ICIC Express Letters
Volume **15**, Number **1**, January **2021**

pp. **27–36**

CERTAINTY COGNITIVE MAP (CCM) FOR ASSESSING COGNITIVE MAP CAUSALITY USING CERTAINTY FACTORS FOR CARDIAC FAILURE

Sumiati[1,3], Hoga Saragih[2], Titik Khawa Abdul Rahman[3] and Agung Triayudi[4]

[1]Information and Communication Technology
Universitas Serang Raya
Raya Cilegon No. Km. 5, Taman, Drangong, Serang 42162, Indonesia
sumiati82@yahoo.com

[2]Information and Communication Technology
Universitas Bakrie
H. R Rasuna Said Kav C-22, Kuningan, Jakarta 12940, Indonesia
hogasaragih@gmail.com

[3]Department of School and Graduates Studies
Asia e University
Wisma Subang Jaya, No. 106, Jalan ss15/4 Subang Jaya, Selangor 47500, Malaysia
titik.khawa@aeu.edu.my

[4]Information and Communication Technology
Universitas Nasional
Sawo Manila, Pejaten Barat, Pasar Minggu, Jakarta 12540, Indonesia
agungtriayudi@civitas.unas.ac.id

Received April 2020; accepted July 2020

Abstract. *This study aims to resolve existing problems, which is to resolve weaknesses that have both the certainty factor approach and the cognitive map approach in diagnosing cardiac failure, so that the Certainty Cognitive Map (CCM) approach is used to diagnose cardiac abnormalities, which is an approach of certainty factor modification and Cognitive Map (CM) modification. The results of the study show that with the Certainty Cognitive Map (CCM) approach, it is able to form an intact cognitive map where a causal relationship is seen between the evidence with other evidence, and certainty cognitive map is able to have one evidence value with other evidence, the causality value of abnormal cognitive maps include: causality value of E1 to E2 of* -0.6*, E2 of E6 of* -0.6*, E6 of E12 of* -0.64*, E1 of E13 of* -0.64*, E14 to E15 amounted to* -0.85*, E1 to E6 amounted to* -0.6*, E6 against E7 of* -0.64*, E7 of E8 of* -0.85*, E7 of E9 of* -0.94*, E9 of E10 of 0.25, E10 of E11 of* -0.84*, E8 of E3 of* -0.94*, E3 against E4 of* -0.97*, E4 of E5 of* -0.93*, E2 of Abnormal at* -0.99*, E12 of Abnormal at* -0.24*, E15 of Abnormal at 0.71, E16 of Abnormal at* -0.36*, E11 against Abnormal at* -0.69 *and E5 against Abnormal at 0.93, while the normal cognitive causality map values are as follows: E1 against E2 of* -0.8*, E2 to E3 of 0.84, E3 of E4 of 0.6, E4 of E5 of 0.24, E3 of E4 of 0.6, E5 of E7 of 0.02, E7 against E8 of* -0.95*, E3 of E9 of 0.89, E9 of E10 of* -0.84*, E10 of E11 of* -0.44*, E11 of E12 of* -0.13*, E2 of E3 of 0.84, E3 to E4 of 0.6, E4 to E10 of 0.47, E10 to E13 of* -0.66*, E6 to Normal of* -0.22*, E8 to Normal of 0.77, E12 to Normal of* -0.72 *and E13 against Normal of 0.84.*
Keywords: Certainty factor, Cognitive map, Certainty Cognitive Map (CCM), Cardiac abnormalities, Causality

DOI: 10.24507/icicel.15.01.27

1. **Introduction.** Information technology is currently developing very rapidly, and it happens in various fields of science, such as the discovery of the field of data mining, fuzzy logic and others [1]. These fields of science are used for development in education such as online learning, then in the field of diseases for expert systems and more [2-4]. Heart disease is a very dangerous disease and is a disease that ranks the highest cause of death [5]. The cause of high rates of death caused by heart disease, including the lack of heart disease experts is a fundamental reason. According to data from the Ministry of Health, there only have 5,290 cardiologists (experts) and they have not been evenly distributed throughout Indonesia. The factor is the lack of heart disease experts due to the difficulty of education which really requires a lot of time [6].

Some research in the field of computing has been done to contribute to the world of health, especially in an effort to provide alternative solutions to analyze heart disease. The researchers used the Certainty Factor (CF) approach to diagnose cardiac failure. Certainty Factor (CF) has the ability to make the process of inference in determining the final outcome of a disease diagnosis, with Certainty Factor (CF) approach, having the advantage of each evidence that has been valued based on the level of confidence. However, this Certainty Factor (CF) approach is not able to be seen the relationship between one evidence and another, forming a complete cognitive map [7].

The Cognitive Map (CM) approach is to diagnose cardiac failure, with the cognitive approach, it can be seen the causal relationship between the evidence and other evidence, so that a cognitive map is formed intactly, but with the cognitive map approach it does not have a causality value between the evidence and the evidence, the evidence with the hypothesis. In some of the studies above, there is no research that discusses diagnosing cardiac failure with the Certainty Cognitive Map (CCM) method, which with this approach is able to know the causality between evidence and other evidence and is able to form a causal relationship between evidence and other evidence to form a map cognitive [8].

Several studies that discuss the diagnosis of cardiac failure have been done before. Research in the field of computing has been done to contribute to the world of health, especially in efforts to provide alternative solutions for analyzing heart disease. The researchers used the concept of data mining to diagnose abnormalities and heart disease in patients [9], and several other approaches used to diagnose abnormalities and heart disease are the Particle Swarm Optimization (PSO) algorithm and neural network [10], the patient's facial color analysis approach [11], genetic neural networks and data mining [12], logistic regression [13], Support Vector Machine (SVM) [14], multiscale analysis [15], Extreme Learning Machine algorithm (ELM) [16] and radial techniques based on network classification [17].

Some related studies diagnose cardiac failure using certainty factors and cognitive maps, studies that use certainty factors do not discuss the causality relationship between evidence and other evidence, evidence with hypotheses, so that a complete cognitive map is not formed [18], other than that in other studies with certainty approach only determines the value of causality between evidence with other evidence and the value of causality between evidence and hypotheses [19], while in research the diagnosis of cardiac death with cognitive map approach does not model the uncertainty in the variable [20]. Based on the literature that has been done there is no research that discusses the causality relationship between evidence and evidence to form an intact cognitive map and has a causality value between the evidence and the evidence.

This study aims to modify the cognitive map to determine the value of causality between an evidence and evidence other than the certainty factor approach. This research was conducted to develop a new approach called Certainty Cognitive Map (CCM) which is a modification of certainty factors and modification of cognitive maps, which with this approach can form an intact cognitive map and have a causal relationship between evidence and evidence, and have values causality of evidence with other evidence and evidence with a hypothesis [21]. The results of research in early identification of cardiovascular disease can be done better because it compares the value of expert causality with the value of user causality through CF values combined with cognitive maps.

1.1. **Certainty factor.** Certainty Factor (CF) is one of the techniques used to overcome uncertainty in decision making. Certainty Factor (CF) can occur with various conditions. This model is based on certainty factors [20].

1.2. **Cognitive map.** Cognitive Map is a directed map or graph that represents the nodes and has a conceptual direction, particular reasoning, reasonable thinking or confidences in solving existing problems [4].

2. **Research Method.** The study began with the collection of data on 50 electrocardiogram medical record data from RSUD. A total of 50 electrocardiogram data were made in this research data. In this study, 50 electrocardiogram data were used as a decision tree, and the tools used by RapidMiner Studio were used in this study. The steps taken in this research are first to conduct a literature study related to the research topic, data collection, data obtained from primary data, initial classification of electrocardiogram medical record data, then do the process of modifying certainty factors, modifying cognitive maps, developing Certainty Cognitive Map (CCM) methods, testing the system to determine the level of accuracy of the system is carried out by the Success Rate (SR) method, evaluating the results of clarification with Kappa Statistics.

Certainty Cognitive Map (CCM) approach is a modification of the certainty factor method and modification of cognitive map, where this method has advantages when inference performs in the final process, this method can overcome the weaknesses that have both certainty factor and cognitive map methods, with the certainty method approach cognitive map is able to have a confidence value based on the level of confidence a person experiences with the evidence, so that the Certainty Cognitive Map (CCM) method is able to see a causal relationship between one evidence with other evidence, and evidence on the hypothesis so that a cognitive map is formed that is intact, in addition to the visible relationship causality between evidence, and has a value of causality between evidence and evidence, evidence against the hypothesis. Following are the stages of the process of developing the Certainty Cognitive Map (CCM) method based on Figure 1 as follows:

- The electrocardiogram data is first read and analyzed by a doctor to diagnose normal and abnormal heart failure.
- Usage is given a choice of answers with each weight.
- Solving rules with multiple premises becomes a single premise.
- Make a decision tree, so that rules are formed.
- The new rule rule then makes a semantic relationship between one evidence and another, thus forming a knowledge of the need to form a cognitive map.
- Determine the value of the CF expert for each premise.
- Determine the value of CF users for each premise.
- Determine the CF value of the evidence data to determine the causality of the evidence, evidence against evidence, evidence against hypotheses.
- Calculate the combined causality value of two or more evidences using the CF formulation to search.

In the initial stage of the study it was to diagnose normal and abnormal heart failure with the Certainty Cognitive Map (CCM) approach, and CCM is a certainty factor modification and cognitive map modification. The data used in this study were 50 electrocardiogram data. The result shows the electrocardiogram medical record data. The results of the certainty cognitive map method will show a causality relationship between one evidence with other evidence, and the value of causality between evidence and evidence and the value of causality between evidence and hypothesis. As explained Figure 1 shows the description of the Certainty Cognitive Map (CCM) model for analysis of normal and abnormal cardiac abnormalities.

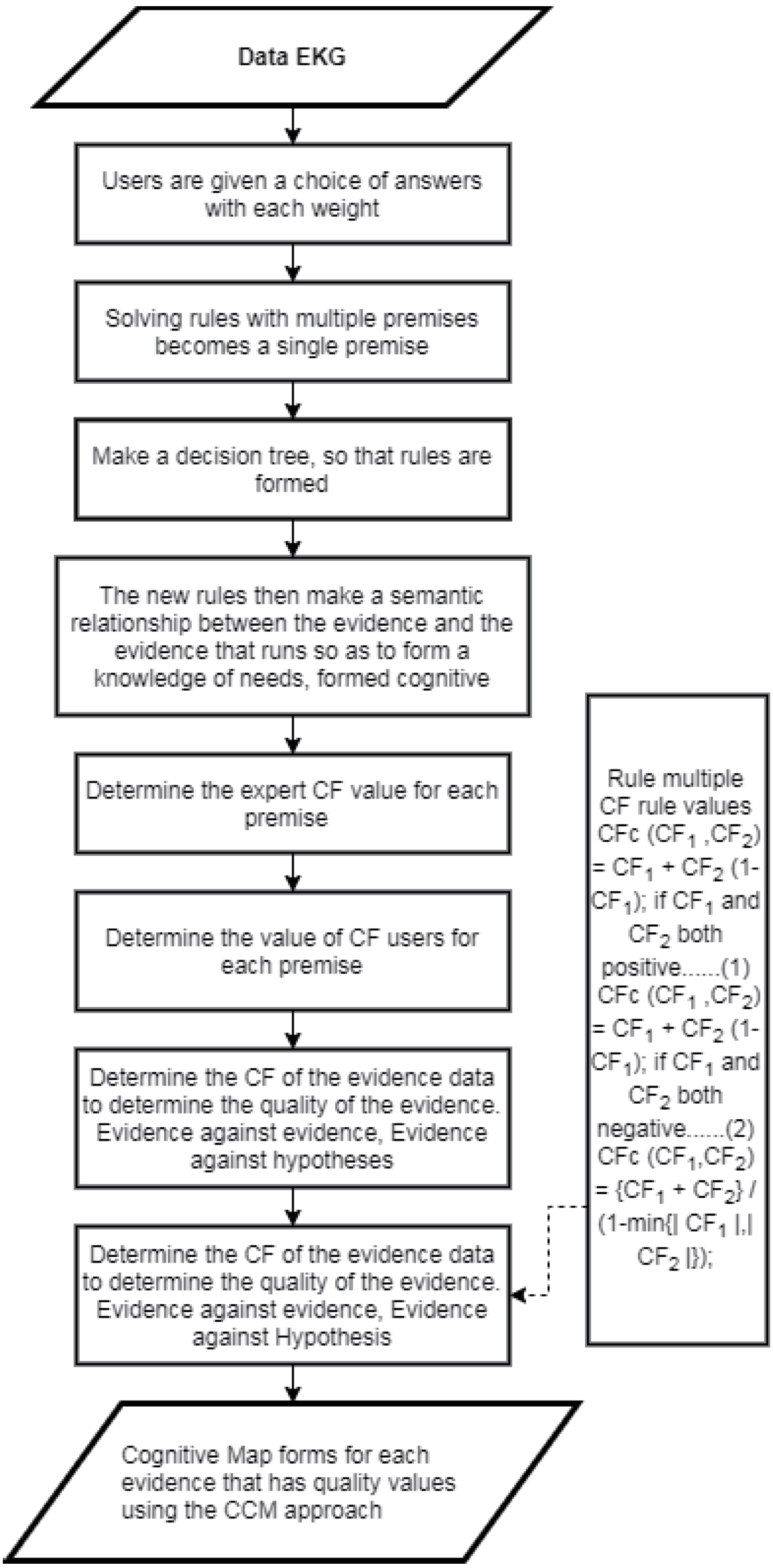

FIGURE 1. Modification of certainty factor models with the cognitive map approach

3. Evaluation Result.

Cognitive map formation for patients

Electrocardiogram medical record data that has been read and analyzed by cardiologists to identify normal and abnormal heart. Normal and abnormal ECG data were analyzed by cardiologists (experts). After the data is analyzed by a cardiologist, the next process is to go forward in the process of inference, assisted with RapidMiner Studio software tools to produce a decision tree, so that rules are formed that form a complete cognitive map. Figure 2 shows the results of the decision tree of the RapidMiner software.

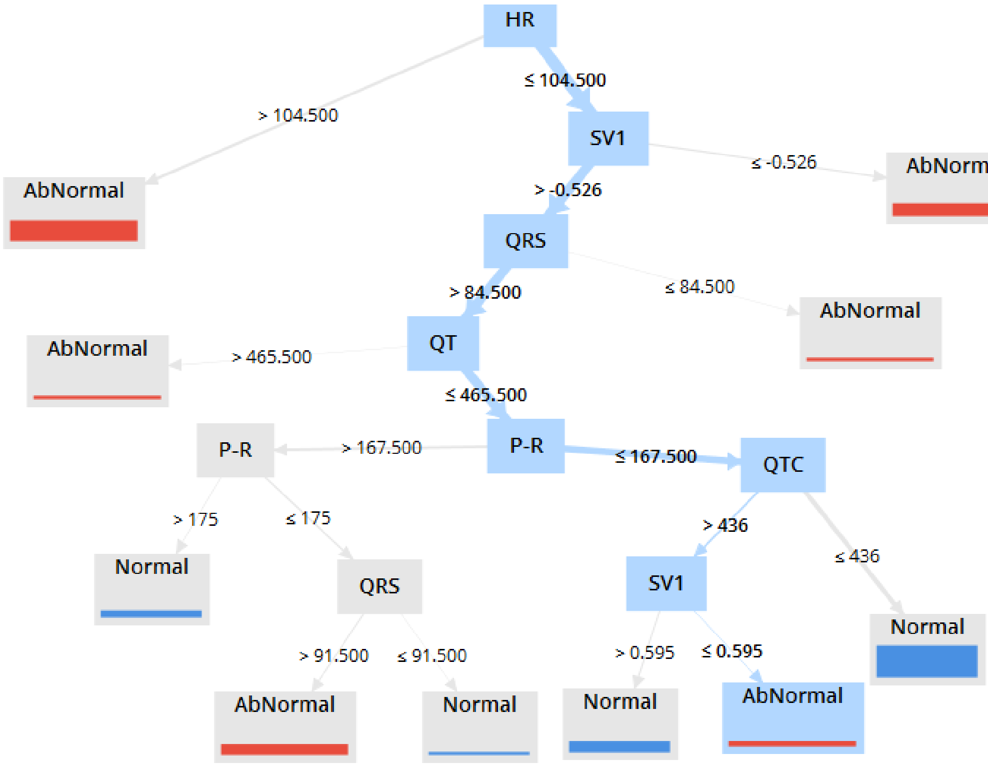

FIGURE 2. Decision tree result with RapidMiner

Based on Figure 2, the results of the advanced inference process formed 10 rule rules consisting of 6 abnormal rule rules and 4 normal rule rules as follows:

Abnormal Rule Rules as follows:

R1: IF HR $\leq$ 104.5 AND IF SV1 ≤ -0.526 AND **THEN ABNORMAL**

R2: IF HR $\leq$ 104.5 AND IF SV1 > -0.526 AND IF QRS $\leq$ 84.5 AND **THEN ABNORMAL**

R3: IF HR $\leq$ 104.5 AND IF SV1 ≥ -0.526 AND IF QRS $\geq$ 84.5 AND IF QT $>$ 465.5 AND **THEN ABNORMAL**

R4: IF HR $>$ 104.5 AND **THEN ABNORMNAL**

R5: IF HR $\leq$ 104.5 AND IF SV1 > -0.526 AND IF QRS $>$ 84.5 AND IF QT $\leq$ 465.5 AND IF P-R $>$ 167.5 AND IF P-R $\leq$ 175 AND IF QRS $>$ 91.5 AND **THEN ABNORMAL**

R6: IF HR $\leq$ 104.5 AND IF SV1 > -0.526 AND IF QRS $>$ 84.5 AND IF QT $\leq$ 465.5 AND IF P-R $\leq$ 167.5 AND IF QTC $>$ 436 AND IF SV1 $\leq$ 0.595 AND **THEN ABNORMAL**

Normal Rule Rules as follows:

R1: HR $\leq$ 104.5 AND IF SV1 > -0.526 AND IF QRS $>$ 84.5 AND IF QT $\leq$ 465.5 AND IF P-R $>$ 167.5 AND IF P-R $>$ 175 AND **THEN NORMAL**

R2: IF HR $\leq$ 104.5 AND IF SV1 > -0.526 AND IF QRS $>$ 84.5 AND IF QT $\leq$ 465.5 AND IF P-R $>$ 167.5 AND IF P-R $\leq$ 175 AND IF QRS $\leq$ 91.5 AND **THEN NORMAL**

R3: HR $\leq$ 104.5 AND IF SV1 $>$ -0.526 AND IF QRS $>$ 84.5 AND IF QT $<$ 465.5 AND IF P-R $\leq$ 167.5 AND IF QTC $>$ 436 AND IF SV1 $>$ 0.595 **THEN NORMAL**

R4: IF HR $\leq$ 104.5 AND IF SV1 $>$ -0.526 AND IF QRS $>$ 84.5 AND IF QT $\leq$ 465.5 AND IF P-R $\leq$ 167.5 AND IF QTC $\leq$ 436 AND **THEN NORMAL**.

After making an advanced inference process to produce rules, the rules that have been formed from the results of the tools of the RapidMiner software are formed into a complete cognitive map. Figure 3 shows cognitive map of causal abnormal positive and negative causal heart. Figure 4 shows cognitive map of causal normal positive and negative causal heart.

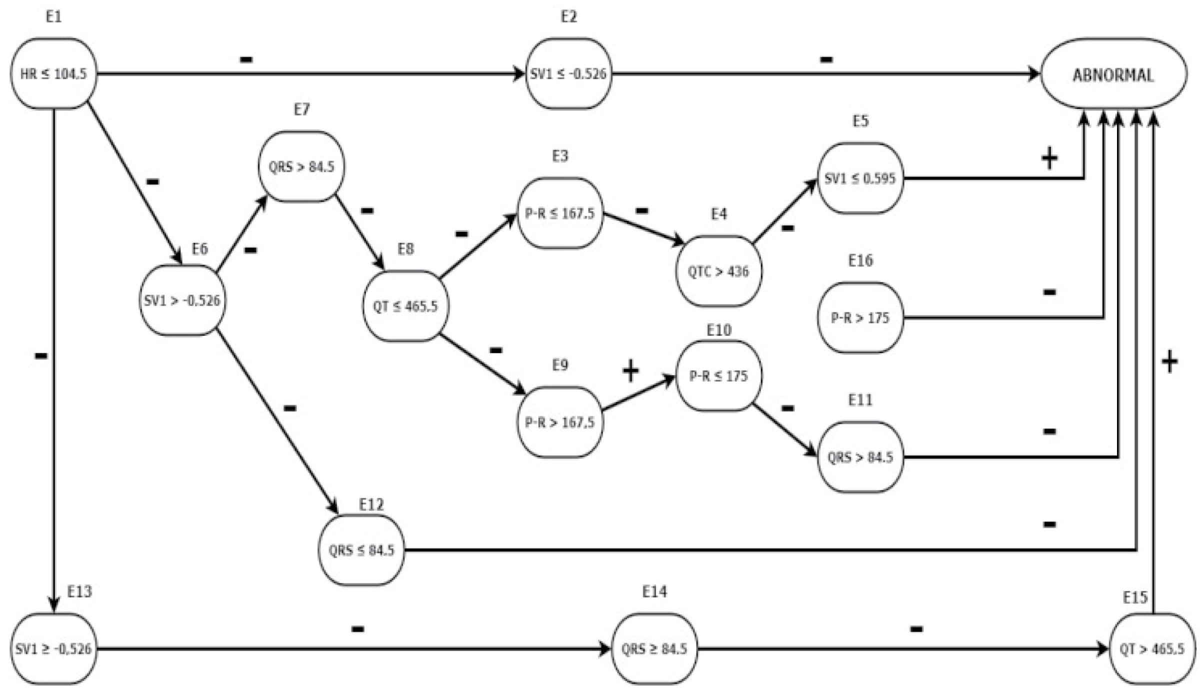

Figure 3. Cognitive map of causal abnormal positive and negative causal heart

The path in the cognitive map where the initial node and the vertex coincide is called cycles, based on Figure 3 taken from the abnormal heart cognitive map as follows:

$E1(-) \to E6(-) \to E7(-) \to E8(-) \to E3(-) \to E4(-) \to E5(+) \to$ Abnormal

$E1(-) \to E2(-) \to$ Abnormal

$E1(-) \to E6(-) \to E12(+) \to$ Abnormal

$E1(-) \to E6(-) \to E7(-) \to E8(-) \to E9(+) \to E10(+) \to E11(-) \to$ Abnormal

The path in the cognitive map where the initial node and the vertex coincide is called cycles, based on Figure 4 taken from the cognitive map of the normal heart as follows:

$E1(-) \to E2(+) \to E3(+) \to E4(+) \to E5(+) \to E6(-) \to$ Normal

$E1(-) \to E2(+) \to E3(+) \to E9(-) \to E10(-) \to E11(-) \to E12(-) \to$ Normal

$E1(-) \to E2(+) \to E3(+) \to E4(+) \to E10(-) \to E13(+) \to$ Normal

$E1(-) \to E2(+) \to E3(+) \to E4(+) \to E5(+) \to E7(-) \to E8(+) \to$ Normal

Giving cognitive causality value using certainty factor

Based on the process regarding the formation of cognitive maps, then giving causality values to cognitive maps that use the Certainty Factor (CF) formulation to find the relationship between evidence and evidence, with hypotheses. This process is done based on the value of the level of confidence given from an expert and user.

Abnormal rule rules obtained from the advanced inference process are as follows:

R1: IF HR $\leq$ 104.5 ($CF_e = 0.6$) AND IF SV1 $\leq$ -0.526 ($CF_e = 0.4$) AND THEN ABNORMAL ($CF_R = 0.4$)

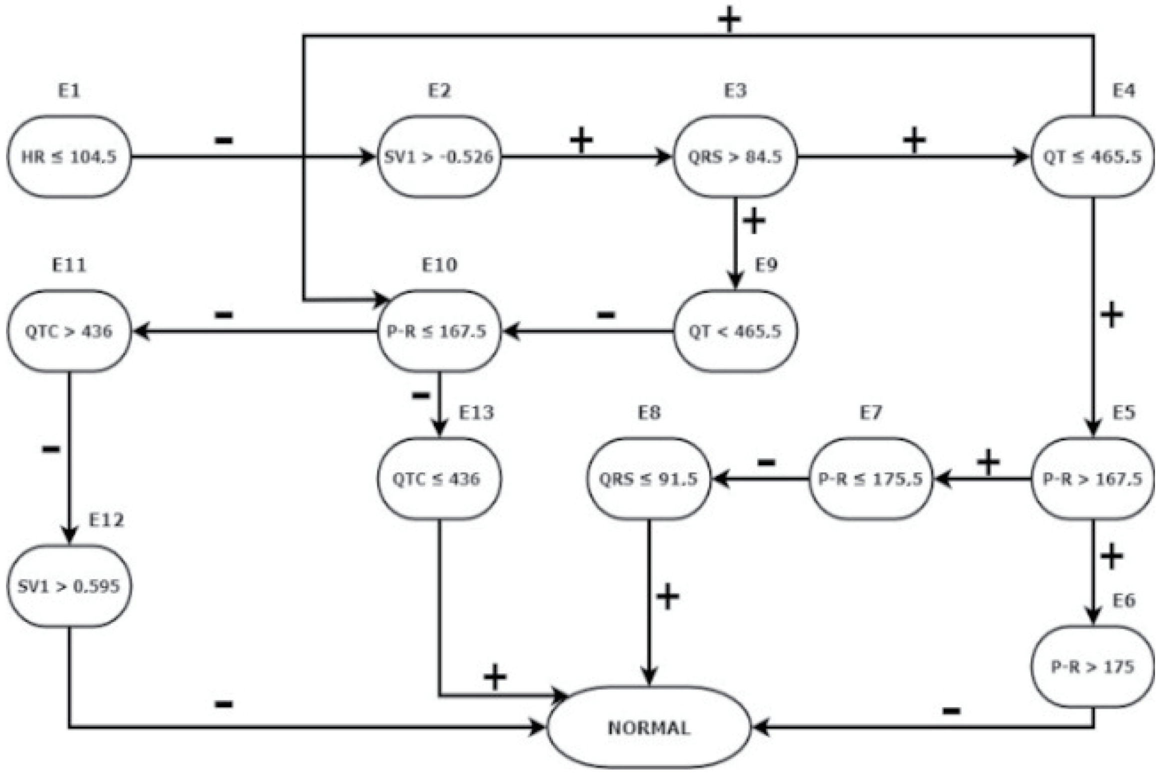

FIGURE 4. Cognitive map of causal normal positive and negative causal heart

R2: IF HR $\leq$ 104.5 (CF_e = 0.6) AND IF SV1 $>$ -0.526 (CF_e = 0.4) AND IF QRS $\leq$ 84.5 (CF_e = 0.6) AND THEN ABNORMAL (CF_R = 0.6)

R3: IF HR $\leq$ 104.5 (CF_e = 0.6) AND IF SV1 $\geq$ -0.526 (CF_e = 0.4) AND IF QRS $\geq$ 84.5 (CF_e = 0.6) AND IF QT $>$ 465.5 (CF_e = 0.6) AND THEN ABNORMAL (CF_R = 0.6)

R4: IF HR $>$ 104.5 (CF_e = 0.6) AND THEN ABNORMNAL (CF_R = 0.6)

R5: IF HR $\leq$ 104.5 (CF_e = 0.6) AND IF SV1 $>$ -0.526 (CF_e = 0.4) AND IF QRS $>$ 84.5 (CF_e = 0.6) AND IF QT $\leq$ 465.5 (CF_e = 0.6) AND IF P-R $>$ 167.5 (CF_e = 0.6) AND IF P-R $\leq$ 175 (CF_e = 0.8) AND IF QRS $>$ 91.5 (CF_e = 0.6) AND THEN ABNORMAL (CF_R = 0.6)

R6: IF HR $\leq$ 104.5 (CF_e = 0.6) AND IF SV1 $>$ -0.526 (CF_e = 0.6) AND IF QRS $>$ 84.5 (CF_e = 0.6) AND IF QT $\leq$ 465.5 (CF_e = 0.6) AND IF P-R $\leq$ 167.5 (CF_e = 0.6) AND IF QTC $>$ 436 (CF_e = 0.6) AND IF SV1 $\leq$ 0.595 (CF_e = 0.6) AND THEN ABNORMAL (CF_R = 0.8)

Based on the process of advanced inference, and the value of evidence with other evidence, evidence with hypotheses obtained from the value of the confidence level of an expert, then the next step is the rule rules that have formed a relationship and get the value of causality obtained by breaking into a new sub-rule, and each rule has a CF rule value that uses the combined rule concept, so that the causality value of each node is combined with the CF of each rule. Figure 5 shows the abnormal cognitive causality map value.

Figure 6 shows the normal cognitive causality map with value of causality, the value of causality between evidence and evidence.

While the results of advanced inference for normal rules are as follows:

R1: HR $\leq$ 104.5 (CF_e = 0.8) AND IF SV1 $>$ -0.526 (CF_e = -0.6) AND IF QRS $>$ 84.5 (CF_e = 0.6) AND IF QT $\leq$ 465.5 (CF_e = 0.6) AND IF P-R $>$ 167.5 (CF_e = 0.4) AND IF P-R $>$ 175 (CF_e = 0.4) AND THEN NORMAL (CF_R = 0.6)

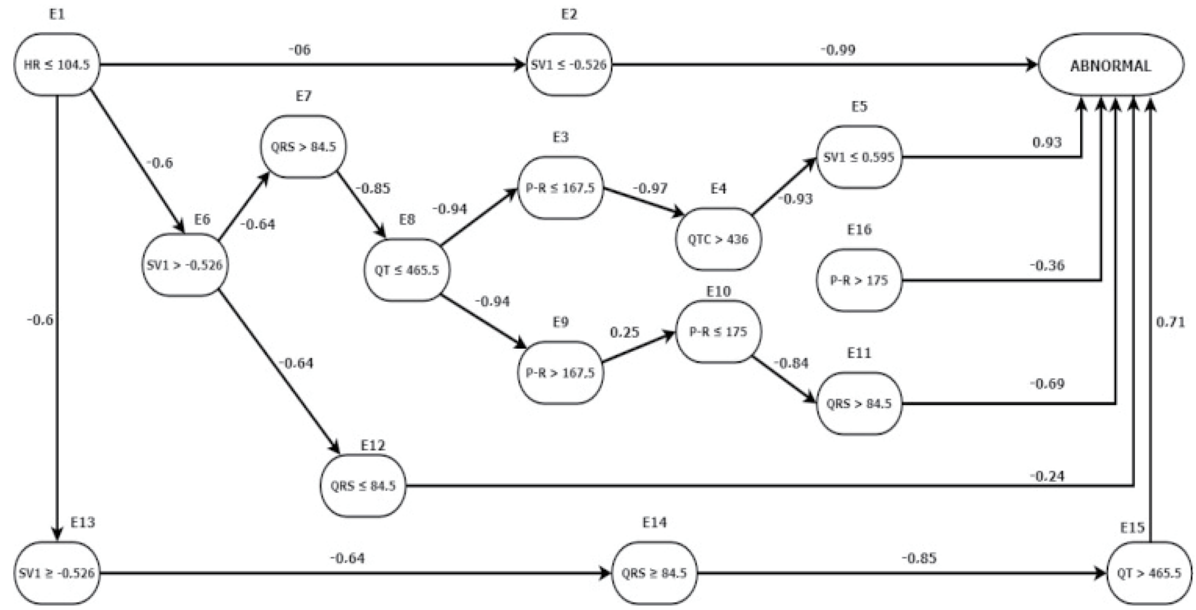

FIGURE 5. The abnormal cognitive causality map value

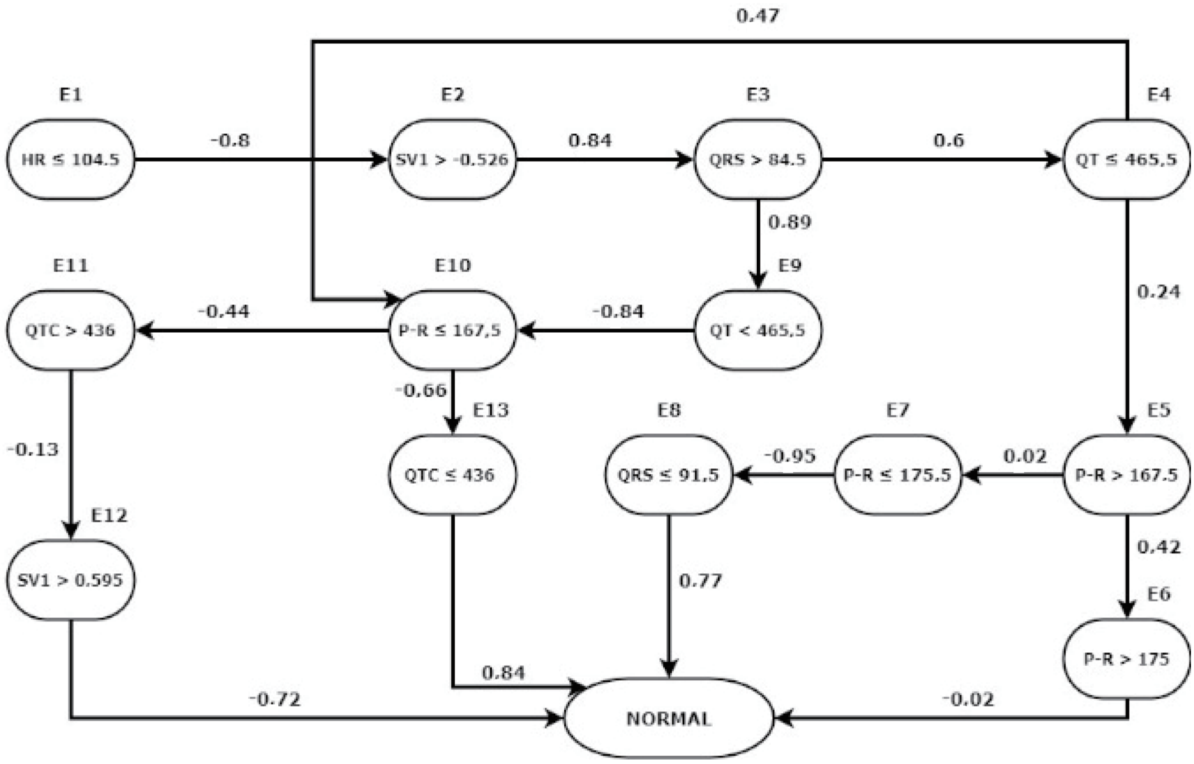

FIGURE 6. A normal cognitive map with causality

R2: IF HR ≤ 104.5 ($\mathrm{CF_e} = 0.8$) AND IF SV1 > -0.526 ($\mathrm{CF_e} = -0.6$) AND IF QRS > 84.5 ($\mathrm{CF_e} = 0.6$) AND IF QT ≤ 465.5 ($\mathrm{CF_e} = 0.6$) AND IF P-R > 167.5 ($\mathrm{CF_e} = 0.4$) AND IF P-R ≤ 175 ($\mathrm{CF_e} = 0.8$) AND IF QRS ≤ 91.5 ($\mathrm{CF_e} = 0.6$) AND THEN NORMAL ($\mathrm{CF_R} = 0.6$)

R3: HR ≤ 104.5 ($\mathrm{CF_e} = 0.8$) AND IF SV1 > -0.526 ($\mathrm{CF_e} = -0.6$) AND IF QRS > 84.5 ($\mathrm{CF_e} = 0.6$) AND IF QT < 465.5 ($\mathrm{CF_e} = 0.6$) AND IF P-R ≤ 167.5 ($\mathrm{CF_e} = 0.6$) AND IF QTC > 436 ($\mathrm{CF_e} = 0.4$) AND IF SV1 > 0.595 ($\mathrm{CF_e} = 0.6$) THEN NORMAL ($\mathrm{CF_R} = 0.6$)

R4: IF HR ≤ 104.5 ($CF_e = 0.8$) AND IF SV1 > -0.526 ($CF_e = -0.6$) AND IF QRS > 84.5 ($CF_e = 0.6$) AND IF QT ≤ 465.5 ($CF_e = 0.6$) AND IF P-R ≤ 167.5 ($CF_e = 0.6$) AND IF QTC ≤ 436 ($CF_e = 0.8$) THEN NORMAL ($CF_R = 0.6$)

Based on the process of advanced inference, and the value of evidence with other evidence, evidence with hypotheses obtained from the value of the confidence level of an expert, then the next step is the rule rules that have formed a relationship and get the value of causality obtained by breaking into a new sub-rule, and each rule has a CF rule value that uses the combined rule concept, so that the causality value of each node is combined with the CF of each rule. Figure 6 shows the value of cognitive map causality with the value of causality.

4. **Conclusions.** Based on the research conducted, it can be concluded that the certainty cognitive map approach to diagnosing cardiac failure is able to resolve the deficiencies that exist in both the certainty factor and cognitive map approaches, with the Certainty Cognitive Map (CCM) approach, the relationship between evidence and evidence can be seen hypothesis, so that a cognitive map can be formed intactly, in addition to that the Certainty Cognitive Map (CCM) method in addition to having a causal relationship, has a causality value between evidence and evidence, the causality value of evidence with a hypothesis, so it seems clear with the certainty cognitive map method that is able to solve problems better owned by the certainty factor method, where the weaknesses are only the value of the causality of the evidence and the cognitive map is not visible, although seen from the rules the rules are interconnected, besides the certainty cognitive map method is able to solve add weaknesses to the cognitive map approach, where cognitive maps are only able to form cognitive relationships, but do not have a causal value between the nodes.

REFERENCES

[1] A. Triayudi and I. Fitri, Comparison of parameter-free agglomerative hierarchical clustering methods, *ICIC Express Letters*, vol.12, no.10, pp.973-980, 2018.

[2] A. Triayudi and I. Fitri, ALG clustering to analyze the behavioural patterns of online learning students, *Journal of Theoretical & Applied Information Technology*, vol.96, no.16, pp.5327-5337, 2018.

[3] A. Triayudi and I. Fitri, A new agglomerative hierarchical clustering to model student activity in online learning, *Telkomnika*, vol.17, no.3, pp.1226-1235, 2019.

[4] V. A. Niskanen, A statistical random variable approach to fuzzy cognitive map modeling, *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pp.1-6, 2019.

[5] M. S. Satu, F. Tasnim, T. Akter and S. Halder, Exploring significant heart disease factors based on semi supervised learning algorithms, *International Conference on Computer, Communication, Chemical, Material and Electronic Engineering (IC4ME2)*, pp.1-4, 2018.

[6] T. Widiyaningtyas, I. A. E. Zaeni and P. Y. Wahyuningrum, Self-organizing map (SOM) for diagnosis coronary heart disease, *The 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, pp.286-289, 2019.

[7] Y. Deng, X. Duan, B. Jiao, T. Zhu and Z. Wang, Electrocardiographic criteria for the diagnosis of left ventricular hypertrophy based on data mining, *The 10th Biomedical Engineering International Conference (BMEiCON)*, pp.1-5, 2017.

[8] P. Ghaderyan and A. Abbasi, A novel cepstral-based technique for automatic cognitive load estimation, *Biomedical Signal Processing and Control*, vol.39, pp.396-404, 2018.

[9] D. M. Mirvis and A. L. Goldberger, The 12-lead ECG in acute coronary syndromes, in *Electrocardiography, Braunwald's Heart Disease: A Textbook of Cardiovascular Medicine*, D. P. Zipes, P. Libby, R. O. Bonow and E. Braunwald (eds.), 2015.

[10] S. Faziludeen and P. Sankaran, ECG beat classification using evidential K-nearest neighbours, *Procedia Computer Science*, vol.89, pp.499-505, 2016.

[11] T. Lindow, O. Pahlm and K. Nikus, A patient with non-ST-segment elevation acute coronary syndrome: Is it possible to predict the culprit coronary artery?, *Journal of Electrocardiology*, vol.49, no.4, pp.614-619, 2016.

[12] D. Magrì, C. Santolamazza, L. Limite, V. Mastromarino, M. Casenghi, P. Orlando, E. Pagannone, M. B. Musumeci, A. Maruotti, A. Ricotta and G. Oliviero, QT spatial dispersion and sudden cardiac death in hypertrophic cardiomyopathy: Time for reappraisal, *Journal of Cardiology*, vol.70, no.4, pp.310-315, 2017.

[13] S. M. Mathews, C. Kambhamettu and K. E. Barner, A novel application of deep learning for single-lead ECG classification, *Computers in Biology and Medicine*, vol.99, pp.53-62, 2018.

[14] J. S. Steinberg, N. Varma, I. Cygankiewicz, P. Aziz, P. Balsam, A. Baranchuk, D. J. Cantillon, P. Dilaveris, S. J. Dubner, N. El-Sherif and J. Krol, ISHNE-HRS expert consensus statement on ambulatory ECG and external cardiac monitoring/telemetry, *Heart Rhythm*, vol.14, no.7, pp.e55-e96, 2017.

[15] D. D. Salcido, R. H. Schmicker, N. Kime, J. E. Buick, S. Cheskes, B. Grunau, S. Zellner, D. Zive, T. P. Aufderheide, A. C. Koller and H. Herren, Effects of intra-resuscitation antiarrhythmic administration on rearrest occurrence and intra-resuscitation ECG characteristics in the ROC ALPS trial, *Resuscitation*, vol.129, pp.6-12, 2018.

[16] D. Saini, A. F. Grober, D. Hadley and V. Froelicher, Normal computerized Q wave measurements in healthy young athletes, *Journal of Electrocardiology*, vol.50, no.3, pp.316-322, 2018.

[17] M. Singh, L. M. Martins, P. Joanis and V. K. Mago, Building a cardiovascular disease predictive model using structural equation model & fuzzy cognitive map, *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, pp.1377-1382, 2016.

[18] I. Astuti and H. Sutarno, The expert system of children's digestive tract diseases diagnostic using combination of forward chaining and certainty factor methods, *The 3rd International Conference on Science in Information Technology (ICSITech)*, pp.608-612, 2017.

[19] A. S. Novikov, A. Ivutin and A. Troshina, The method for automated determination of certainty coefficients values of initial facts in decision-making systems based on fuzzy approximate reasoning networks, *The 8th Mediterranean Conference on Embedded Computing (MECO)*, pp.1-4, 2019.

[20] A. R. Hassan and M. A. Haque, An expert system for automated identification of obstructive sleep apnea from single-lead ECG using random under sampling boosting, *Neurocomputing*, vol.235, pp.122-130, 2019.

[21] M. G. Feshki and O. S. Shijani, Improving the heart disease diagnosis by evolutionary algorithm of PSO and feed forward neural network, *Artificial Intelligence and Robotics (IRANOPEN)*, pp.48-53, 2016.

[22] D. Shan, W. Lu and J. Yang, The data-driven fuzzy cognitive map model and its application to prediction of time series, *International Journal of Innovative Computing, Information and Control*, vol.14, no.5, pp.1583-1602, 2018.