

Comparison of Naive Bayes Method and Certainty Factor for Diagnosis of Preeclampsia

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Abstract

Preeclampsia is a disease often suffered by pregnant women caused by several factors such as a history of heredity, blood pressure, urine protein, and diabetes. The data sample used in this study is data on pregnant women in the 2020 time period recorded at health services in the former Cilacap Regency. This study was conducted to compare the final results of the Naive Bayes method and the certainty factor method in providing the results of a diagnosis of preeclampsia seen from the symptoms experienced by these pregnant women. The naïve Bayes approach provides decisions by managing statistical data and probabilities taken from the prediction of the likelihood of a pregnant woman showing symptoms of preeclampsia. Symptoms of preeclampsia, while the certainty factor method determines the certainty value of the diagnosis of preeclampsia in pregnant women based on the calculation of the CF value. The research output compares the two methods, showing that the certainty factor method provides more accurate diagnostic results than the Naive Bayes method. It happens because the CF method requires a minimum value of 0.2 and a maximum of 1 for each rule on the factors/symptoms involved, while the Naive Bayes method only requires values of 0 and 1 for each factor causing preeclampsia in pregnant women.

Keywords: Preeclampsia, Expert System, Naïve Bayes, Certainty Factor, Pregnant Women

1. Introduction

Preeclampsia is a hypertensive disorder in pregnant women that significantly affects morbidity and is one of the causes of death in pregnant women and fetuses [1], [2]. Maternal Mortality Ratio (MMR), according to the World Health Organization (WHO), is the incidence of death in pregnant women during the period around delivery, which is 42 days after the end of pregnancy, which is caused by all causes related to pregnancy or the wrong way of handling it and is not caused by injury or accident [3]. Maternal Mortality Ratio (MMR) and Infant Mortality Ratio (IMR) are some of the benchmarks for the health and welfare of the people in a country [4]. WHO reports from various sources that the direct cause of maternal deaths occurs during and after childbirth and is caused by bleeding, infection, or high blood pressure during pregnancy by 75% [5]. According to WHO data, the prevalence of preeclampsia is 1.8-18% in developing countries, while in developed countries, it is 1.3-6%. This value indicates that the case of pregnant women with preeclampsia in developing countries is higher than in developed countries because preventive treatment of pregnant women with preeclampsia is handled faster in developed countries than in developing countries [6]. In Indonesia alone, the Maternal Mortality Ratio (MMR) for the last ten years was 459 maternal and fetal deaths from 100,000 births, with a frequency of preeclampsia incidence of

around 3% to 10% of all pregnancies. The MMR value in Indonesia as a developing country is still relatively high. Data from the Inter-Census Population Survey (SUPAS) recorded MMR in as many as 305 cases during the last five years; this means that there are 305 cases of maternal death caused by pregnancy until delivery for 42 days after delivery per 100,000 live births [7]. In Cilacap Regency, according to data from the Cilacap Regency Health Office, it shows that during the last two years, MMR was 15 cases while for IMR it was 155 cases. Meanwhile, for the maximum target of the Regional Medium-Term Development Plan (RPJMD) of Cilacap Regency, the MMR is 19 cases and the IMR is 139 cases [8]. Based on this target, the MMR in Cilacap Regency is still quite high even though it is below the maximum standard set [9]. This has become the concern of relevant institutions in Cilacap Regency to continue suppressing MMR and IMR so that the level of community welfare increases. MMR can be identified based on the mother's general condition during the gestation of 40 weeks [10].

One of the identifications can be done through health examination of pregnant women in available health facilities [11]. This identification reduces the risk of death of pregnant women and fetuses, which can be predicted based on the symptoms experienced during pregnancy through prompt and correct handling in the most dangerous period, namely the period around delivery [12]. An expert system can be simply a transfer of knowledge from an expert to a computer through an information system that can be utilized without time and place restrictions [13]. The expert system asks for facts that will later be used as knowledge inference which is then processed to provide conclusions or decisions that are conical to a result of these facts [14]. The conclusion is considered the result of consultation with experts, who provide non-expert advice and explain possible solutions to the consequences [15].

Several studies have been conducted on implementing the naïve Bayes method and certainty factors to detect various diseases, including the research conducted by Hanny, which mapped the spread of respiratory tract infections (ARI) using the Naive Bayes method. Classification is carried out using ARI data so that the community is responsive to the spread of ARI diseases and helps medical personnel to complete the eradication of ARI diseases that have been targeted. The result of this study is the visualization used for mapping the spread of ARI disease based on classification using naïve Bayes [16]. Further research was conducted by Yovita et al., who implemented the naïve Bayes method in an expert system for diagnosing dysmenorrhea. Diagnosis is made to produce a conclusion about the dysmenorrhea suffered by a woman, whether it is included in the category of primary dysmenorrhea or secondary dysmenorrhea using the Naive Bayes classification. The analysis results show that the Naive Bayes method classification accuracy is 90% for the ten tested data [17]. Subsequent research was carried out by Muhammad et al., who used the Naive Bayes algorithm to determine the credit given to prospective customers. The naïve Bayes algorithm is used to predict and classify potentially problematic and non-problematic customers to get credit so that the company does not lose money with customers who have the potential to cause problems with bad loans in the future [18]. Subsequent research by Khairina et al. applied the certainty factor to an expert system for diagnosing ENT diseases. The expert in this study is an ENT specialist who provides complete and detailed information about the causes and symptoms experienced by patients who have problems with their ears, nose, and throat. The results of this study are a website-based information system that can diagnose ENT diseases by selecting the symptoms experienced by patients, and search results provided by the system results in the form of information about ENT diseases suffered based on the selected symptoms [19].

Based on several studies that have been done before, the authors are interested in comparing the certainty factor method and the naïve Bayes method in diagnosing preeclampsia in pregnant women. The search results for preeclampsia by comparing the naïve Bayes method and the certainty factor method are used to design and develop an expert system. It is conducted by exploring expert knowledge, used as a knowledge base in an expert system development environment [20]. The consulting environment has a user interface, annotation facilities, and an inference engine connected to the development environment [21]. After extracting expert knowledge, forming rules based on facts on a knowledge base that will later be used in the tracing process, becomes the next step in designing an expert system for diagnosing preeclampsia in pregnant women [22]. The conclusions/decision results given are non-expert; if there are doubts about the results, they can later be consulted with real experts [23]. With the results, it is hoped that the developed expert system will be able to suppress the Maternal Mortality Ratio (MMR) to

Calculations on the Naive Bayes method to generate disease opportunities go through several stages of the process as explained below [28]:

- a. Calculate the average of each class by using the equation below to find the initial value for each class involved [29]:

$$X(pi|aj) = \frac{qd+(r*x)}{q+r} \quad (1)$$

Description:

Qd = the value of the data record in the training data that have a = aj and p = pi

X = 1 / many types of class / disease

r = number of symptoms/parameter

q = the value of the data record in the training data that has a value of

a = aj/each class/disease

- b. Determine the likelihood value for each existing class using the equation below [30]:

$$X(aj) = \frac{q}{r} \quad (2)$$

- c. Determine the posterior value for each class involved using the following equation [31]:

$$X(aj|pi) = X(pi|aj) * X(aj) \quad (3)$$

The final result of the Naive Bayes method is to classify the classes involved in the process of appearing the chance of preeclampsia disease by comparing the posterior end values of each class involved [32]. And the result of the naïve bayes method of classification is the highest posterior value of several classes being compared [33].

2.2. Certainty Factor Method

The certainty factor method is a method for tracing a conclusion that begins by observing the symptoms [28]. Tracing a conclusion is used to measure the certainty of a set of facts or rules [34]. In this case, the set of facts in question is the symptoms experienced by pregnant women during pregnancy from the first trimester to the last trimester. The data is collected to make rules for tracing preeclampsia [35]. The certainty factor (CF) value is calculated to show confidence in the facts of an event [36]. One of the reasons for choosing the certainty factor method to diagnose preeclampsia in pregnant women is that this method can measure something certain and uncertain in deciding on an expert system that is being developed [37]. The measure of the certainty of a fact is denoted by MB (Measure of increased Belief), while the measure of uncertainty is denoted by MD (Measure of increased Disbelief) [19]. The stages of the CF value search process are as follows [38]:

- a. Determine the value of CF

$$CF[H, E] = MB[H, E] - MD[H, E] \quad (4)$$

Description

CF [H, E]: a measure of the certainty of the hypothesis H that affected by symptoms E

MB [H, E]: a measure of MB's confidence in H affected by E

MD [H, E]: a measure of MD's distrust of H affected by E

- b. Determine the value of CF Combination determined by one premise

$$CF[X\wedge Y] = \text{Min}(CF[x], CF[y]) * CF[RULE] \quad (5)$$

- c. Determine the value of CF Combination determined by more than one premise

$$CF[X\wedge Y] = \text{Max}(CF[x], CF[y]) * CF[RULE] \quad (6)$$

- d. Determine the CF value for the same conclusion

$$CF \text{ Comb}[CF1, CF2] = CF1 + CF2 * (1 - CF1) \quad (7)$$

The final result of the certainty factor method provides a certainty value for a decision, namely determining diseases that attack pregnant women [11]. The accuracy of the calculation results of this method is maintained because it can only process two data for one calculation [39], [40].

Figure 2 shows the stages of the certainty factor method, starting with determining the CF value for each premise of the rule used, then proceeding with determining the combination CF value determined by one or more premises, and ending with determining the CF value for the same conclusion, namely the diagnosis of preeclampsia [41].

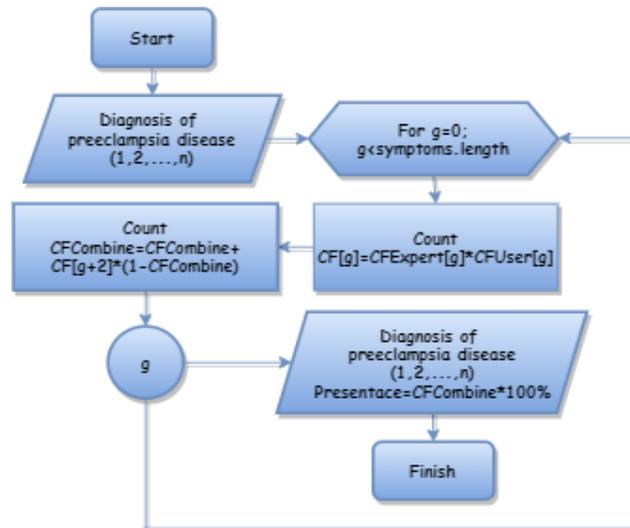


Figure 2. Flowchart of Certainty Factor Method

2.3. Preeclampsia

The data on symptoms/factors causing preeclampsia used in this study are shown in table 1. While table 2 shows the data description of elements grouped by symptoms in table 1. Table 3 shows examples of rule data used to diagnose preeclampsia based on data in table 1, and Table 2 is data on symptoms/factors causing preeclampsia. The rules in table 3 are formed based on the knowledge base obtained after consulting with experts, namely obstetricians and midwives. The category itself is divided into four categories, namely severe preeclampsia with the symbol (B), moderate preeclampsia with the symbol (S), mild preeclampsia with the symbol (R), and undetected preeclampsia with the symbol (T).

Table 1. Preeclampsia Symptom Factor Data

Factor Code	Information	Factor Description
F01	Age	U1, U2, U3
F02	Parity	P1, P2
F03	Pregnancy Distance	JK1, JK2
F04	Multiple Pregnancy	KG1, KG2
F05	History of Preeclampsia	RP1, RP2
F06	History of Hypertension	RH1, RH2
F07	Descendants History	RK1, RK2
F08	History of DM	RD1, RD2
F09	Nutritional status	SG1, SG2
F10	Antenatal Care	AC1, AC2
F11	Family Planning Acceptor History	RA1, RA2
F12	Educational status	SP1, SP2
F13	Knowledge	P1, P2, P3
F14	Economic Status	SE1, SE2
F15	Work	PK1, PK2
F16	Health Service Distance	J1, J2, J3

Table 2. Description of the Causes of Preeclampsia

Code Description Factor	Description	Code Description Factor	Description
U1	<= 18 years	SG1	Obesity
U2	18 - 38 years	SG2	Not
U3	>= 38 years	AC1	</= 3 times
P1	First	AC2	> 3 times
P2	Second/more	RA1	There is
JK1	< 24 months	RA2	Not
JK2	>/ 24 months	SP1	Elementary/ Junior High School
KG1	Double	SP2	High School/ College
KG2	Single	P1	Not enough
RP1	There is	P2	Currently
RP2	Not	P3	Good
RH1	There is	SE1	<500k
RH2	Not	SE2	>/= 500k
RK1	There is	PK1	Unemployment
RK2	Not	PK2	Work
RD1	There is	J1	>1000 meters
RD2	Not	J2	</= 1000 meters

Table 3. Example of Preeclampsia Diagnostic Rules

Rule Code	Rule	Then
R01	If U1 and P2 and JK1	Severe Preeclampsia
R02	If U1 and RP1 and RH1	Severe Preeclampsia
R03	If U3 and RH1 and RP1	Severe Preeclampsia
R04	If U3 and SG1 and RH1	Severe Preeclampsia
R05	If U3 and SG1 and RD1	Severe Preeclampsia
R06	If P1 and SG2 and RD2	Moderate Preeclampsia
R07	If AC1 and RH2 and RD2	Moderate Preeclampsia
R08	If P1 and RP1 and RH2	Moderate Preeclampsia
R09	If RK1 and RH2 and RP2	Moderate Preeclampsia
R10	If U2 and P1 and KG2	Mild Preeclampsia
R11	If U2 and RP2 and RH2	Mild Preeclampsia
R12	If U2 and RH2 and RD2	Mild Preeclampsia
R13	If U2 and SG2 and RH2	Mild Preeclampsia
R14	If RK2 and AC2 and SG2	Not Detected Preeclampsia
R15	If RP2 and RH2 and RD2	Not Detected Preeclampsia
R16	If SG2 and RD2 and AC2	Not Detected Preeclampsia
R17	If RD2 and RA1 and SP2	Not Detected Preeclampsia

3. Result and Discussion

At the stage of the results and discussion of this research, it will be explained about the comparison of the calculation of the certainty factor method and the Naive Bayes method. The results of the calculations of the two approaches will be compared with the level of accuracy. The calculation of the two methods uses the example rule to diagnose preeclampsia in table 3.

3.1. Naïve Bayes Method

- a. Find the average probability value for each class of preeclampsia disease using equation (1) [42].
 1. There are four classes: severe preeclampsia, moderate preeclampsia, mild preeclampsia, and no preeclampsia.
 2. The number of data on symptoms/factors causing preeclampsia is 34, as described in table 2.
 3. The average probability of each class of disease is as follows:

Table 4. Average Probability Value of Each Class

Disease Class	Mean Score
Severe Preeclampsia (B)	0,31
Moderate Preeclampsia (S)	0,26
Mild Preeclampsia (R)	0,23
Not Detected Preeclampsia (T)	0,2

- b. Determine the like hood value for each preeclampsia disease using equation (2) [43].
 Some of the factors that cause preeclampsia:

1. U3 : Age \geq 38 years old
2. RH1: There is a history of hypertension
3. RP1: There is a history of preeclampsia
4. RD2: No history of diabetes
5. AC1: Antenatal care \leq 3 times
6. RA1: There is a history of using family planning acceptors

Table 5. Like Hood Value for Each Class

Disease Class	U3	RH1	RP1	RD2	AC1	RA1
B	1	1	1	1	1	1
S	0	0	1	1	1	0
R	0	0	0	1	1	1
T	0	0	0	0	0	1

- c. Determine the posterior value for each preeclampsia disease class using equation (3) [44].

Table 6. Posterior Value of Each Class

Disease Class	Posterior Grade
B	$0,17 \times 0,17 \times 0,17 \times 0,17 \times 0,17 \times 0,17 : 0,00024$
S	$0 \times 0 \times 0,11 \times 0,11 \times 0,11 \times 0 : 0$
R	$0 \times 0 \times 0,125 \times 0,125 \times 0,125 : 0$
T	$0 \times 0 \times 0 \times 0 \times 0,143 : 0$

- d. The posterior value for the class of severe preeclampsia is 0,00024, the class for moderate preeclampsia is 0, the class for mild preeclampsia is 0, and the class for undetected preeclampsia is 0.

3.2. Certainty Factor Method

- a. Calculations using the Certainty Factor method begin by finding the user CF and expert CF values for each of the factors/symptoms that cause preeclampsia using equation (4). Table 7 shows the user CF and expert CF values for each factor causing preeclampsia.

Table 7. An Expert Interpretation

Code	Description	CF	CF	Code	Description	CF	CF
	Factor	User	Expert		Factor	User	Expert
U1		0.8	0.8	SG1		0.8	0.9
U2		0.6	0.6	SG2		0.7	0.6
U3		0.8	0.9	AC1		0.8	0.9
P1		0.7	0.8	AC2		0.7	0.6
P2		0.6	0.6	RA1		0.7	0.6
JK1		0.8	0.9	RA2		0.8	0.9
JK2		0.7	0.7	SP1		0.8	0.8
KG1		0.8	0.9	SP2		0.7	0.7
KG2		0.7	0.7	P1		0.8	0.9
RP1		0.8	0.9	P2		0.7	0.8
RP2		0.7	0.6	P3		0.7	0.7
RH1		0.8	0.9	SE1		0.8	0.9
RH2		0.7	0.6	SE2		0.7	0.6

Code Description Factor	CF User	CF Expert	Code Description Factor	CF User	CF Expert
RK1	0.8	0.9	PK1	0.9	0.9
RK2	0.7	0.6	PK2	0.7	0.6
RD1	0.8	0.9	J1	0.8	0.9
RD2	0.7	0.6	J2	0.6	0.6

- b. After knowing the user CF value and CF expert value, proceed with determining the CF Combine value, which is determined by more than one premise using equation (6). Table 8 shows the results of the CF values for symptom 1 (G1), symptom 2 (G2), and symptom 3 (G3) according to the rules in table 3.

Table 8. CF Value For Each Symptom

Rule Code	CF G1	CF G2	CF G3
R01	0,64	0,36	0,72
R02	0,64	0,72	0,72
R03	0,72	0,72	0,72
R04	0,72	0,8075	0,72
R05	0,72	0,8075	0,6375
R06	0,56	0,42	0,455
R07	0,72	0,42	0,455
R08	0,56	0,72	0,42
R09	0,72	0,42	0,42
R10	0,42	0,56	0,49
R11	0,42	0,42	0,42
R12	0,42	0,42	0,455
R13	0,42	0,42	0,42
R14	0,42	0,12	0,42
R15	0,42	0,42	0,455
R16	0,42	0,455	0,12
R17	0,455	0,42	0,09

- c. The last step is to determine the CF Combine value for each rule in the expert system for early detection of preeclampsia in pregnant women using equation (7) [45].

Table 9. CF Value For Each Symptom

Rule Code	CF C1	CF C2
R01	0,36	0,6912
R02	0,4896	0,61738
R03	0,4032	0,670326
R04	0,4277	0,656829
R05	0,4277	0,609614
R06	0,4312	0,504071
R07	0,3192	0,527075
R08	0,5632	0,429462
R09	0,3192	0,503247
R10	0,5684	0,456805
R11	0,4872	0,465212
R12	0,4872	0,48316
R13	0,4872	0,465212
R14	0,3132	0,503562
R15	0,4872	0,48316
R16	0,5075	0,309044
R17	0,476875	0,296546

Figure 3 shows the results of the comparison of the CF Combine 1 value and the CF Combine 2 value from the previous calculation process. The graph explains that the value of CF Combine 2,

symbolized by a red line, shows the results of the calculation of the value of certainty factors for diseases suffered by pregnant women in the category of severe preeclampsia. This value is better than the CF Combine 1, symbolized by a blue line for all factors/symptoms involved in each rule of the expert system for early detection of preeclampsia in pregnant women.

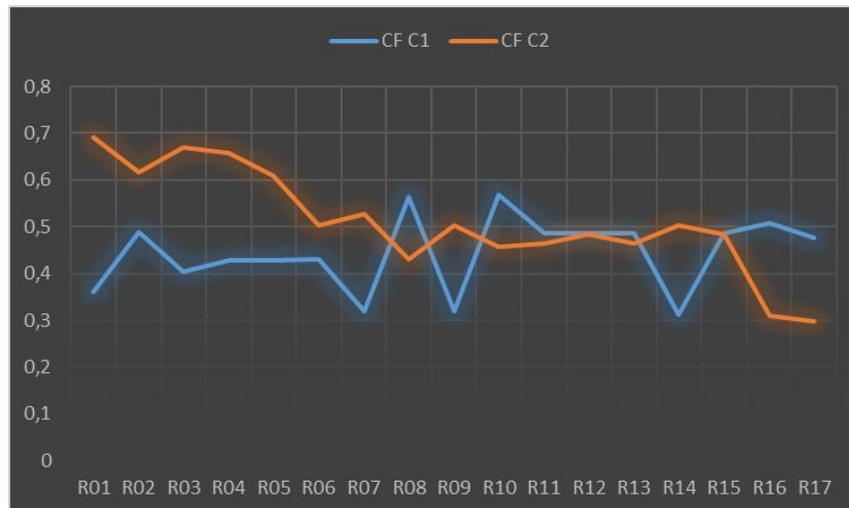


Figure. 3 Results of CF C1 and CF C2

3.3. Comparison Results

The results of the comparison of the naive bayes method and the certainty factor method are as follows:

- Based on the calculation results of the naive Bayes method for the largest probability value, the diagnosis is in the form of preeclampsia with a severe category according to the results in table 6 of 0,00024.
- As for the calculation of the certainty factor method, the diagnosis results show that the disease detected early is preeclampsia with a severe category with the CF Combine value according to Figure 3, where the peak of the curve is shown in the CF C2 value of 0,6912.

From the above comparison results based on the results obtained using the Naive Bayes method and the certainty factor method, the certainty factor method is more accurate in the early detection of preeclampsia in pregnant women than the naive bayes method based on calculations obtained and has been done previously. This is because the certainty factor method requires the provision of values for each rule on all symptoms/factors causing preeclampsia to determine the value of the CF Combine. Different treatment for the Naive Bayes method only requires a value of 0 and a value of 1 for all factors/symptoms involved in the expert system rule base [46].

4. Conclusion

Based on the background of the problem, the method is compared, the discussion of the calculation of each method, and the final results that have been compared, it can be concluded that the comparison of the results of the Naive Bayes method and the certainty factor method for early detection of preeclampsia in pregnant women shows the certainty factor method is more accurate. The reason is that the certainty factor method requires a minimum certainty value of 0.2 and a maximum of 1 for the user CF value and the expert CF value, while the Naive Bayes method only requires 0 and 1 values for each factor/symptom involved. And the expert system for early detection of preeclampsia produces a more accurate diagnosis based on the tracing process according to the symptoms experienced by the patient by implementing the certainty factor method.

References

- [1] N. Saraswati and Mardina, "Unnes Journal of Public Health Berdasarkan data World Health Organization Berdasarkan laporan Dinas Kesehatan," *Unnes Journal of Public Health*, vol. 5, no. 2, pp. 90–99, 2016.
- [2] H. Bracken *et al.*, "Congo red test for identification of preeclampsia: Results of a prospective diagnostic case-control study in Bangladesh and Mexico," *EClinicalMedicine*, vol. 31, 2021, doi: 10.1016/j.eclinm.2020.100678.
- [3] Y. Gustri, R. Januar Sitorus, and F. Utama, "Determinants Preeclampsia in Pregnancy At Rsup Dr. Mohammad Hoesin Palembang," *Jurnal Ilmu Kesehatan Masyarakat*, vol. 7, no. 3, pp. 209–217, 2016, doi: 10.26553/jikm.2016.7.3.209-217.
- [4] M. J. Aguilar-Cordero, A. Lasserrot-Cuadrado, N. Mur-Villar, X. A. León-Ríos, T. Rivero-Blanco, and I. M. Pérez-Castillo, "Vitamin D, preeclampsia and prematurity: A systematic review and meta-analysis of observational and interventional studies," *Midwifery*, vol. 87, p. 102707, 2020, doi: 10.1016/j.midw.2020.102707.
- [5] T. C. C. Macedo *et al.*, "Prevalence of preeclampsia and eclampsia in adolescent pregnancy: A systematic review and meta-analysis of 291,247 adolescents worldwide since 1969," *European Journal of Obstetrics Gynecology and Reproductive Biology*, vol. 248, no. March, pp. 177–186, 2020, doi: 10.1016/j.ejogrb.2020.03.043.
- [6] P. Qiao *et al.*, "Impact of growth discordance in twins on preeclampsia based on chorionicity," *American Journal Obstetrics Gynecology*, vol. 223, no. 4, pp. 572.e1-572.e8, 2020, doi: 10.1016/j.ajog.2020.03.024.
- [7] B. Aini, Fajaria Nur; Widyawati, Melyana Nurul, Santor, "Diagnosa Preeklamsia Pada Ibu Hamil Menggunakan Sistem Informasi Berbasis Web," *Jurnal Keperawatan Silampari*, vol. 2, no. 2, pp. 18–27, 2019.
- [8] Tri Budiarti, Dhiah Dwi Kusumawati., Nikmah Nuur Rochmah, "Hubungan Berat Bayi Lahir Dengan Kematian Bayi," *Jurnal Kesehatan Al-Irsyad*, vol. 12, no. 2, pp. 63–70, 2019, doi: 10.36746/jka.v12i2.42.
- [9] Tim Dinas Kesehatan Prop Jateng, "Renstra Dinas Kesehatan Jawa Tengah Tahun 2018-2023," 2019.
- [10] Y. Wang *et al.*, "Exposure to multiple metals and prevalence for preeclampsia in Taiyuan, China," *Environmental International*, vol. 145, no. August, p. 106098, 2020, doi: 10.1016/j.envint.2020.106098.
- [11] A. H. Aji, M. T. Furqon, and A. W. Widodo, "Sistem Pakar Diagnosa Penyakit Ibu Hamil Menggunakan Metode Certainty Factor (CF)," *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 2, no. 5, pp. 2127–2134, 2018, [Online]. Available: <http://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/1556>.
- [12] D. Kurniasari, F. A.-H. JURNAL, and undefined 2015, "Hubungan Usia, Paritas Dan Diabetes Mellitus Pada Kehamilan Dengan Kejadian Preeklamsia Pada Ibu Hamil Di Wilayah Kerja Puskesmas Rumbia Kabupaten," *Ejurnalmalahayati.Ac.Id*, vol. 9, no. 3, pp. 142–150, 2015, [Online]. Available: <http://ejurnalmalahayati.ac.id/index.php/holistik/article/view/232>.
- [13] S. Dai *et al.*, "SeDeM expert system for directly compressed tablet formulation: A review and new perspectives," *Powder Technology*, vol. 342, pp. 517–527, 2019, doi: 10.1016/j.powtec.2018.10.027.
- [14] M. Castelli, L. Manzoni, L. Vanneschi, and A. Popovič, "An expert system for extracting knowledge from customers' reviews: The case of Amazon.com, Inc.," *Expert Syst. Appl.*, vol. 84, pp. 117–126, 2017, doi: 10.1016/j.eswa.2017.05.008.
- [15] D. Santra, S. K. Basu, J. K. Mandal, and S. Goswami, "Rough set based lattice structure for knowledge representation in medical expert systems: Low back pain management case study," *Expert System Application*, vol. 145, p. 113084, 2020, doi: 10.1016/j.eswa.2019.113084.
- [16] Y. Prasetyo and H. Haryanto, "Visualisasi Berbasis Naive Bayes untuk Pemetaan Penyebaran Penyakit Infeksi Saluran Pernafasan Akut," *Sisfotenika*, vol. 7, no. 1, 2017, doi: 10.30700/jst.v7i1.135.
- [17] Y. Nurfarianti, "Sistem Pakar Untuk Diagnosis Dismenore Menggunakan Metode Naive Bayes," *Program Studi Informatika Universitas Tanjungpura*, vol. 4, no. 1, pp. 1–6, 2016.
- [18] M. H. Rifqo and A. Wijaya, "Implementasi Algoritma Naive Bayes Dalam Penentuan Pemberian Kredit," *Pseudocode*, vol. 4, no. 2, pp. 120–128, 2017, doi:

- 10.33369/pseudocode.4.2.120-128.
- [19] K. E. Setyaputri, A. Fadlil, and S. Sunardi, "Analisis Metode Certainty Factor pada Sistem Pakar Diagnosa Penyakit THT," *Jurnal Teknik Elektro*, vol. 10, no. 1, pp. 30–35, 2018, doi: 10.15294/jte.v10i1.14031.
- [20] L. P. Wanti, I. N. Azroha, and M. N. Faiz, "Implementasi User Centered Design Pada Sistem Pakar Diagnosis Gangguan Perkembangan Motorik Kasar Pada Anak Usia Dini," *Media Aplikom*, vol. 11, no. 1, pp. 1–10, 2019.
- [21] L. P. Wanti and S. Romadlon, "Implementasi Forward Chaining Method Pada Sistem Pakar Untuk Deteksi Dini Penyakit Ikan," *Infotekmesin*, vol. 11, no. 02, pp. 74–79, 2020, doi: 10.35970/infotekmesin.v11i2.248.
- [22] R. Rusdiansyah, S. Setiawan, and M. Badrul, "Diabetes Mellitus Diagnosis Expert System With Web-Based Forward Chaining," *Sinkron*, vol. 3, no. 2, p. 61, Mar. 2019, doi: 10.33395/sinkron.v3i2.10055.
- [23] A. H. Oluwole, A. A. Adekunle, A. O. Olasunkanmi, and A. O. Adeodu, "A shoveling-related pain intensity prediction expert system for workers' manual movement of material," *International Journal of Technology*, vol. 7, no. 4, pp. 603–615, 2016, doi: 10.14716/ijtech.v7i4.2208.
- [24] S. A. Sabab, M. A. R. Munshi, A. I. Pritom, and S. Shihabuzzaman, "Cardiovascular disease prognosis using effective classification and feature selection technique," *1st International Conference on Medical Engineering, Health Informatics Technology MediTec 2016*, no. November, pp. 1–6, 2017, doi: 10.1109/MEDITEC.2016.7835374.
- [25] K. NainSukhia, A. Ashraf Khan, and M. Bano, "Introducing Economic Order Quantity Model for Inventory Control in Web based Point of Sale Applications and Comparative Analysis of Techniques for Demand Forecasting in Inventory Management," *International Journal Computer Applications*, vol. 107, no. 19, pp. 1–8, 2014, doi: 10.5120/18856-7385.
- [26] F. Ali, K. S. Kwak, and Y. G. Kim, "Opinion mining based on fuzzy domain ontology and Support Vector Machine: A proposal to automate online review classification," *Applied Soft Computing Journal*, vol. 47, pp. 235–250, 2016, doi: 10.1016/j.asoc.2016.06.003.
- [27] A. P. Wibawa *et al.*, "Naïve Bayes Classifier for Journal Quartile Classification," *International Journal of Recent Contributions from Engineering, Science & IT*, vol. 7, no. 2, p. 91, 2019, doi: 10.3991/ijes.v7i2.10659.
- [28] A. A. S. Nugraha, N. Hidayat, and L. Fanani, "Sistem Pakar Diagnosis Penyakit Kucing Menggunakan Metode Naive Bayes – Certainty Factor Berbasis Android," *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer Universitas Brawijaya*, vol. 2, no. 2, pp. 650–658, 2018.
- [29] S. Shastri *et al.*, "Development of a Data Mining Based Model for Classification of Child Immunization Data," *International Journal of Computational Engineering Research*, vol. 8, no. 6, pp. 41–49, 2018, [Online]. Available: www.ijceronline.com.
- [30] A. Saleh and F. Nasari, "Penerapan Equal-Width Interval Discretization Dalam Metode Naive Bayes Untuk Meningkatkan Akurasi Prediksi Pemilihan Jurusan Siswa," *Masyarakat Telematika Dan Informasi: Jurnal Penelitian Teknologi Informasi dan Komunikasi*, vol. 9, no. 1, p. 1, 2018, doi: 10.17933/mti.v9i1.113.
- [31] A. Saleh, "Implementasi Metode Klasifikasi Naïve Bayes Dalam Memprediksi Besarnya Penggunaan Listrik Rumah Tangga," *Creative Information Technology Journal*, vol. 2, no. 3, pp. 207–217, 2015.
- [32] M. F. A. Saputra, T. Widiyaningtyas, and A. P. Wibawa, "Illiteracy classification using K means-naïve bayes algorithm," *International Journal on Informatics Visualization*, vol. 2, no. 3, pp. 153–158, 2018, doi: 10.30630/joiv.2.3.129.
- [33] S. Ernawati, E. R. Yulia, Friyadie, and Samudi, "Implementation of The Naïve Bayes Algorithm with Feature Selection using Genetic Algorithm for Sentiment Review Analysis of Fashion Online Companies," in *2018 6th International Conference on Cyber and IT Service Management (CITSM)*, Aug. 2018, pp. 1–5, doi: 10.1109/CITSM.2018.8674286.
- [34] M. Arifin, S. Slamim, and W. E. Y. Retnani, "Penerapan Metode Certainty Factor Untuk Sistem Pakar Diagnosis Hama Dan Penyakit Pada Tanaman Tembakau," *Berkala Sainstek*, vol. 5, no. 1, p. 21, 2017, doi: 10.19184/bst.v5i1.5370.
- [35] J. Wang *et al.*, "Refined micro-scale geological disaster susceptibility evaluation based on UAV tilt photography data and weighted certainty factor method in Qingchuan County," *Ecotoxicology and Environmental Safety*, vol. 189, no. November, p. 110005, 2020, doi:

- 10.1016/j.ecoenv.2019.110005.
- [36] J. Li and Y. Zhang, "GIS-supported certainty factor (CF) models for assessment of geothermal potential: A case study of Tengchong County, Southwest China," *Energy*, vol. 140, pp. 552–565, 2017, doi: 10.1016/j.energy.2017.09.012.
- [37] A. Azareh *et al.*, "Modelling gully-erosion susceptibility in a semi-arid region, Iran: Investigation of applicability of certainty factor and maximum entropy models," *Science Total Environment*, vol. 655, pp. 684–696, 2019, doi: 10.1016/j.scitotenv.2018.11.235.
- [38] A. A. Zain and E. Z. Astutik, "Analisis Metode Certainty Factor Dalam Sistem Pakar Untuk Mendeteksi Penyakit Sapi Pedaging", Universitas Dian Nuswantoro, Semarang, 2015.
- [39] P. F. Aprilliani and H. Mustafidah, "Implementasi Certainty Factor Pada Diagnosa Penyakit Infeksi Tropis," *Jurnal Riset, Sains dan Teknologi*, vol. 1, no. 1, pp. 22–24, 2017, [Online]. Available: <http://jurnalnasional.ump.ac.id/index.php/JRST/article/download/1081/1245>.
- [40] A. Riadi, "Penerapan Metode Certainty Factor Untuk Sistem Pakar Diagnosa Penyakit Diabetes Melitus Pada Rsud Bumi Panua Kabupaten Pohuwato," *ILKOM Jurnal Ilmiah.*, vol. 9, no. 3, pp. 309–316, 2017, doi: 10.33096/ilkom.v9i3.162.309-316.
- [41] J. Yuan, S. Zhang, S. Wang, F. Wang, and L. Zhao, "Process abnormality identification by fuzzy logic rules and expert estimated thresholds derived certainty factor," *Chemometrics and Intelligent Laboratory System*, vol. 209, no. August 2020, p. 104232, 2021, doi: 10.1016/j.chemolab.2020.104232.
- [42] V. Balakrishnan and W. Kaur, "ScienceDirect ScienceDirect String-based Multinomial Naïve Bayes for Emotion Detection String-based Multinomial Naïve Bayes for Emotion Detection among Facebook Diabetes Community among Facebook Diabetes Community," *Procedia Computer Science*, vol. 159, pp. 30–37, 2019, doi: 10.1016/j.procs.2019.09.157.
- [43] T. Olsson, M. Ericsson, and A. Wingkvist, "The Journal of Systems & Software To automatically map source code entities to architectural modules with Naive Bayes ☆," *J. System Software*, vol. 183, p. 111095, 2022, doi: 10.1016/j.jss.2021.111095.
- [44] S. H. Alizadeh, A. Hediehloo, and N. Shiri, "Knowledge-Based Systems Multi independent latent component extension of naive Bayes classifier," *Knowledge-Based System*, vol. 213, p. 106646, 2021, doi: 10.1016/j.knosys.2020.106646.
- [45] C. Jiang, W. Fan, N. Yu, and E. Liu, "Spatial modeling of gully head erosion on the Loess Plateau using a certainty factor and random forest model," *Science of the Total Environment.*, vol. 783, p. 147040, 2021, doi: 10.1016/j.scitotenv.2021.147040.
- [46] W. A. Van Eeden *et al.*, "Predicting the 9-year course of mood and anxiety disorders with automated machine learning : A comparison between auto-sklearn , naïve Bayes classifier , and traditional logistic regression," *Psychiatry Research.*, vol. 299, no. October 2020, p. 113823, 2021, doi: 10.1016/j.psychres.2021.113823.