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HILL CLIMBING ALGORITHM ON BAYESIAN NETWORK TO DETERMINE PROBABILITY VALUE OF SYMPTOMS AND EYE DISEASES

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Abstract. *One of the five human senses referred to as photoreceptors is the eye because the eye is very sensitive to light stimuli. Refractive abnormalities in the eyes are often experienced, which are abnormalities that occur when the eyes cannot see clearly in the open or blurred vision. An unhealthy lifestyle is a trigger for an increase in individuals who experience complaints of eye diseases. In diagnosing a disease, doctors need patient information in the form of symptoms experienced so that patients can be treated immediately. Information in the form of symptoms and types of eye diseases can be used to make conjectures about eye diseases through the structure of BN. The symptom information and type of the disease are represented through nodes, while the relationships are represented through the edge. BN is one of the Probabilistic Graphical Models (PGM) consisting of nodes and edges. BN is also known as a directed acyclic graph (DAG), which is a directed graph that does not have a cycle. The approach method used is scored-based on the evaluation process with the bayesian information criterion (bic) scoring function. The algorithm used in this study is the HC algorithm. The research data used consisted of 52 symptoms and 15 eye diseases. The results of the study were obtained by the final structure of BN formed by the HC algorithm produced 93 edges and 65 connected nodes, and the probability value of the disease and the symptoms of the disease in the eye.*

Keywords: *bayesian network, Conditional Probability (CPT), hill climbing, symptoms and eye disease.*

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1. INTRODUCTION

One of the five human senses is referred to as photoreceptor, namely the eye, because the eyes are very sensitive to light stimulation. Refraction abnormalities in the eye are often experienced, namely abnormalities that occur when the eye cannot see clearly in the open so that the view becomes blurred [1]. WHO data shows that more than 285 million population in the world experience visual impairment [2]. Along with the factors that affect a person's lifestyle, such as rarely exercising, irregular eating patterns, high levels of stress, and age, resulting in an increase of the number of individuals who experience complaints of eye disease. When diagnosing eye diseases, doctors need patient information as a consideration in making alleged diseases so that patients can be treated quickly and precisely. The information is in the form of symptoms felt by the patient.

Information in the form of symptoms and diseases is used to make alleged eye diseases through the structure of the Bayesian Network (BN). This structure is used to store information about the relationship between symptoms and diseases of the eye. In the BN structure, variables are needed in the form of symptoms and diseases of the eye. BN is one of the probabilistic graphical models (PGM) or simple probabilistic graphs [3]. BN is formed based on probability and graph values. The probability value is directly related to the data while the graph is directly related to the form of representation to be obtained.

One method of approach used to make BN structure is searching and scoring (scored-based). In addition, to obtain the best structure, an evaluation process is needed with the Bayesian Information Criterion (BIC) scoring function which is a method of selecting the best structure of several other structural choices. The best structure is the structure that has the smallest BIC value [4].

There are several types of algorithms that can be used to continue the scored-based method approach, one of which is the Hill Climbing (HC) algorithm. The HC is a value-based learning algorithm in directed graphics space and is included in the heuristic search method that works in greedy, namely working to get the optimal solution [5]. The heuristic function is used to evaluate the condition so that the desired solution can be obtained. Therefore, in this study, the HC algorithm was applied to the BN to determine the probability value of symptoms and diseases in the eye.

2. RESEARCH METHODS

The method used in this study is to apply the HC algorithm to BN to determine the probability value of symptoms and diseases in the eye. The data used is secondary data sourced from Ilyas research in **[6]**. The data used in this study consisted of 52 symptoms and 15 eye diseases. Some of the variables used in this study are shown in Table 1 and Table 2.

Table 1. Research Variable (Disease ID)

Disease ID	Information
PM001	Xerophthalmia
PM002	Selulitis Orbitalis
PM003	Glaucoma
PM004	Dacryoritis
PM005	Cataract

Table 2. Research Variable (Symptoms ID)

Symptom ID	Information
G001	Sore eyes
G002	Protruding eyes
G003	Blurred vision
G004	Sensitive the light
G005	Red eyes

2.1. Bayesian Network

Bayes theory is taken from a person's name, namely Thomas Bayes around 1950. This theory takes into account the probability of a case that depends on another event or is generally called the management of uncertainty [7]. Basically, the theory states that future events can be predicted on the condition that the events that had previously occurred [8]. In 1988, Judea Pearl used Bayes theory to obtain the probability of an event that was influenced by another event with graphics, which is currently known as BN. BN is a probabilistic graphical model that represents a series of variables and the relationship between variables. The link between these variables shows the probability of a relationship between interconnected or unrelated events [9]. BN was built from the Bayes Theorem namely Conditional Probability which is a calculation of the opportunity for an event X if it is known that the event has been denoted by P (X | Y). The Bayes formula was written as

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)} \quad (1)$$

with $P(X|Y)$ is the posterior probability, that is the probability X occurs after probability Y has occurred, $P(Y|X)$ is likelihood, that is the probability Y occurs after probability X has occurred, $P(X)$ that is the probability of the event X, and $P(Y)$ that is the probability of the event Y. Furthermore, related to BN, BN consists of (i) a structure known as a directed acyclic graph (DAG) which is a directed graph that does not have a cycle with each node represented as a random variable and edge that represents the probability of dependence [10]; and (ii) a collection of conditional probability distribution defined for each variable given by parents in graphs [11], [12]. The advantages of Bayesian networks are that built models and the connections of their elements can be visualized as easily understandable graphs [13]. The simple structure of the DAG in BN consists of A, B, C, D as nodes while edge is a line that connects one node with another, and node A is the parent of node B and C as shown in Figure 1.

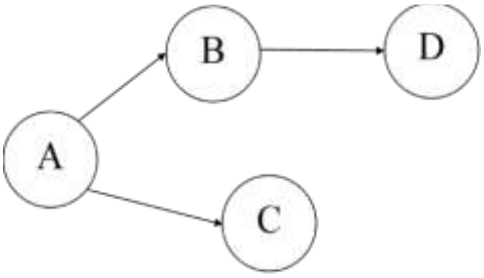

Figure 1. Structure of the DAG

2.2. Construction of BN Structure and Scored-Based Method

The stages of BN structure construction are described as follows [14], [15].

1. The qualitative stage, which is to make a relationship between modeled variables. BN has a DAG structure that can represent a pattern of a set of data. Representation in the form of graphs is done by identifying information obtained. Furthermore, this information is known as a collection of variables. Then, the set of variables is represented as a node in the graph. The relationship between variables is explicitly stated with edge contained in the graph. There are two approaches in building BN structures, namely the scored-based method and the constraints-based method [16]. In the scored-based method, BN is considered as a distribution of variable probability related to data. On the other hand, the scored-based method is a method that provides a score in BN and maximizes the provision of the score with several heuristic search algorithms. Therefore the scored-based method is used at this qualitative stage.
2. The estimated parameter or known as the quantitative stage, which is calculating probability values. After the BN structure is made, the parameters and the dependency relationship between the node are determined using expert knowledge.

2.3. Prior Probability

Prior probability or probability value functions to describe the level of trust of an event [17], [15]. Prior probability is used when there is no other information that can be used to determine the probability of an event. However, if there is new information, the probability must be updated. Prior probability is written as

$$P(R) = \frac{n(H)}{n(S)} \tag{2}$$

with *P(R)* is prior probability from *R*, *n(H)* is the amount of data incidence H, and *n(S)* is the total amount of data.

2.4. Posterior Probability

The posterior probability is a change that occurs to the probability value by utilizing new information obtained [17], [15]. The calculation of the posterior probability value is written as

$$P(R|A) = \frac{P(A|R)P(R)}{P(A)} \tag{3}$$

with *P(R|A)* is likelihood, that is the probability *A* occurs after probability *R* has occurred, *P(R)* is prior, that is the probability of the event *R*, and *P(A)* that is the probability of the event *A*.

2.5. The BIC Scoring Function

The BIC concept was first introduced by Schwarz (1978). In statistics, the BIC or Schwarz information criteria also known as Schwarz's Bayesian Information Criterion (SBIC) or Schwarz Bayesian Criterion (SBC) is a criterion for the selection of structures between a limited collection of structures. In determining the score for BN can be calculated in several different ways [18]. This leads to the generalization of the Minimum Description Length (MDL) scoring function written as

$$BIC(B|T) = LL(B|T) - \frac{1}{2} log(N)|B| \tag{4}$$

with *B* is a set of data set in BN, *T* is a BN pair between nodes and edges, *LL* is a log-likelihood function, and *N* is a lot of data in observations.

2.6. Scored-based Method with HC Algorithm

HC is often used to evaluate the node heuristically [19]. In 2018, related research was conducted comparing the algorithm constraint-based, scored-based, and hybrid, the results obtained that the scored-based method produced the best network [20]. In the same year, conducted research related to scoring function, which is using a BIC that is continued with the HC algorithm produces a better score in a short time [21]. In 2019, research was conducted to predict respiratory diseases using the BN modeling followed by the HC algorithm [22]. One of the advantages of using the HC algorithm is that it can be used in almost all search procedures [23]. The BN structure is built from a combination of existing nodes with a search method, then continued by a scoring function in its evaluation. The construction process is carried out repeatedly (iterative), starting from a graph without edge followed by a search method to add edge, and stop when there is no new structure than the previous structure. Score on the BN structure [24] is written as

$$Score(G, D) = Pr(G|D) \tag{5}$$

The scored-based method is used to maximize the score with G as the DAG of BN and D as the main data. The HC algorithm in the Scored-based method for D data is described as follows.

1. Choose a structure from a collection of G in BN.
2. Calculate the score from G assuming that $Score_G = Score$(G).
3. Define value $maxscore = Score_G$.
4. Repeat the following steps until the value is obtained *maxscore*.
   a. for each possible addition, deletion, or reversing edge does not experience cyclic networks, do:
      i. calculate the score from the network that has been modified as *G**,
      $Score{*}G = Score(G{*})$;
      ii. if value $Score_G{*} > Score_G$, then a group from $G{=}G{*}$ and value $Score_G = Score_G{*}$.
   b. update the maxscore score with a new value from $Score_G{*}$ that has been obtained.

5. Repeating step 4a until the best score is obtained and stops when there is no new new structure than the previous structure.

2.7. Conditional Probability Table (CPT)

CPT is a table that contains the probability of an event R if event A has occurred or commonly referred to as Conditional Probability **[17]**, **[15]**. CPT is written as

$$\boldsymbol{P(R|A)} = \frac{\boldsymbol{P(R \cap A)}}{\boldsymbol{P(A)}} \tag{6}$$

with *P(R∩A)* is the probability of event *R* and event *A* while *P(A)* is the prior probability of event A.

3. RESULTS AND DISCUSSION

In this study discussed the application of the HC algorithm in the BN to determine the probability value of symptoms and diseases in the eye including data description, making the initial structure of the BN and displaying it in the form of DAG, determining the prior probability value, determining the posterior probability value, displaying the final structure of the BN in the form of DAG through the BIC scoring function evaluation process and the application of the HC algorithm, making a conditional probability table, and analyzing the BN structure formed.

3.1. Description of Data

Description of the data symptoms and diseases used in this study refers to Ilyas' research in [6], in the form of a relationship between symptoms and the name of the eye disease shown in Table 3. Based on Table 3, eye diseases with ID number PM002 have the most symptoms of disease when compared to other diseases. The disease has 9 symptoms of disease. Therefore, the disease with the PM002 ID number also has the most edges of 9 edges.

In addition, Table 3 shows that there are symptoms that affect more than one type of disease name, namely symptoms with ID numbers G001, G003, G004, G005, G006, G009, G012, G021, G043, and G052. In this table also appears that symptoms with ID number G029 and ID G032 have no effect on any disease ID number.

Table 3. Description of the Relationship of Symptoms and the Eye Disease

Disease ID	Disease Name	Symptoms ID be perceived
PM001	*Xerophthalmia*	G020, G021, G022
PM002	*Orbital Cellulitis*	G001, G002, G023, G009, G024, G005, G010, G018, G025
PM003	*Glaucoma*	G026, G011, G052, G027, G019
PM004	*Dacryocystitis*	G012, G001, G052
PM005	*Cataract*	G028, G021, G030, G031, G001, G033
PM006	*Conjunctivitis*	G006, G001, G008, G003, G004, G034
PM007	*Retinitis Pigmentosa*	G035, G036, G009
PM008	*Trachoma*	G037, G009, G038, G039, G040, G041
PM009	*Uveitis*	G014, G006, G004, G042, G043
PM010	*Hordeolum*	G005, G001, G006, G004
PM011	*AMD (Degenerasi Makula)*	G044, G045, G046
PM012	*Ablatio Retina*	G047, G048, G03, G013
PM013	*Pterygium*	G043, G005, G016, G015, G006, G049, G003
PM014	*Myopia*	G001, G007, G012, G050
PM015	*Ophthalmia Neonatorum*	G005, G009, G017, G051, G003

3.2. Initial Structure of BN

The relationship between symptoms and types of disease names in the eye, can be known through visualization by making the initial structure of BN in the form of DAG. DAG is formed using the Python programming language. In carrying out Python programming, a program syntax is needed, namely a series of structured rules for the preparation of code in the Python programming language. The first step taken is to do the required install and import syntax commands, as written as

```
!pip install  -q pyvis
!pip install  -q bnlearn
!pip install  -q openpyxl
!pip install  -q XlsxWriter
!pip install  matplotlib==3.3.4
import bisect
import functools
import itertools
import os
import operator
import random
from collections import namedtuple
from pprint import pprint
from typing import List,  Tuple
import numpy  as  np
import pandas as  pd
import matplotlib.pyplot  as  plt
import seaborn  as  sns; sns.set()
import bnlearn as  bn
from pyvis.network  import  Network
from pgmpy.factors.discrete  import  TabularCPD
from IPython import display
```

After that, prepare data on the name of the disease and symptoms of eye disease in the form of Ms. Excel files, then import into Python programming. Furthermore, the initial structure of the BN shown in Figure 2.

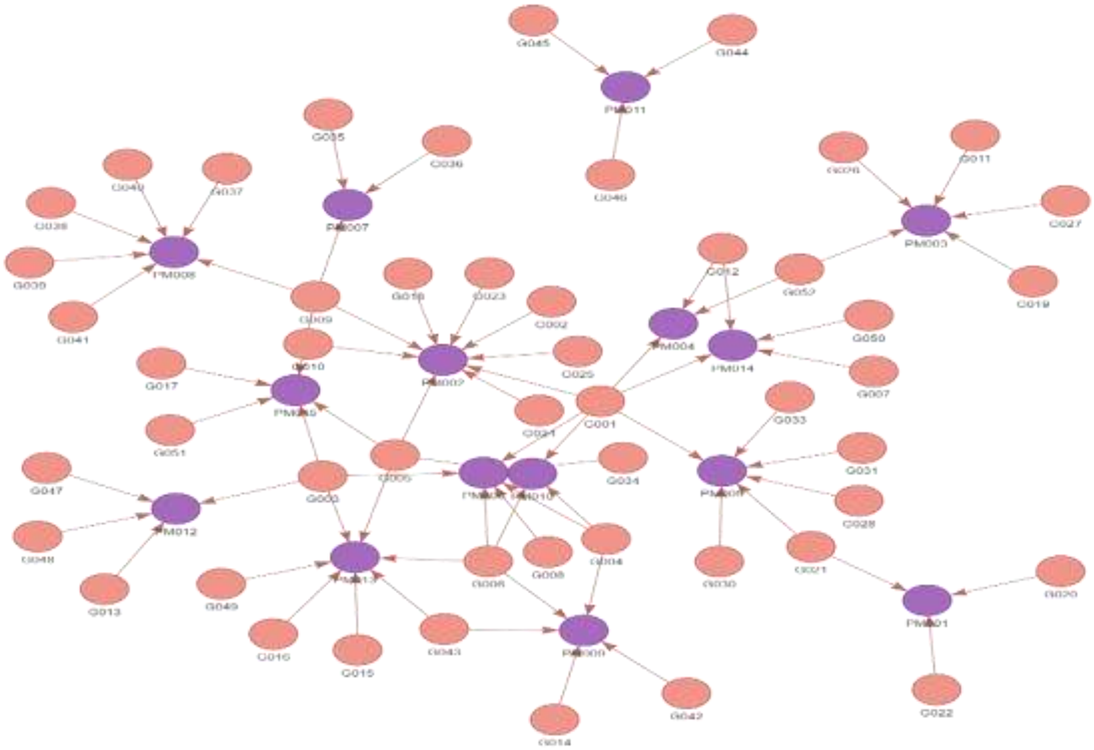

Figure 2. Initial Structure of BN

Seen in Figure 2 that the initial structure of the BN has 73 edges and 65 nodes. The nodes can be divided into 2 types, namely orange nodes representing the variable symptoms of eye disease while purple nodes representing the variable name of eye disease. In addition, from the structure, it appears that there is a link between the variable name of the disease and the symptoms of eye disease. The direction of the arrow in the BN structure shows the incident as a result of other incidents. Based on Figure 2, it can be seen that nodes disease variable with ID PM011, symptom variable with ID G044, G045, and G046 clustered separately or does not merge with other nodes. This happens because the symptom variable nodes are ID G044, G045, and G046 only affects the occurrence of disease ID PM011 only and has no effect on other disease IDs so that the symptom nodes do not have edges with other disease nodes.

3.3. Calculate Value of Prior Probability

Determination of prior probability values is obtained using Equation 2 which is carried out in data symptoms of eye disease. The number of ID numbers that arise from each symptom ID number are divided by the total amount of data that refers to Table 3. Determination of prior probability values can be seen in Table 4. Based on Table 4, the prior probability value of the G029 and G032 symptoms ID is not used because the symptom variable has no direct relationship with the variable name of the disease.

Table 4. Value of Prior Probability

No.	Symptoms	Unit	Prior value
1.	G001	6	0.082192
2.	G002	1	0.013699
3.	G003	4	0.054795
4.	G004	3	0.041096
5.	G005	4	0.054795

3.4. Calculate Value of Posterior Probability

Determination of the posterior probability value is obtained from the CF rule value data which refers to Permana, et al. research [6]. Determination of the posterior probability value is carried out in the relationship data between symptoms and the name of the eye disease which can be seen in Table 5. Based on

Table 5 shows that not all symptoms have a high posterior probability value so it is not enough with only one symptom to find out the disease suffered.

Table 5. Value of Posterior Probability

No.	Disease ID	Symptoms ID	CF *rule*	Posterior value
1.	PM001	G020	0.1	0.6
		G021	-1.0	0.0
		G022	0.6	0.8
2.	PM002	G001	1.0	1.0
		G002	1.0	1.0
		G023	1.0	1.0
		G009	1.0	1.0
		G024	-1.0	0.0
		G005	1.0	1.0
		G010	-1.0	0.0
		G018	0.4	0.7
		G025	0.4	0.7
3.	PM003	G026	1.0	1.0
		G011	1.0	1.0
		G052	-0.4	0.3
		G027	-1.0	0.0
		G019	-0.6	0.2

In addition, the posterior probability value is also obtained for the linkages between the symptom variables with the name of the eye disease in each node. The link between the symptoms id variables complies with the PM001 ID variable is shown in Table 6. Based on Table 6, it was found that if someone experienced symptoms with ID G020, G021, and G022, the probability of the person affected by the disease with ID PM001 was 0.6. If the symptoms experienced are only symptoms with ID G020 and G021, the probability of the person affected by the disease with ID PM001 is 0.3.

Table 6. Value of Posterior Probability from Symptoms ID with ID PM001

Symptoms / Disease	G020				NO			
	G021		NO		G021		NO	
	G022	NO	G022	NO	G022	NO	G022	NO
NO PM001	0.4	0.7	0.2	0.4	0.6	1.0	0.2	0.6
PM001	0.6	0.3	0.8	0.6	0.4	0.9	0.8	0.4

3.5. The Final Structure of BN

The final structure of BN in this study was made using the BIC Scoring Function by applying the HC algorithm. The BN structure is formed after the iteration in the HC algorithm is complete. In addition, the BIC scores are also obtained. The syntax used in the iteration of the HC algorithms and the acquisition of the BIC scores are written as

```
# sample dfSekarang60rb  = bn.sampling(model  true,  n=60000)
methodtype='hc'
scoretype='bic'
sample_ dfSekarang60rb  = pd.read  csv("sample  dfSekarang60rb.csv")
model learned  = bn.structure  learning.fit(sample_dfSekarang60rb,
                    bw_list_ method="white list",
                    white_ list=edges  +  list(set(symptoms)) +  list(set(diseases)),
                  verbose=3)
bn.plot(model_learned)
# sample dfSekarang60rb.to  csv("sample  dfSekarang60rb.csv")
```

The results of the acquisition of BIC scores that begin in the 90th iteration to the 99th iteration of the HC algorithm conducted to obtain the BN structure can be seen in Table 7. Based on Table 7, a BIC score was obtained in 2.2737×10^{-13} and stopped at the 99th iteration. This shows that the formation of the final BN structure with the presence of nodes and edges in the final structure of BN is obtained after going through 99 iterations. The iteration stops because the number of nodes produced is in accordance with the previous number of nodes are 65 nodes. This shows that no nodes are missing. It is also seen that the BIC score obtained in the 99th iteration is the smallest BIC score when compared to the BIC scores in previous iterations.

Table 7. The BIC Score and Iteration

***Score* BIC**	**Iteration**
10.6110	90
9.0458	91
9.0002	92
6.7698	93
5.0704	94
2.9481	95
22.3050	96
2.2798	97
0.8304	98
2.2737×10^{-13}	99

Furthermore, the representation of the final structure of the BN displayed via DAG is seen in Figure 3.

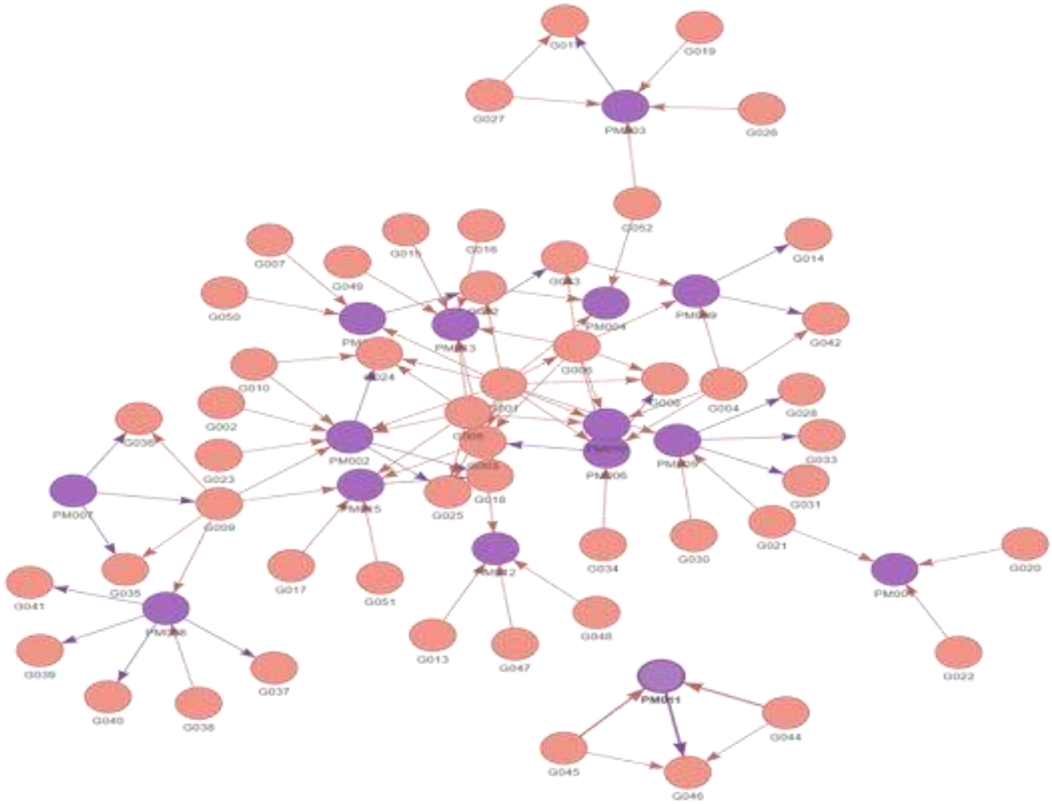

Figure 3. The Final Structure of the BN

Based on Figure 3, it appears that the final structure of the BN has 93 edges and 65 nodes. The nodes can be divided into 2 types, namely orange nodes representing the variable symptoms of eye disease while purple nodes representing the variable name of eye disease. It turns out that the edges resulting from the formation of BN structures with HC algorithms are more than the previous BN structure (BN's initial structure). In addition, from the structure it appears that there is a relationship between the variable name of the disease and the symptoms of eye disease. The direction of the arrow on picture of the BN structure shows events that occur as a result of the occurrence of other events. Based on the figure, it can be seen that nodes disease variable with ID PM011, symptom variable with ID G044, G045, and G046 clustered separately or does not merge with other nodes. This happens because the symptom variable nodes are ID G044, G045, and G046 only affects the occurrence of disease ID PM011 only and has no effect on other disease IDs so that the symptom nodes do not have edges with other disease nodes.

3.6. Calculate Value of Conditional Probability Table

The CPT is a table that contains the probability of an event when another event has occurred. The CPT is made based on the final structure of the BN obtained previously. The CPT value between the symptoms id variables complies with the PM001 ID variable is shown in Table 8. Based on Table 8, it was found that if someone experienced symptoms with ID G020, G021, and G022, the probability of the person affected by the disease with ID PM001 was 0.50. If the symptoms experienced are only symptoms with ID G020 and G021, the probability of the person affected by the disease with ID PM001 is 0.46.

Table 8. Value CPT of ID PM001

Symptoms / Disease	**G020**				**NO**			
	G021		**NO**		**G021**		**NO**	
	G022	**NO**	**G022**	**NO**	**G022**	**NO**	**G022**	**NO**
NO PM001	0.50	0.54	0.48	0.40	0.53	0.96	0.24	0.60
PM001	0.50	0.46	0.52	0.60	0.47	0.04	0.76	0.40

4. CONCLUSIONS

Based on the results and discussion, it is concluded that the formation of the final structure of the BN is obtained through determining the posterior probability value, iteration of the HC algorithm, and the BIC scoring function. In the discussion obtained the results of the application of BN structure with the HC algorithm in eye disease data have a BIC score of $2.2737\text{x}10^{-13}$ and stop at the 99th iteration. The final structure of the BN formed by the HC algorithm produces 93 edges and 65 connected nodes. In addition, the probability value of symptoms and diseases in the eye is obtained.

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REFERENCES

[1] L. Fauzi, L. Anggorowati and C. Heriana, "Skrining Kelainan Refraksi Mata pada Siswa Sekolah Dasar Menurut Tanda dan Gejala," *Journal of Health Education,* vol. 1, no. 1, pp. 78-84, 2016.

[2] A. Dwiana, C. Lestari and L. Astuty, "Hubungan Pengetahuan Siswa tentang Kesehatan Mata dengan Sikap Penggunaan Gadget yang Berlebihan di SD N 13 Engkasan Kalimantan Barat," *Avicenna : Journal of Health Research,* vol. 4, no. 1, pp. 1-8, 2021.

[3] R. Kurniawan and L. K. Wardhani, "Sistem Pakar untuk Mendiagnosa Penyakit Mata dengan Metode Bayesian Network," *SNTIKI* , vol. III, pp. 309-315, 2011.

[4] Qudratullah, M. Farhan and Subanar, "Bayesian Information Criterion (BIC) dalam Pemilihan Model Terbaik Feed Forward Neural Network (FFNN) : Studi Kasus Data Posisi Simpanan Tabungan Bank Umum dan BPR di Propinsi D.I.Yogyakarta," 2007.

[5] O. H. Choon and K. Chandrasekaran, "A Bayesian Network Approach to Identify Factors Affecting Learning of Additional Mathematics," *Jurnal Pendidikan Malaysia,* vol. 40, no. 2, pp. 185-192, 2015.

[6] Y. Permana, I. G. P. S. Wijaya and F. Bimantoro, "Sistem Pakar Diagnosa Penyakit Mata Menggunakan Metode Certainty Factor Berbasis Android," *J-COSINE,* vol. 1, no. 1, pp. 1-10, 2017.

[7] D. Heckerman, "A Tutorial on Learning With Bayesian Networks," *Microsoft Research Advanced Technology Division Redmond, WA 98052,* 2008.

[8] D. R. S. Saputro, P. Widyaningsih, F. Handayani and N. A. Kurdhi, "Prior and Posterior Dirichlet Distributions on Bayesian Networks (BNs)," in *AIP Conference Proceedings 1827, 020036*, 2017.

[9] K. W. Przytula and D. Thompson, "Construction of Bayesian' Networks for Diagnostics," in *IEEE Aerospace Conference Proceedings* , Malibu, 2000.

[10] E. Mokhtarian, S. Akbari, F. Jamshidi, J. Etesami and N. Kiyavash, "Learning Bayesian Networks in the Presence of Structural Side Information," in *Association for the Advancement of Artificial Intelligence (AAAI)*, 2022.

[11] A. H. C. Correia, J. Cussens and C. P. d. Campos, "On Pruning for Score-Based Bayesian Network Structure Learning," p. 108, 2019.

[12] J. Cussens, "Bayesian Network Learning with Cutting Planes," in *Proceedings of the 27th Conference on Uncertainty in Artificial Intelligence*, UK, 2011.

[13] N. Olivain, P. Tiefenbacher and J. Kohl, "Bayesian Structural Learning for an Improved Diagnosis of Cyber-Physical Systems," *cs.LG, http://https://arxiv.org/pdf/2104.00987.pdf,* pp. 1-9, 2021.

[14] R. P. Adhitama and D. R. S. Saputro, "Hill Climbing Algorithm for Bayesian Network Structure," in *AIP Conf. Proc. 2479, https://doi.org/10.1063/5.0099793*, 2022.

[15] I. Suryana, M. Suryani, E. Paulus, R. Rosadi and D. Syahfitri, "Metode Bayesian Network untuk Menetukan Probabilitas Terdampak Penyakit Kanker Payudara," *Jurnal Euclid*, vol. 5, no. 2, pp. 45-60, 2018.

[16] B. Sitohang and G. P. Saptawati, "Improvement of CB & BC Algorithms (CB* Algorithm) for Learning Structure of Bayesian Networks as Classifier in Data Mining," *ITB J.ICT,* vol. 1, no. 1, pp. 29-41, 2007.

[17] Hasniati, Arianti and W. Philip, "Penerapan Metode Bayesian Network Model pada Sistem Diagnosa Penyakit Sesak Nafas Bayi," *Jurnal IKRA-ITH Informatika,* vol. 3, no. 2, pp. 19-26, 2019.

[18] A. M. Carvalho, "Scoring Functions for Learning Bayesian Networks," *INESC-ID Tec. Rep. 54/2009*, pp. 1-37, 2009.

[19] Suyanto, Artificial Intelligence : Searching, Reasoning, Planing, and Learning, Bandung: Informatika, 2014.

[20] M. Scutari, C. E. Graafland and J. M. Gutierrez, "Who Learns Better Bayesian Network Structures: Constraint-Based, Score-based or Hybrid Algorithms?," in *Proceedings of Machine Learning Research Vol. 72, 416-427,* 2018.

[21] N. Sharma, "Hierarchical Clustering Based Structural Learning of Bayesian Networks," in *Artificial Intelligence and Robotics Commons*, Ames, Creative Components 11, 2018.

[22] N. I. Pradasari, F. T. P. W. and D. Triyanto, "Aplikasi Jaringan Saraf Tiruan untuk Memprediksi Penyakit Saluran Pernapasan dengan Metode Backpropagation," *Jurnal Coding Sistem Komputer Untan,* vol. 1, no. 1, 2013.

[23] T. A. Kung and M. S. Mohamad, "Using Bayesian Networks to Construct Gene Regulatory Networks from Microarray Data," *Jurnal Teknologi,* vol. 58, pp. 1-6, 2012.

[24] D. Margaritis, Learning Bayesian Network Model Structure from Data, Pittsburgh: CMU-CS-03-153, 2003.