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Comparing Fuzzy Logic Mamdani and Naïve Bayes for Dental Disease Detection

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Abstract

Background: Dental disease detection is essential for the diagnosis of dental diseases.
Objective: This research compares the Mamdani fuzzy logic and Naïve Bayes in detecting dental diseases.
Methods: The first is to process data on dental disease symptoms and dental support tissues based on complaints of toothache consulted with experts at a community health centre (*puskesmas*). The second is to apply the Mamdani fuzzy logic and the Naïve Bayes to the proposed expert system. The third is to provide recommended decisions about dental diseases based on the symptom data inputted into the expert system. Patient data were collected at the North Cilacap *puskesmas* between July and December 2021.
Results: The Mamdani fuzzy logic converts uncertain values into definite values, and the Naïve Bayes method classifies the type of dental disease by calculating the weight of patients' answers. The methods were tested on 67 patients with dental disease complaints. The accuracy rate of the Mamdani fuzzy logic was 85.1%, and the Naïve Bayes method was 82.1%.
Conclusion: The prediction accuracy was compared to the expert diagnoses to determine whether the Mamdani fuzzy logic method is better than the Naïve Bayes method.

Keywords: Dental Disease, Expert System, Mamdani Fuzzy Logic, Naïve Bayes, Prediction

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I. Introduction

Oral health can be determined from a) the teeth's hard and soft tissues and b) the elements connected to the oral cavity. Healthy dental and oral conditions allow individuals to eat and speak without a problem. They may also lead to aesthetical problems, discomfort, occlusion deviations, and tooth loss [1]. According to the World Dental Federation (FDI), prevalent problems in teeth and mouth are as follows. 1) Caries is often caused by excessive sugar consumption, lack of dental healthcare, and difficult access to standard dental health services. 2) Periodontal causes difficulty chewing and speaking, and is the main cause of tooth loss in adults (gingivitis leading to periodontitis). 3) Oral cancer is one of the ten most common types of cancer in humans, affecting lips, gums, tongue, oesophagus, inside of the cheeks, and the top and bottom of the mouth. Oral cancer can be life-threatening if not treated immediately. The main causes of this cancer are cigarettes and alcohol consumption [2].

Consumption of cigarettes and alcoholic beverages significantly affects tooth decay and tooth-supporting tissues. Toothache is pain around the teeth and jaw, often felt when one consumes food or drinks that are too hot or cold. Tooth decay is the main cause of toothache in most children and adults [3]. Some conditions that cause toothache include 1) infection of the teeth caused by bacteria; 2) broken teeth; 3) dental treatment, such as fillings, tooth extraction, or crown placement; 4) abnormality in bones and gums protecting the roots [4]. Based on WHO data, the ideal ratio of dentists to population is 1:2000. In Indonesia, the ratio is far from ideal, namely 1:22000 [5]. One of the solutions to overcome these problems is professional interventions. Another solution is to develop an information system imitating a dentist in diagnosing dental diseases. The system can be developed based on the observed symptoms.

Research by Putu et al. developed an expert system to detect eye diseases using fuzzy logic and Naïve Bayes methods. This expert system uses 16 symptoms to determine ten types of eye diseases. The process begins by changing the uncertain input value using fuzzy logic. The next step is calculating the weight of all patient answers using the

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Naïve Bayes method. The result shows that the similarity in the diagnosis between the expert system and ophthalmologists was 81% [6]. Yovita et al. implemented the Naïve Bayes method as an expert system for the early detection of dysmenorrhea. The Naïve Bayes method is used to classify the type of dysmenorrhea two: primary or secondary. Based on the analysis of 10 test data with 10 and 20 training data, the accuracy rate was 90% for 10 training data and 100% accuracy for 20 training data [7]. Fahmiyanto et al. developed an expert system involving the android-based fuzzy Tsukamoto method. In an ENT disease diagnosis system based on Android, the demand variable consists of two fuzzy sets: down and up. The inventory variables include two fuzzy sets: a little and a lot. The production variable consists of two fuzzy sets: reduced and increased. The accuracy in this study was calculated not by each disease but by the whole disease. The accuracy value was 93.75% [8].

This study aims to compare the accuracy of the prediction results using the Mamdani fuzzy logic and the Naïve Bayes method in diagnosing dental diseases with initial symptom data. The purpose of this research is threefold. The first is to process data on dental disease symptoms and dental support tissues based on complaints of toothache consulted with experts at a community health centre (*puskesmas*). The second is to apply the Mamdani fuzzy logic and the Naïve Bayes to the proposed expert system. The third is to provide recommended decisions about dental diseases based on the symptom data inputted into the expert system. This research provides recommendations for dental disease and dental support tissues using the Mamdani fuzzy logic method and the Naïve Bayes method. The results can be used for preventive dental treatments. The novelty of this research is to compare the Mamdani fuzzy logic and the Naïve Bayes against experts' judgment (dentists) to measure the accuracy.

II. Methods

A. *Overview of Expert System*

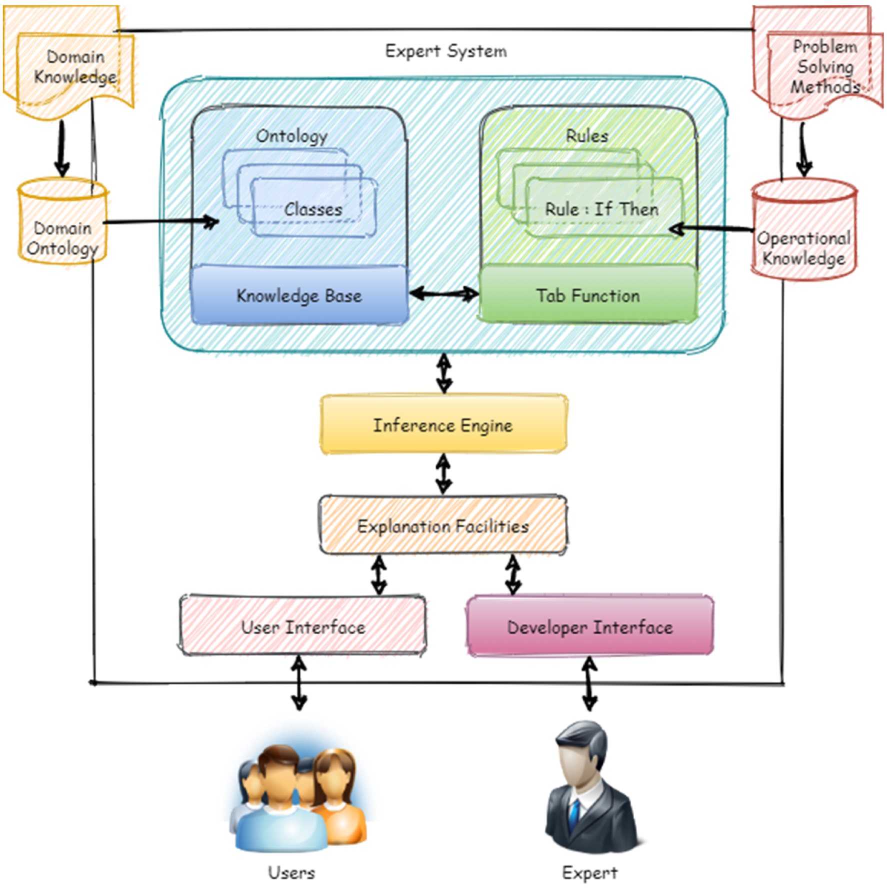

Fig. 1 Expert system overview

Fig. 1 shows an overview of the stages in the expert system and all the implemented modules. The expert system applies the Mamdani fuzzy logic and the Naïve Bayes method. The two actors in the picture are end-users and experts [9] [10]. The consultation identifies the problem through a series of questions displayed on the user interface [11] [12]. The symptomatic data of dental disease go through the knowledge acquisition process. The rules are made by considering the Mamdani fuzzy logic, changing the uncertain values input by patients. Meanwhile, the Naïve Bayes classifies the type of disease by calculating the weight of all patient input. The output generated in the expert system processing is then displayed to the end users.

B. Fuzzy Logic

Fuzzy logic is based on the fuzzy set theory, which was first introduced by Zadeh in 1965. In this theory, a membership degree is an important determinant of the existence of elements [13]. The value, function, or degree of membership is the main reasoning characteristic of fuzzy logic–a black box connecting the input to the output space [14] [15]. The black box contains a method to process input data into output through good information [16]. Fig. 2 shows the input and output mapping in the form of good information.

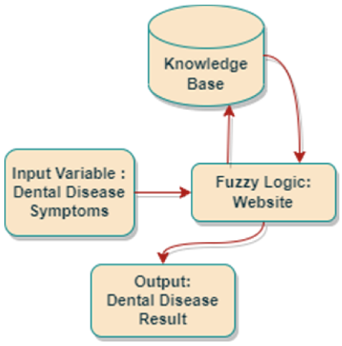

Fig. 2 Input output mapping

A fuzzy inference system is a computational framework with fuzzy rules set in the form of IF-THEN and fuzzy reasoning [17]. The fuzzy inference system accepts crisp input to be sent to a knowledge base that stores n fuzzy rules in the form of IF-THEN [18]. If the number of rules is more than one, all rules will be accumulated. The aggregation results will then be defuzzied to induce a crisp value as a system output [19]. The control system performance can be improved by applying fuzzy logic, stifling the emergence of other functions in the output caused by fluctuations in the input variable [15]. The fuzzy logic is applied in three stages as can be seen in Fig. 3, as follows:

1. The fuzzification stage is a mapping from a firm input to a fuzzy set.
2. The inference stage includes the generation of fuzzy rules.
3. The affirmation stage (defuzzification) is when the output transforms from fuzzy values to firm values.

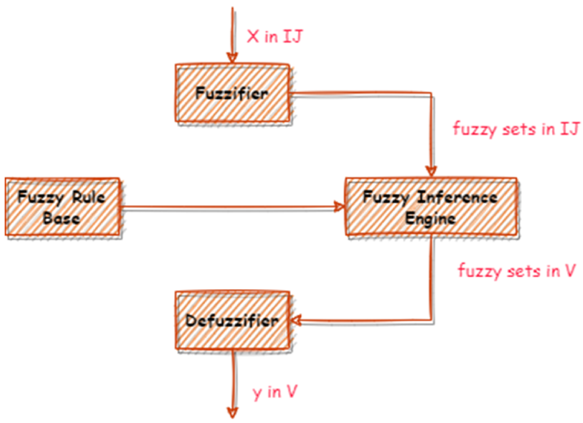

Fig. 3 Process Stages in Fuzzy Logic

A rule is a knowledge structure that connects some known information to other information to draw conclusions. Rules are a procedural form of knowledge [20]. Therefore, a rule-based expert system uses an inference engine to generate new information and a set of rules in its knowledge base to process a problem from the information contained in its active memory program [21]. The rule structure logically connects one or more antecedents (also called premises) in the IF section with one or more consequences (also called conclusions) in the THEN section. In general, a rule can have multiple premises associated with AND statements (conjunctions), OR statements (disjunctions) or a combination of both [12].

Linear representation is the process of mapping input to form a straight line representing the degree of membership. The linear fuzzy set has three states, as follows [9]:

1. Linear Up
   To represent an ascending linear curve, the curve movement starts from a set with the domain having zero membership to the right towards the domain with a higher membership value.

$$\mu[x] = \begin{Bmatrix} 0;\ x \leq a \\ \frac{(x-a)}{b-a};\ a \leq x \leq b \\ 1;\ x \geq b \end{Bmatrix} \quad (1)$$

2. Linear Down
   For the descending linear representation, the movement starts from a set with the domain having the highest/largest membership value on the left. The curve moves from the left to the right, where the domain has a smaller/lower membership value.

$$\mu[x] = \begin{Bmatrix} 1;\ x \leq a \\ \frac{(b-x)}{b-a};\ a \leq x \leq b \\ 0;\ x \geq b \end{Bmatrix} \quad (2)$$

3. Triangle Curve
   The triangular curve represents a combination of an ascending linear curve and a descending linear curve.

$$\mu[x] = \begin{Bmatrix} 0;\ x \leq a\ or\ x \geq c \\ \frac{(x-a)}{(b-a)};\ a \leq x \leq b \\ \frac{(b-x)}{(c-b)};\ b \leq x \leq c \end{Bmatrix} \quad (3)$$

The stages in the Mamdani fuzzy logic method, namely [10]:

1. Formation of fuzzy sets
   The formation of rules will later be used in the expert system's knowledge base. One or more fuzzy sets are the quotient of the input and output variables in the Mamdani fuzzy. An ascending or descending linear curve is used according to Equations (1) and (2) for the membership function of each variable involved.
2. Implication function app
   For the Mamdani fuzzy method, the implication function uses the min function. Then the value of the -predicate and z was determined using (4) and (5).

$$\alpha - predicate = MIN\ \mu(g1), \mu(g2), \ldots (\mu gn) \quad (4)$$

$$\alpha - predicate = \frac{upper\ limit - Z}{upper\ limit - lower\ limit} \quad (5)$$

3. Composition of rules
   Based on each rule's implication function, all rules were then composed using the max method. The fuzzy set solution is taken from the maximum value of each rule. Then the value is used to modify the fuzzy set and implement it to the output using the OR operator or the union concept. When all propositions have been evaluated, the output will contain a fuzzy set that reflects the contribution of each proposition. The equation is in (6).

$$\mu sf[xi] \leftarrow \max(\mu sf[xi], \mu kf[xi]) \quad (6)$$

   Description: sf[xi] represents the membership value of the fuzzy solution up to the i-th rule, and kf[xi] represents the consequent fuzzy membership value of the i-rule.
4. Affirmation/Defuzzification

The last step in this method is to determine the crisp output value to find the centralised average defuzzification value using (7).

$$z = \frac{M1+M2+M3+\cdots+Mn}{A1+A2+A3+\cdots+An} \tag{7}$$

C. *Naïve Bayes Method*

Naïve Bayes was first proposed by British scientist Thomas Bayes, which predicts future probabilities based on experience. Naïve Bayes is an algorithm that utilises a probability theory based on Bayes' theorem and is combined with 'Naïve', which means that each attribute or variable has independent properties (free assumptions) [22]. Naïve Bayes calculates a class's probability based on its attributes and determines the class with the highest probability [23]. The advantage of classification is that Naïve Bayes requires only a small amount of training data to estimate the parameters (means and variance of the variables) for the classification [24]. Only the variation of the variables for each class should be determined because independent variables are assumed, not the entire covariance matrix [25]. Calculations on the Naïve Bayes method to generate disease predictions go through several stages below [26] and is shown in (8)-(10).

1. Each class involves:

$$X(pi|aj) = \frac{qd+(r*x)}{q+r} \tag{8}$$

   Description:
   qd = the value of the data record on the training data has a = aj and p = pi
   x = 1 / many types of classes / diseases
   r = number of symptoms/ parameters
   q = the value of the data record on the training data has a value of a = aj/per class/disease

2. The likelihood value for each existing class is determined using the equation below:

$$X(aj) = \frac{q}{r} \tag{9}$$

3. The posterior value for each class involved is determined using the following equation:

$$X(aj|pi) = X(pi|aj) * X(aj) \tag{10}$$

The final result of the Naïve Bayes method is to classify the classes involved in presenting dental disease possibilities by comparing the posterior final values of each class involved [27]. The Naïve Bayes classification method results in the highest posterior value of several classes being compared.

III. RESULTS

This study uses dental patient data from the Community Health Centre (*puskesmas*) of North Cilacap collected between July and December 2021, totalling 67 patients with various complaints such as gum inflammation, cavities, pain when chewing or biting, and bad breath. The dataset used in this study was in the form of dental disease symptoms obtained from interviews with the patients. These symptoms are consulted by an expert, i.e., a dentist.

TABLE 1
EXPERT CONFIDENCE WEIGHT

Answer Choices Expert Confidence	Weight
Not Sure 0	0
Less Sure 0.3	0.3
Yes/Yes 0.8	0.8
Very Confident 1	1

Table 1 shows expert (dentist) confidence in the problem identification, and Table 2 shows the codes of the dental disease symptoms and problems with its supporting tissues. The weight of expert confidence will later be input into the expert system's knowledge base. This is then adjusted and applied to the answers given by the patients. Table 3 shows the symptoms of dental and its supporting tissue diseases.

TABLE 2
DISEASES AND SYMPTOMS OF DENTAL DISEASE

Disease	Disease Code
Reversible Pulpitis	P01
Irreversible Pulpitis	P02
Pulp Necrosis	P03
Periapical Abscess	P04
Periodontal Abscess	P05
Gingivitis	P06
Chronic Periodontitis	P07
Pericoronitis	P08
Tooth Crown Fracture	P09
Radicular Cyst	P10
Granulomas	P11

TABLE 3
SYMPTOMS OF DENTAL DISEASE

Disease Symptoms Code	Description	Dental Disease Code
S01	Short pain or aches	P01
S02	Pain or aches for a long time	P02
S03	Pain that does not occur spontaneously	P01
S04	Pain may occur spontaneously	P02
S05	Pain when lying down or bending over	P02
S06	Discolouration of teeth	P03
S07	Bad breath	P03, P04, P08
S08	No pain	P03
S09	Teeth hurt when biting	P04, P05
S10	Teeth feel elongated	P04, P07, P10
S11	With swelling or not	P04
S12	Accompanied by systemic reactions	P04, P05, P08
S13	Taste disturbance	P04
S14	Large swelling	P05, P10
S15	Teeth feel loose	P05, P07, P09, P11
S16	Bleeding gums	P06
S17	Teeth may fall out prematurely	P07
S18	Swelling of the area of the growing tooth	P08
S19	Sometimes accompanied by Trismus	P08
S20	Asymmetrical face	P08
S21	Sharp and stabbing pain	P09
S22	Asymptomatic	P10, P11

The diagnosis results were analysed to ensure that both the expert system diagnoses and the expert's diagnoses align. For example, Table 4 shows the results of a comparison between the expert system' and the expert's diagnoses for periodontal abscess disease.

TABLE 4
ILLUSTRATED RESULTS OF PATIENT ANSWERS FOR PERIODONTAL ABSCESS DISEASE

Symptom Code	Symptom Name	Patient Answer	Answer Weight
S07	Bad breath	Yes	0.8
S09	Teeth hurt a lot when biting	Yes	0.8
S10	Teeth feel elongated	Not sure	0.3
S11	With swelling or no	Yes	0.8
S12	Accompanied by systemic reaction	Yes	0.8
S13	Taste disturbance	Uncertain	0.3

A. Mamdani Fuzzy Logic Method

For implementing the Mamdani fuzzy logic method, the first step is to create a membership function for each variable (the periodontal abscess symptoms). The variables consist of six symptoms, according to Table 4. Experts, i.e., dentists, transform knowledge about dental diseases and their supporting tissues into the knowledge base, which includes data on dental disease symptoms and their supporting tissues, category predictions, and the rules. Fig. 5 shows the likeliness of periodontal abscess disease. Table 5 shows the rules for periodontal abscess disease. The symbol H represents high, L represents low, T represents not indicated, and Y represents indicated. The steps taken for solving using Mamdani fuzzy logic are as follows:

1. Formation of fuzzy sets in (11) and (12)

TABLE 5
PERIODONTAL ABSCESS DISEASE RULE

Rule Code	S07	S09	S10	S11	S12	S13	Output	Rule Code	S07	S09	S10	S11	S12	S13	Output
R01	R	R	R	R	R	R	N	R33	T	R	R	R	R	R	N
R02	R	R	R	R	R	T	N	R34	T	R	R	R	R	T	N
R03	R	R	R	R	T	R	N	R35	T	R	R	R	T	R	N
R04	R	R	R	R	T	T	N	R36	T	R	R	R	T	T	Y
R05	R	R	R	T	R	R	N	R37	T	R	R	T	R	R	Y
R06	R	R	R	T	R	T	Y	R38	T	R	R	T	R	T	Y
R07	R	R	R	T	T	R	Y	R39	T	R	R	T	T	R	Y
R08	R	R	R	T	T	T	Y	R40	T	R	R	T	T	T	Y
R09	R	R	T	R	R	R	N	R41	T	R	T	R	R	R	N
R10	R	R	T	R	R	T	N	R42	T	R	T	R	R	T	N
R11	R	R	T	R	T	R	N	R43	T	R	T	R	T	R	N
R12	R	R	T	R	T	T	Y	R44	T	R	T	R	T	T	N
R13	R	R	T	T	R	R	Y	R45	T	R	T	T	R	R	Y
R14	R	R	T	T	R	T	Y	R46	T	R	T	T	R	T	Y
R15	R	R	T	T	T	R	Y	R47	T	R	T	T	T	R	Y
R16	R	R	T	T	T	T	Y	R48	T	R	T	T	T	T	Y
R17	R	T	R	R	R	R	N	R49	T	T	R	R	R	R	N
R18	R	T	R	R	R	T	N	R50	T	T	R	R	R	T	N
R19	R	T	R	R	T	R	N	R51	T	T	R	R	T	R	N
R20	R	T	R	R	T	T	N	R52	T	T	R	R	T	T	N
R21	R	T	R	T	R	R	Y	R53	T	T	R	T	R	R	N
R22	R	T	R	T	R	T	Y	R54	T	T	R	T	R	T	Y
R23	R	T	R	T	T	R	Y	R55	T	T	R	T	T	R	Y
R24	R	T	R	T	T	T	Y	R56	T	T	R	T	T	T	Y
R25	R	T	T	R	R	R	N	R57	T	T	T	R	R	R	N
R26	R	T	T	R	R	T	N	R58	T	T	T	R	R	T	N
R27	R	T	T	R	T	R	N	R59	T	T	T	R	T	R	N
R28	R	T	T	R	T	T	N	R60	T	T	T	R	T	T	Y
R29	R	T	T	T	R	R	N	R61	T	T	T	T	R	R	Y
R30	R	T	T	T	R	T	Y	R62	T	T	T	T	R	T	Y
R31	R	T	T	T	T	R	Y	R63	T	T	T	T	T	R	Y
R32	R	T	T	T	T	T	Y	R64	T	T	T	T	T	T	Y

The functions for periodontal abscess disease likeliness are illustrated in Fig. 4.

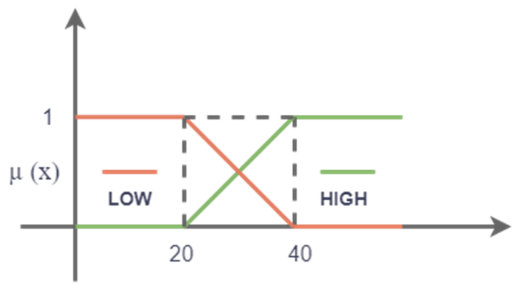

Fig. 4 Degree of likeliness of periodontal abscess disease

$$\mu\ Low\ [x] = \begin{Bmatrix} 1;\ x \leq 20 \\ \frac{40-x}{20};\ 20 \leq x \leq 40 \\ 0;\ x \geq 40 \end{Bmatrix} \tag{11}$$

$$\mu\ High\ [x] = \begin{Bmatrix} 0;\ x \leq 20 \\ \frac{x-20}{20};\ 20 \leq x \leq 40 \\ 1;\ x \geq 40 \end{Bmatrix} \tag{12}$$

The next process is fuzzification, where a crisp value is converted into a fuzzy value involving six variables/symptoms for periodontal abscess disease: S07, S09, S10, S11, S12, and S13. For example, for the case of patients with a variable of S07 of 15, S09 of 16, a variable of S10 of 18, a variable of S11 of 22, a variable of S12 of 20, and the variable of S13 of 21. There are two kinds of outputs based on the rule-based outcome. As shown in Table 5: yes and no. By using Equations 1 and 2, the degree of linear membership increases and the degree of linear membership decreases for each symptom variable of dental disease and its supporting tissues, as shown in Table 6.

TABLE 6
DEGREE OF MEMBERSHIP SYMPTOMS OF ILLNESS

Symptom Code	**µ min**	**µ max**
S07	0.25	0.75
S09	0.33	0.66
S10	0.5	0.5
S11	0.83	0.16
S12	0.66	0.33
S13	0.75	0.25

2. Implication Function Application

After knowing the min and max values, we look for the value of α-predicate and the value of z using Equations 4 and 5 for each rule. The implication function uses the min function for the Mamdani fuzzy method. By using the rules in Table 5 and the value of the degree of membership of each disease symptom in Table 6, the values for α-predicate and Z values are shown in Table 7.

TABLE 7
DEGREE OF MEMBERSHIP SYMPTOMS OF ILLNESS

Result	Rule Code	α Value	Z Value	Result	Rule Code	α Value	Z Value
R06	Y	0.16	23.2	R37	Y	0.16	23.2
R07	Y	0.16	23.2	R38	Y	0.16	23.2
R08	Y	0.16	23.2	R39	Y	0.16	23.2
R12	Y	0.25	25	R40	Y	0.16	23.2
R13	Y	0.16	23.2	R45	Y	0.16	23.2
R14	Y	0.16	23.2	R46	Y	0.16	23.2
R15	Y	0.16	23.2	R47	Y	0.16	23.2
R16	Y	0.16	23.2	R48	Y	0.16	23.2
R21	Y	0.16	23.2	R54	Y	0.16	23.2
R22	Y	0.16	23.2	R55	Y	0.16	23.2
R23	Y	0.16	23.2	R56	Y	0.16	23.2
R24	Y	0.16	23.2	R60	Y	0.16	23.2
R30	Y	0.16	23.2	R61	Y	0.16	23.2
R31	Y	0.16	23.2	R62	Y	0.16	23.2
R32	Y	0.16	23.2	R63	Y	0.16	23.2
R36	Y	0.25	25	R64	Y	0.16	23.2

3. Composition of Rules and Affirmations

The max method is used to perform the composition. All the rules used are taken from each implication function in Table 7. The equation used is equation (12). The last step is to determine the value of z using the centroid method according to equation (7).

$$z = \frac{(0{,}16*23{,}2)+(0{,}16*23{,}2)+\ldots+(0{,}16*23{,}2)}{0{,}16+0{,}16+\ldots+0{,}16} = 30{,}445$$

The defuzzification value of the severity of periodontal abscess is:

$$30{,}445 * 100\% = 30{,}445\ \%$$

The severity of the disease is divided into four categories, namely 1) mild at an interval of 0% to 25%, 2) moderate with an interval of 26% to 50%, 3) severe with an interval of 51% to 75%, and 4) is very severe with an interval of 76% to 100% [28]. Table 8 shows the severity of dental disease according to the system diagnosis suffered by the 67 patients calculated using the Mamdani fuzzy logic method.

TABLE 8
PATIENT SEVERITY

Patient Code	Disease	Percentage Severity	Category	Patient Code	Disease	Percentage Severity	Category
PS01	Granulomas	58,6%	Critical	PS34	Radicular Cyst	41,37%	Currently
PS02	Irreversible Pulpitis	67%	Critical	PS35	Granulomas	25%	Light
PS03	Granulomas	43,4%	Currently	PS36	Reversible Pulpitis	69,1%	Critical
PS04	Periapical Abscess	23,1%	Light	PS37	Tooth Crown Fracture	63,2%	Critical
PS05	Granulomas	15,9%	Light	PS38	Pulp Necrosis	73,2%	Critical
PS06	Gingivitis	24,4%	Light	PS39	Tooth Crown Fracture	68,1%	Critical
PS07	Chronic Periodontitis	55,5%	Critical	PS40	Periodontal Abscess	89,2%	Awfully
PS08	Pericoronitis	69,7%	Critical	PS41	Periodontal Abscess	92,1%	Awfully
PS09	Granulomas	35,7%	Currently	PS42	Chronic Periodontitis	59,9%	Critical
PS10	Irreversible Pulpitis	21,1%	Light	PS43	Pericoronitis	58,2%	Critical
PS11	Tooth Crown Fracture	64,9%	Critical	PS44	Periodontal Abscess	70,2%	Critical
PS12	Periapical Abscess	65,5%	Critical	PS45	Tooth Crown Fracture	85,9%	Awfully
PS13	Periodontal Abscess	61,7%	Critical	PS46	Granulomas	59,3%	Critical
PS14	Gingivitis	55,2%	Critical	PS47	Tooth Crown Fracture	64,9%	Critical
PS15	Tooth Crown Fracture	71,1%	Critical	PS48	Irreversible Pulpitis	67,5%	Critical
PS16	Pericoronitis	34,1%	Currently	PS49	Pulp Necrosis	68,3%	Critical
PS17	Tooth Crown Fracture	24,5%	Light	PS50	Periapical Abscess	37,5%	Currently
PS18	Radicular Cyst	49,7%	Currently	PS51	Periodontal Abscess	13,9%	Light
PS19	Granulomas	75%	Critical	PS52	Gingivitis	33,1%	Currently
PS20	Gingivitis	41,3%	Currently	PS53	Chronic Periodontitis	65,4%	Critical
PS21	Gingivitis	14,2%	Light	PS54	Pericoronitis	45,6%	Currently
PS22	Pulp Necrosis	61,7%	Critical	PS55	Tooth Crown Fracture	19,1%	Light
PS23	Tooth Crown Fracture	51,4%	Critical	PS56	Gingivitis	61,7%	Critical
PS24	Periodontal Abscess	65,2%	Critical	PS57	Irreversible Pulpitis	71,3%	Critical
PS25	Tooth Crown Fracture	61,8%	Critical	PS58	Gingivitis	74,2%	Critical
PS26	Gingivitis	74,2%	Critical	PS59	Gingivitis	58,5%	Critical
PS27	**Periodontal Abscess**	**30,45%**	**Currently**	PS60	Periodontal Abscess	61,1%	Critical
PS28	Periapical Abscess	91,2%	Awfully	PS61	Gingivitis	75%	Critical
PS29	Periodontal Abscess	71,2%	Critical	PS62	Chronic Periodontitis	81,1%	Awfully
PS30	Periodontal Abscess	33,7%	Currently	PS63	Pericoronitis	54,7%	Critical
PS31	Chronic Periodontitis	11,9%	Light	PS64	Tooth Crown Fracture	67,5%	Critical
PS32	Pericoronitis	24,9%	Currently	PS65	Gingivitis	56,3%	Critical
PS33	Tooth Crown Fracture	58,3%	Critical	PS66	Gingivitis	85,6%	Awfully
				PS67	Reversible Pulpitis	72,2%	Critical

B. Naïve Bayes Method

Calculations using the Naïve Bayes method are used to classify and determine the diagnosis of the symptoms of dental disease and its supporting tissues selected by a patient. Sixty-seven patient data were analysed to classify dental diseases and their supporting tissues. For example, a sample of a patient with the initials PS27 experienced symptoms such as bad breath (S07), a very painful tooth when biting (S09), a tooth that felt elongated (S10), swelling (S11), a systematic reaction (S12), and conversational disorder (S13). These symptoms include pulp necrosis disease (P03), periapical abscess (P04), periodontal abscess (P05), chronic periodontitis (P07), pericoronitis (P08), and radicular cyst (P10). The implementation of the Naïve Bayes method with the calculation stages is as follows:

1. Determine the number of records in the learning data for each class of diseases.

Using Equation 8, the number of disease classes involved with a total symptom value of 22 symptoms, with a value of x=0.091 and r=1, are shown in Table 9.

TABLE 9
NUMBER OF DISEASE CLASSES

Diseases	Symptoms					
	S07	S09	S10	S11	S12	S13
P03	1	0	0	0	0	0
P04	1	1	1	1	1	1
P05	0	1	0	0	1	0
P07	0	0	1	0	0	0
P08	1	0	0	0	1	0
P10	0	0	1	0	0	0

2. Determine the likelihood value

Determination of the likelihood value was also carried out for diseases with codes P03, P04, P05, P07, P08, and P10. The likelihood value is determined using equation (9).

TABLE 10
THE LIKELIHOOD VALUE

Diseases	Symptoms					
	S07	S09	S10	S11	S12	S13
P03	0,1304	0,087	0,087	0,087	0,087	0,087
P04	0,090909	0,1304	0,1304	0,1304	0,1304	0,1304
P05	0,087	0,1304	0,087	0,087	0,1304	0,087
P07	0,087	0,087	0,1304	0,087	0,087	0,087
P08	0,1304	0,087	0,087	0,087	0,1304	0,087
P10	0,087	0,087	0,1304	0,087	0,087	0,087

3. Determine the posterior value

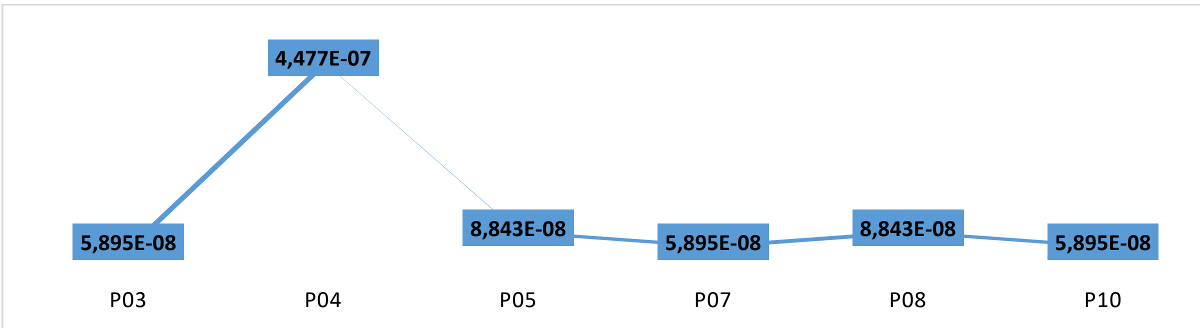

Fig. 5 The Posterior Value

Fig. 5 explains the calculation results of determining the posterior value for diseases with codes P03, P04, P05, P07, P08, and P10. It can be concluded that patients with code PS27 suffer from a periapical abscess, namely a disease severing the tip of the tooth's root, with a posterior value of 4,477 x10-7. The calculation results also found that there were two diseases coded P05 and P08 with the same posterior value, namely 8.843 x 10-8. Diseases coded P03, P07, and P10 have the same posterior value of 5.895 x 10-8. Therefore it is necessary to calculate the percentage of user/patient confidence in the conclusion of the disease using the following equation [29]:

$$P = Q * R \qquad (13)$$

Information:
P = Disease Percentage Value
Q = $\left(\frac{1}{n} * 100\%\right)$, where n is the number of symptoms for each type of disease
R = Number of symptoms the patient chooses for each disease

The results of calculating the percentage value are exemplified for the case of patients with the PS27 code with each symptom in each disease shown in Fig. 6.

1. For diseases coded P03, namely pulp necrosis with symptoms of S06, S07, and S08
2. For disease coded P04, namely periapical abscess with symptoms of S07, S09, S10, S11, S12, and S13
3. For disease coded P05, namely periodontal abscess with symptoms of S09, S12, S14, and S15
4. For disease coded P07, namely chronic periodontitis with symptoms of S10, S14, and S22
5. For diseases coded P08, namely pericoronitis with symptoms of S07, S12, S18, S19, and S20
6. For diseases coded P10, namely radicular cyst disease with symptoms of S10, S14, and S22

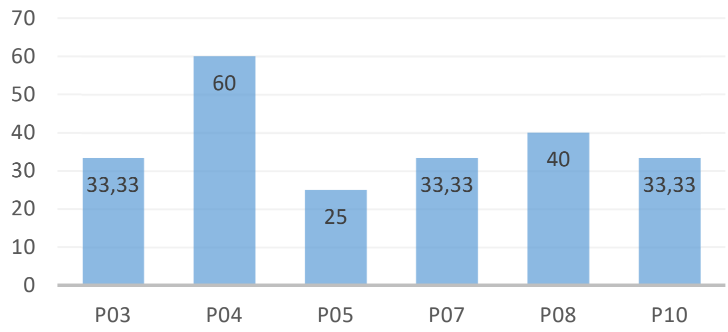

Fig. 6 The disease percentage value

The next stage is to compare the classification results between the Naïve Bayes method and dentists.

TABLE 10
COMPARISON RESULTS OF MAMDANI FUZZY LOGIC AND NAÏVE BAYES WITH EXPERT HYPOTHESES

Patient Code	Expert	Mamdani Fuzzy Logic	Naïve Bayes	Patient Code	Expert	Mamdani Fuzzy Logic	Naïve Bayes
PS01	P	TP	TP	PS34	P	FP	FP
PS02	P	TP	TP	PS35	P	FP	FP
PS03	P	TP	TP	PS36	P	TP	TP
PS04	P	TP	TP	PS37	P	TP	TP
PS05	P	TP	TP	PS38	P	TP	TP
PS06	P	TP	TP	PS39	P	TP	TP
PS07	P	TP	TP	PS40	P	TP	TP
PS08	P	TP	TP	PS41	P	TP	TP
PS09	P	TP	TP	PS42	P	TP	TP
PS10	P	TP	TP	PS43	P	TP	TP
PS11	P	TP	TP	PS44	P	FP	TN
PS12	P	TP	TP	PS45	P	FP	TN
PS13	P	FN	TP	PS46	P	TP	TP
PS14	P	TN	TN	PS47	P	TP	TP
PS15	P	TN	TN	PS48	P	TP	TP
PS16	P	TP	TP	PS49	P	TP	TP
PS17	P	TP	TP	PS50	P	TP	TP
PS18	P	TP	TP	PS51	P	TP	TP
PS19	P	TP	TP	PS52	P	TP	TP
PS20	P	TP	TP	PS53	P	TP	TP
PS21	P	FP	FP	PS54	P	TP	TP
PS22	P	TP	TP	PS55	P	TP	TP
PS23	P	TP	TP	PS56	P	TN	TN
PS24	P	TP	TP	PS57	P	TN	FN
PS25	P	TP	TP	PS58	P	FP	FP
PS26	P	FN	TN	PS59	P	TP	TP
PS27	P	TP	FN	PS60	P	FP	FP
PS28	P	TN	TN	PS61	P	TP	TP
PS29	P	FP	FP	PS62	P	TP	TP
PS30	P	TP	TP	PS63	P	TP	TP
PS31	P	TP	TP	PS64	P	TN	FN
PS32	P	TN	TN	PS65	P	TN	TN
PS33	N	TN	TN	PS66	P	TN	FP
				PS67	P	TN	FP

The data was obtained during an interview with the dentist at South Cilacap Health Centre. It is based on medical record data of patients with complaints of toothache. Performance calculations using the Naïve Bayes method are carried out to determine the confusion matrix [30]. From Table 10 above, it can be concluded that the value of True Positive (TP) is 46, True Negative (TN) is 11, False Positive (FP) is 8, and False Negative (FN) is 2 for the Mamdani fuzzy logic. Meanwhile, the value of True Positive (TP) is 45, True Negative (TN) is 10, False Positive (FP) is 9, and False Negative (FN) is 3 for the Naïve Bayes. From these data, the accuracy value, precision value, sensitivity value and specificity value can be calculated, the result is shown in Fig. 7.

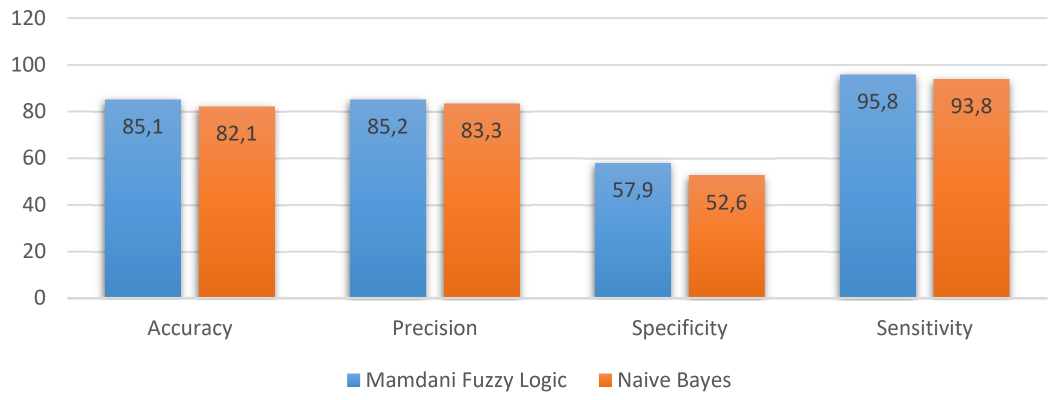

Fig. 7 Comparison of the mamdani fuzzy logic method and the naïve bayes method on dental disease results

The calculation results using the confusion matrix above conclude that the system's accuracy value using the Mamdani fuzzy logic method is 85.1%. In comparison, the Naïve Bayes classification method is 82.1%. Both methods' performance is good because the accuracy value exceeds 50% based on the test results.

IV. Discussion

Expert systems have been widely implemented in various fields. Fuzzy and Naïve Bayes methods have also been widely used to solve various problems. As in the [6], [14], [31], [9], [22] research that has been carried out by implementing the Mamdani fuzzy logic method and the Naïve Bayes method, this research has a novelty in that comparing the results of the diagnosis of dental disease and its supporting network from an expert, a dental specialist with the results diagnosis of an expert system that implements the Mamdani fuzzy logic method and also the Naïve Bayes method. The results of the diagnosis are then compared with the accuracy level to be used as a decision recommendation about the dental disease. The process of diagnosing dental disease and its supporting tissues begins with the selection of the symptoms.

V. Conclusions

The calculation results show the accuracy of dental and surrounding tissue disease prediction and surrounding tissue by implementing the Mamdani fuzzy logic method, which is compared and weighted by experts, namely dentists, reaching 85.1%. Meanwhile, the Naïve Bayes method has an accuracy rate of 82.1%. For example, a patient with code PS27 was diagnosed by an expert as having a periodontal abscess. Using a system that implements the Mamdani fuzzy logic method, PS27 was diagnosed with symptoms that lead to periodontal abscess with severity of 30.45%, while using a system that implemented the Naïve Bayes method diagnosed with periapical abscess disease with a percentage of 60%. Based on the results of the accuracy of the diagnosis of dental disease using the Mamdani fuzzy logic method and the Naïve Bayes method exceeding 50%, it can be concluded that the performance of both methods is quite good.

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