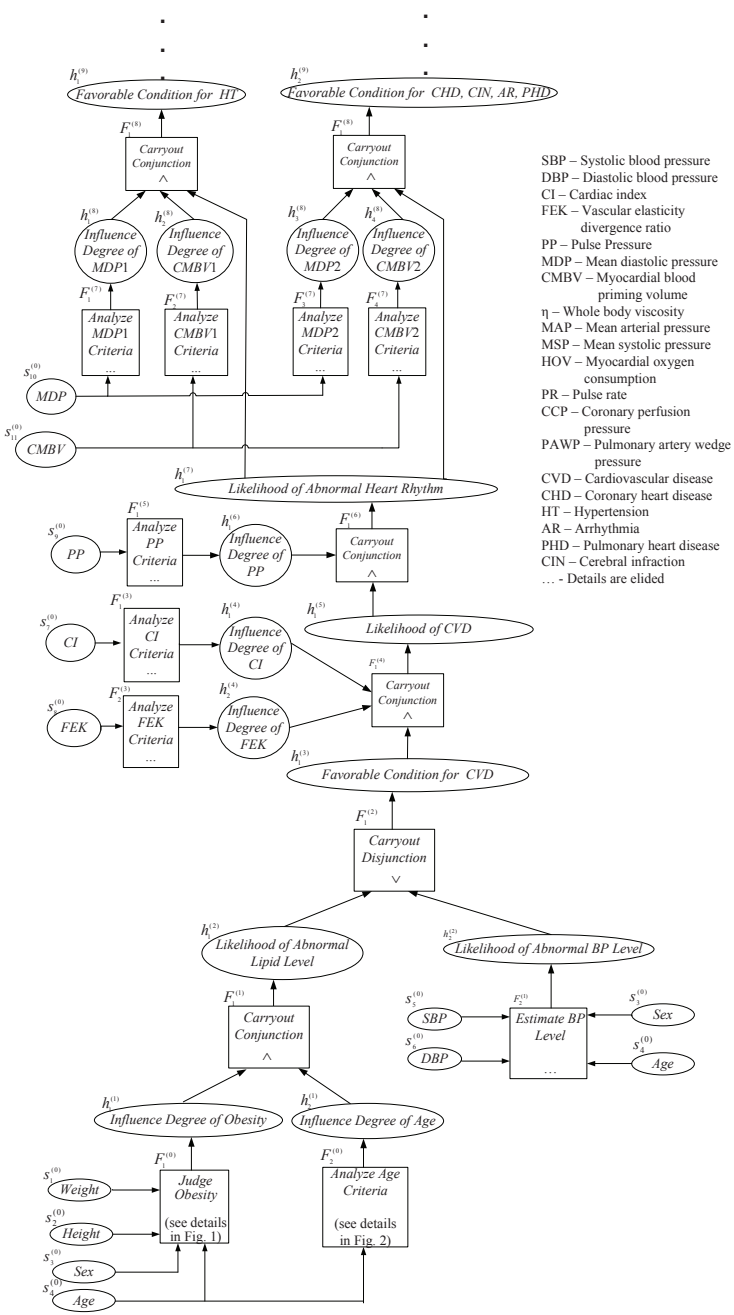

Figure 7. Partially constructed HBFIN for diagnosing CVD.

Input Symptoms* **(units)**	**Patients' partial medical records**				
	Patient 1	**Patient 2**	**Patient 3**	**Patient 4**	**Patient 5**
Height (m)	150	185	158	163	153
Weight (kg)	65	100	70	80	60
Age (yrs)	56	50	38	60	74
SBP (mm Hg)	160	120	170	130	164
DBP (mm Hg)	90	90	70	75	96
CI (ml/stroke/m^2)	4.60776	2.63322	5.3797	5.40815	4.88684
FEK	0.35355	0.24234	0.17651	0.51219	0.19612
PP (mm Hg)	70	30	100	55	68
MDP (mm Hg)	108.6619	94.30314	89.33395	88.93535	111.9902
CMBV (ml/min)	460.7703	345.2269	236.9385	675.4612	376.1599
η (cp)	2.4704	5.67668	1.76375	2.60546	2.71815
MAP (mm Hg)	129.6596	101.4547	115.6676	105.0697	131.3186
MSP (mm Hg)	150.6572	108.6063	142.0012	121.204	150.6471
HOV (ml/min)	50.2949	42.29441	63.39966	34.56936	58.94953
PR (beats/min)	59.8515	74.94701	64.81343	59.13684	84.50704
CCP (mm Hg)	65.8790	81.09772	30.98146	66.94517	80.12169
PAWP (mm Hg)	24.1209	8.90228	39.01854	8.05483	15.8783

*The full expansion of symptoms is provided in Figure 7.

Table 4. Partial medical records sampled from five patients.

Patients	**Probability of having certain CVD**					**Doctor's diagnosed conclusion**
	HT	**CHD**	**AR**	**PHD**	**CIN**	
Patient 1	**0.95**	0.63	0.06	0.34	0.02	HT
Patient 2	0.30	**0.86**	**0.92**	0.70	0.02	AR
Patient 3	0.32	0.02	0.04	**0.53**	0.02	PHD, HT
Patient 4	**0.94**	0.64	0.43	0.13	**0.92**	HT, CIN
Patient 5	**0.91**	**0.48**	0.04	0.11	0.02	CHD, HT

Table 5. Diagnostic results of HBFIN.

Person's Health Status	Diagnostic Accuracy (%)
HT	78.12
CHD	68.15
AR	73.20
PHD	65.03
CIN	72.09
Mixed CVD	58.12

Table 6. Diagnostic Accuracy of HBFIN in CVD detection.

HBFIN to ultimately support or disprove the top-level hypothesis/conclusion. In this study, to calculate the propagation of probability, Bayesian theorem [4] is used. The function of constructed HBFIN is examined using the remaining patients' 367 medical records and 150 healthy records, which are partially shown in Table 4. The diagnostic results of HBFIN are shown in Table 5.

Although Table 5 shows the testing result of 5 patients only, HBFIN performs equally good results for the rest of testing medical records. Table 6 shows the diagnostic accuracy of HBFIN for CVD diagnosis in detecting five CVD and their combinations.

It is worth highlighting here that in non-invasive approach the obtained diagnostic accuracy is highly acceptable, which proves that the proposed hybrid intelligent diagnostic system is well suited for home healthcare usage.

5 Conclusion

A GBINM is proposed to simplify the approach of designing and constructing Bayesian inference nets. The significance of GBINM is well illustrated in constructing HBFIN for diagnosing CVD. Guided by GBINM, all important factors, in defining compound propositional logic and linking branches stage by stage are considered coincidently. The testing results indicate that the proposed model not only simplifies the process of constructing the nets but also makes it possible to deduce the inference results faster with high reliability. With the proven results, GBINM is clearly vindicated to be used in various applications. Thus with GBINM, construction, understanding and maintenance of large Bayesian inference nets could practically become easier for researchers and expert system designers.

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