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Web-Based Expert System for Dental Disease Diagnosis Using the Certainty Factor Method: A Case Study at Al-Fatah Primary Clinic

Aria Bima Putra Pradata[1*✉], Supriyono[1], Diana Laily Fithri[1]
[1]Information System,Faculty of Engineering, Muria Kudus University, Kudus, Indonesia
*Corresponding Author: 202153098@std.umk.ac.id

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ABSTRACT

Dental health has an important role in supporting overall body health. However, public awareness of the importance of treatment and early detection of dental diseases is still low. This study aims to design and develop a web-based expert system that is able to help early diagnosis of dental diseases using the Certainty Factor (CF) method. The CF method was chosen because it is able to handle uncertainty and produce probability estimates based on the symptoms inputted by the patient. The system was developed using the Waterfall approach and implemented in the Al-Fatah Primary Clinic case study. Evaluation of the system's performance shows that the CF method has an accuracy of 89%, outperforming the Naïve Bayes comparison method which only reaches 82%. The system is also equipped with an interactive interface for patients and administrators, as well as features for managing data on symptoms, diseases, and diagnosis results. The results show that this CF-based expert system is able to provide efficient solutions for early consultation of dental diseases independently and accelerate diagnosis services in clinics.

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1. INTRODUCTION

Dental health is an important part of overall body health. However, there are still many people who do not realize the importance of early care and treatment of dental complaints. Many factors that cause tooth decay include lack of knowledge of dental diseases that can be experienced by patients and lack of enthusiasm to prevent tooth decay from occurring [1]. This condition often causes patients to come to the clinic in a severe condition, so that treatment becomes more complex and expensive.

In this modern era, awareness of the importance of healthy living and maintaining physical fitness is increasing among the public [2]. With the advancement of information technology, especially in the field of expert systems, it is possible to build a system that is able to provide an initial diagnosis of dental disease based on the symptoms felt by the patient [3]. One effective method used in expert systems is Certainty Factor, which works by calculating probabilities based on existing symptom data [4]. This method is suitable for medical diagnosis cases because it is able to provide accurate estimation results even with limited data [5], CF was chosen because it can handle uncertainty and is suitable for expert rule bases, Naïve Bayes was used as a comparison because it is a common probabilistic method in medical diagnosis, The CF results (89%) were superior to those of Naïve Bayes (82%), especially in classes with similar symptoms..

Currently, most of the dental disease diagnosis services at Al-Fatah Primary Clinic are still carried out conventionally, where patients must meet directly with the doctor to find out the condition of their teeth. This process certainly requires time, energy, and depends on the availability of doctors at the clinic. This condition becomes an obstacle when the number of patients who come increases, especially during peak hours [6]. Therefore, a solution is needed that can help speed up the process of early identification of dental diseases so that it can facilitate service and improve the quality of clinic services. A web-based expert system is the right choice because it can be accessed anytime and anywhere by patients. Thus, patients can conduct initial consultations independently using only devices such as computers, tablets, or smartphones connected to the internet. The results of this initial diagnosis can give patients an idea of the possibility of the disease they are suffering from so that they can immediately take appropriate action [7]. In addition, the use of this system can also help clinics in digitally collecting patient data.

In its implementation, this expert system starts with patients accessing the expert system website through their devices, such as computers, tablets, or smartphones. Patients are then asked to fill out a form containing the symptoms they feel in their teeth [8]. After that, the system will process the symptom data using the Certainty Factor algorithm to calculate the likelihood of the disease experienced based on the resulting probability value. The results of this initial diagnosis will be presented to the patient in the form of clear information regarding the possibility of dental disease they are experiencing [9]. Patients can then choose to proceed with further consultation with the dentist or take the necessary action based on the diagnosis results. Through the development of this dental disease diagnosis expert system, it is expected to provide real benefits for Al-Fatah Primary Clinic in improving dental health services to the community. This system is also expected to be the first step in digitizing dental health services at the clinic, as well as an example of the effective application of information technology in the medical world. With this system, the clinic can provide services that are faster, more efficient, and still accurate, thus increasing overall patient satisfaction. Several previous studies have developed dental diagnosis expert systems using the Forward Chaining [10], Naïve Bayes [11], and Fuzzy Logic [8] methods. However, most are still limited to one or two types of dental diseases and have not been integrated into web-based applications that patients can use independently. This study fills this gap by developing a Certainty Factor-based system that covers 18 dental diseases, is web-based, and includes a comparative evaluation of methods.

2. RESEARCH METHOD

a systematic way or approach used in research to collect, analyze, and interpret data, in order to achieve research objectives. It includes the selection of appropriate methods, techniques and procedures to answer research questions and produce valid and reliable findings.

2.1 Data and Research Sources

2.1.1 Dataset and Diagnosis Classes

The research dataset consists of 200 patient cases. Each case consists of a collection of symptoms reported by the patient and a final diagnosis label as the disease class. There are 18 modeled dental disease classes—including Dental Caries, Gingivitis, Periodontitis, Dental Abscess, Malocclusion, Dental Erosion, Oral Candidiasis, Stomatitis, Bruxism, Dental Fluorosis, Impacted Teeth, Necrotizing Gum Disease, Oral Cancer, Sensitive Teeth, and other classes relevant to clinical services.

The distribution between classes is uneven but controlled, with an average of 10–20 cases per class. Some common classes have a larger share, for example, Dental Caries 25% 50 cases and Gingivitis 15% 30 cases, while rare classes such as Oral Cancer or Necrotizing Gum Disease are in the range of 5–10 cases.

The data source comes from interviews with two dentists at the Al-Fatah Clinic who provided Certainty Factor (CF) weight values for disease symptom rules, as well as dental journal literature as reinforcement.

2.1.2 Data Structure and Pre-Processing

Each patient entry contains a minimum of 4 symptoms, with an average of 6–8 symptoms per case. The data was cleaned of duplicate symptoms per patient, normalized in terms of symptom/disease terminology, and mapped to symptom codes and disease codes to be consistent with the CF rule base. Expert rules are represented as pairs (symptom, disease, expert_CF).

2.1.3 Training and Evaluation Protocol

Data was split according to an 80% training and 20% testing ratio. To test model stability and reduce bias due to split variation, 5-fold cross-validation was applied to the training set; metrics were reported as cross-fold averages. Evaluation focused on overall accuracy and per-class metrics (precision, recall, F1-score) to assess the impact of class imbalance.

2.2 Certainity Factor Method

The methodology used in this research is the Certainty Factor (CF) method applied in a web-based expert system for diagnosing dental diseases. This method was chosen because of its ability to manage the uncertainty of diverse symptom data. Certainty Factor works by calculating the level of certainty of a disease based on a combination of symptoms entered by the patient. This method is effective in situations where the data is incomplete or contains uncertainty.

2.2.1 Diagnosis Process Using Certainty Factor

Certainty Factor is used to provide an estimate of the probability of a disease based on the symptoms detected. For each symptom, the system will match the data entered by the patient with the list of diseases available in the expert system database. This process is done by calculating the Certainty Factor which each has a value between -1 (full uncertainty) to +1 (full certainty

2.2.2 Certainty Factor Formula

The basic formula for calculating the Certainty Factor (CF) can be seen in equation (1):

$$CF = MB - (MC \times (1 - MB)) \tag{1}$$

Where:

1) CF = Certainty Factor
2) MB = Belief Memory (the certainty value given by the expert or system for the corresponding symptom)
3) MC = Contradiction Memory (a value that indicates uncertainty or confusion)

This CF calculation process allows the system to provide an estimated value for the disease suffered based on the symptoms experienced by the patient

2.3 Data Processing

2.3.1 Model Evaluation Concept

In research involving classification models, such as Naive Bayes and Certainty

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Factor models for comparison as decision-making methods in my expert system for dental disease diagnosis, model performance evaluation is essential to assess the accuracy and reliability of predictions [12]. Some commonly used evaluation metrics are confusion matrix, precision, recall, F1-score, and support. The following is an explanation of each of these metrics:

1) Model Accuracy: Accuracy is calculated by comparing the model's prediction to the actual label in the training data [13]. The accuracy results for both methods are as follows
   1. Naive Bayes: 0.82 (82%)
   2. Certainty Factor: 0.885 (88.50%)
2) Cross-Validation: The 5-fold cross-validation technique was used to evaluate the stability and generalization of the model [14]. The cross-validation results are:
   1. Naive Bayes: 0.6900 ± 0.0339
   2. Certainty Factor: 0.8750 ± 0.0632
3) Confusion Matrix: Confusion matrix is an evaluation tool used to describe the performance of classification models in tabular form [11]. This matrix compares the actual label (actual class) with the label predicted by the model, where:
   1. Rows represent the actual class.
   2. Columns represent the predicted class
   3. The main diagonal element shows the number of correct predictions for each class (true positives for that class).
   4. Off-diagonal elements represent prediction errors (false positives and false negatives).

   For binary classification, the confusion matrix can be described as follows:

   Table 1 Binary Classification on Confusion Matrix

	Positive Prediction	**Predicted Negative**
Actual Positive	*True Positive* (TP)	*False Negative* (FN)
Actual Negative	*False Positive* (FP)	*True Negative* (TN)

   In a multi-class context, such as in this study which has 18 dental disease classes, the confusion matrix provides a detailed overview of the number of correctly and incorrectly classified instances for each class. This matrix helps identify which classes are frequently mispredicted and enables analysis of error patterns[15].
4) Precision: Precision measures the proportion of correct positive predictions for a given class [16]. Precision is calculated by the formula:

$$Precision = \frac{True\ Positive(TP)}{True\ Positive\ (TP)\ +\ False\ Positive\ (FP)} \tag{2}$$

   Precision indicates how accurate the model is in predicting a particular class, with a focus on minimizing false positives [17]. A high precision value means that most of the

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instances predicted as a particular class actually belong to that class. In the context of dental disease diagnosis, high precision is important to ensure that patients are not diagnosed with the wrong disease.

5) Recall: Recall (also called sensitivity or true positive rate) measures the proportion of actual instances of a class that are correctly predicted by the model [18].

$$Recall = \frac{True\ Positive(TP)}{True\ Positive\ (TP)\ +\ False\ Negative\ (FN)} \tag{3}$$

Recall indicates the ability of the model to detect all instances of a particular class, with a focus on minimizing false negatives. A high recall value means that the model is able to identify most instances of the class. In a medical context, high recall is essential to ensure that cases of a particular disease are not missed.

6) F1-Score: F1-score is the harmonic mean of precision and recall, which provides a balance between the two metrics [19].

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

F1-score is useful when the class distribution is unbalanced or when precision and recall are equally important. A high F1-score value indicates that the model has a good balance between reducing false positives and false negatives. In this study, F1-score is used to evaluate the performance of the model on each dental disease class, especially for classes with a small number of instances.

7) Support: Support is the actual number of instances for each class in the dataset. This metric provides context about the distribution of data between classes and helps explain model performance. Classes with low support (e.g., only a few instances) are often difficult to predict well because the model has limited training data to learn the patterns of the class. In this research, support is important to understand why some classes perform poorly, especially for classes with a very small number of instances.

2.3.2 System Development Method

The Waterfall method, also known as the classic life cycle or formally called the Linear Sequential Model, is a systematic and phased approach to software development [20]. The development process starts from the stage of identifying user needs, then continues with the stages of planning, design (modeling), system development (construction), to implementation and delivery of the system to users, which ends with the software maintenance stage. In system analysis, the system development method is one of the most important processes. One of the methods used in system design is the Waterfall method [21]. This method proposes a systematic and sequential approach to software development, starting from the stages of analysis, design, code, testing, to maintenance.

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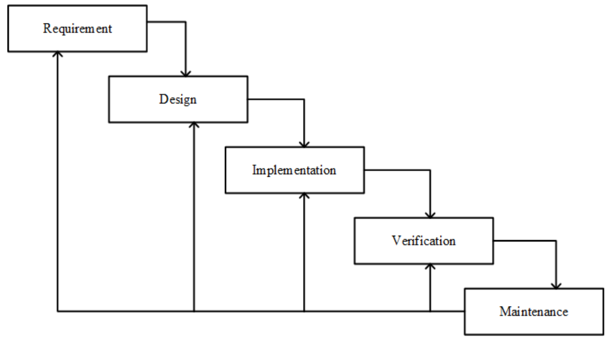

Figure 1. Stages of the Waterfall Method

The Waterfall method has stages that are used during the software development process, namely:

1) Requirement: System developers today need to focus on understanding user expectations of software as well as understanding the various constraints that exist. Some methods that can be used to gather this information include direct surveys, conversations, and interviews. The data obtained is then analyzed to understand user needs in greater depth [22].
2) Design: In this stage, developers create a system design that serves to determine the general system architecture as well as establish system and hardware specifications.
3) Implementation: During this phase, the system is initially designed in small programs called units, which are then combined in the next stage. Unit testing is the process of developing and assessing the effectiveness of each unit.
4) Verification: Applications or systems that have met the client's needs can be launched or marketed.
5) Maintenance: The waterfall method ends with a step where the completed software is used and kept up to date. The process of correcting errors that were not detected in the previous stages is included in the maintenance stage.

3. RESULT AND DISCUSSION

This section presents in detail the results of the research that has been conducted. The presentation begins with a description of the dataset that is the basis for testing, followed by a quantitative evaluation of the methods used, the system implementation process, and ends with a visual display of the successfully developed program.

3.1 Research Dataset

The dataset used in this study consists of 200 patient cases containing records of symptoms and their corresponding diagnoses. The data covers 18 classes of dental diseases, including Dental Caries, Gingivitis, Periodontitis, Dental Abscess, Malocclusion, Dental

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Erosion, Oral Candidiasis, Stomatitis, Bruxism, Dental Fluorosis, Impacted Teeth, Necrotizing Gum Disease, Oral Cancer, Sensitive Teeth, and several other categories. The class distribution is relatively varied, with an average of 10–20 cases per class. The most common categories are Dental Caries (approximately 25% of cases) and Gingivitis (around 15%), while rare categories such as Oral Cancer and Necrotizing Gum Disease have fewer than 10 cases. For model training and testing, the dataset was split into 80% training data and 20% testing data, and performance evaluation was further validated using 5-fold cross-validation. Each patient record contains at least 4 symptoms, with an average of 6–8 symptoms per case, providing sufficient feature combinations for accurate inference using the Certainty Factor method.

Table 2 Summary of Research Dataset

Component	Description
Total patient cases	200 cases
Number of disease classes	18 classes (e.g., Dental Caries, Gingivitis, Periodontitis, etc.)
Distribution per class	Average 10–20 cases per class; Dental Caries ±25%, Gingivitis ±15%, rare cases <10
Train/test ratio	80% training, 20% testing, with 5-fold cross-validation
Symptoms per patient	Minimum 4 symptoms, average 6–8 symptoms

The foundation of this research is a dataset of dental disease cases compiled to represent diagnosis data at Al-Fatah Primary Clinic. This dataset became the sole data source for training and testing the expert system model. The data structure consists of three main columns: Patient ID_Patient, Symptoms, and Disease. Each row represents one symptom experienced by a patient for a particular disease diagnosis. A snapshot of the dataset used is in Table 2 below:

Table 2 Research Dataset

Patient ID_Patient	Symptoms	Disease
P01	Tooth pain especially when eating or drinking hot or cold sweets	Dental Caries (Cavities)
P02	The appearance of holes in the teeth	Dental Caries (Cavities)
P03	The tooth appears to change color usually to brown or black	Dental Caries (Cavities)
P04	Bad breath	Dental Caries (Cavities)
P05	Red swollen gums and bleeding easily when brushing teeth	Gingivitis (Gum Inflammation)

For the evaluation process, this data is aggregated so that each Patient ID_Patient has one record that contains a combination of all the symptoms experienced. Using this dataset, a performance evaluation was conducted to compare the Certainty Factor and Naive Bayes methods.

3.2 Performance Evaluation of *Certainty Factor* Method

The performance evaluation of the Certainty Factor (CF) method is conducted through a series of systematic processes implemented in Python code to ensure objectivity and reliability of the results. The evaluation phase begins with data processing, where the system loads two main datasets: a rule base containing CF values from experts and a dataset of patient cases. The patient case data is then aggregated by unique ID, so that each patient has a combined set of symptoms ready for analysis. This process is a fundamental step to prepare the data before it is fed into the core CF algorithm.

Once the data is ready, the diagnosis process for each patient is run. The algorithm iteratively matches each symptom in the combined set of patients with the rules in the knowledge base. When more than one symptom leads to the same disease, the CF values of the rules are combined using a standard formula resulting in a score, the disease with the highest confidence score is determined as the predicted result of the system.

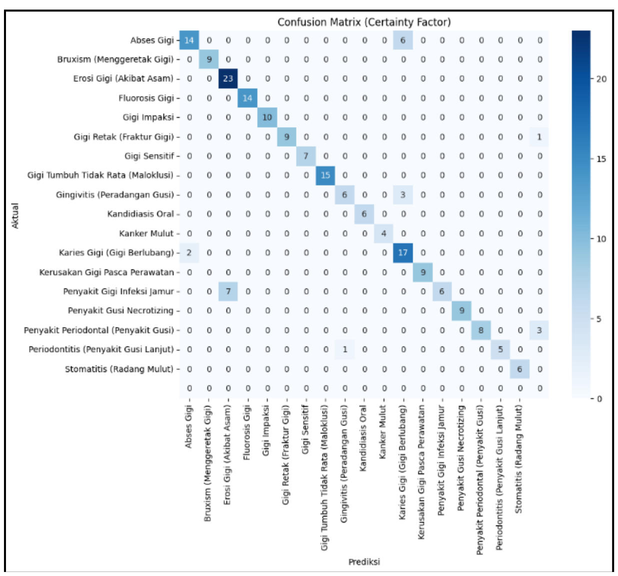

Figure 2. Confusion Matrix Certainty Factor

Evaluation of the performance of the expert system in diagnosing various types of oral and dental diseases was carried out using a confusion matrix based on the Certainty Factor (CF) method. Based on Figure 2, the system shows a high level of accuracy in classifying most disease categories. Some conditions such as Dental Erosion (Acid Induced), Uneven Teeth (Malocclusion), and Dental Caries (Cavities) have very precise predictions, with 23, 15, and 17 correctly classified cases (true positive), respectively. However, there were also some cases of misclassification, such as in Dental Abscess where 6 out of 20 cases were predicted as other diseases, and Dental Caries where 2 cases were misclassified. These results show that although the CF method is able to handle uncertainty and provide a fairly accurate diagnosis, there is still room for improvement in some disease categories that have similar symptoms.

Laporan Klasifikasi (Certainty Factor):

	precision	recall	f1-score	support
Abses Gigi	0.88	0.70	0.78	20
Bruxism (Menggeretak Gigi)	1.00	1.00	1.00	9
Erosi Gigi (Akibat Asam)	0.77	1.00	0.87	23
Fluorosis Gigi	1.00	1.00	1.00	14
Gigi Impaksi	1.00	1.00	1.00	10
Gigi Retak (Fraktur Gigi)	1.00	0.90	0.95	10
Gigi Sensitif	1.00	1.00	1.00	7
Gigi Tumbuh Tidak Rata (Maloklusi)	1.00	1.00	1.00	15
Gingivitis (Peradangan Gusi)	0.86	0.67	0.75	9
Kandidiasis Oral	1.00	1.00	1.00	6
Kanker Mulut	1.00	1.00	1.00	4
Karies Gigi (Gigi Berlubang)	0.65	0.89	0.76	19
Kerusakan Gigi Pasca Perawatan	1.00	1.00	1.00	9
Penyakit Gigi Infeksi Jamur	1.00	0.46	0.63	13
Penyakit Gusi Necrotizing	1.00	1.00	1.00	9
Penyakit Periodontal (Penyakit Gusi)	1.00	0.73	0.84	11
Periodontitis (Penyakit Gusi Lanjut)	1.00	0.83	0.91	6
Stomatitis (Radang Mulut)	1.00	1.00	1.00	6
Tidak ada penyakit yang cocok	0.00	0.00	0.00	0
accuracy			0.89	200
macro avg	0.90	0.85	0.87	200
weighted avg	0.92	0.89	0.89	200

Figure 3. Certainty Factor Model Evaluation Metrics

The metric evaluation results in Figure 3 show that the system has an overall accuracy of 89%, with a macro average f1-score of 0.85, and a weighted average f1-score of 0.89. Some disease categories such as Bruxism, Dental Fluorosis, Sensitive Teeth, and Oral Candidiasis show perfect performance with precision and recall of 1.00. However, categories such as Dental Abscess (f1-score of 0.78) and Dental Caries (f1-score of 0.76) showed potential ambiguities in the symptoms that affected the accuracy of the system. In general, the CF method proved to be effective in handling diagnostic uncertainty, and was able to provide stable and reliable performance in the classification process of oral diseases.

3.3 Performance Evaluation of *Naïve Bayes* Method

As a comparison method, performance evaluation was also performed on the Naïve Bayes algorithm. The process is similar, where an aggregated dataset of patient cases is used to train the model. The Naïve Bayes model is then used to predict the type of disease based on the combination of symptoms present in each case.

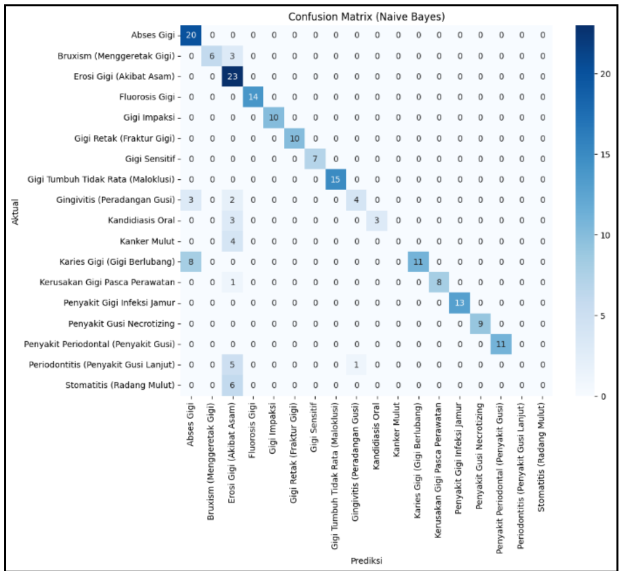

Figure 4. Naïve Bayes Confusion Matrix

Based on Figure 4, it can be seen that some disease categories were classified well, such as Dental Erosion (Acid Induced), Malocclusion, and Fungal Infection Dental Disease, where all cases were classified correctly (true positive). However, there were quite a few misclassifications in other categories. For example, Dental Caries (Cavities) and Gingivitis (Gum Inflammation) each had several cases predicted to other classes. In addition, categories such as Periodontitis and Oral Cancer had very low classification performance, and even Stomatitis was not classified successfully at all.

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Laporan Klasifikasi (Naive Bayes):

	precision	recall	f1-score	support
Abses Gigi	0.65	1.00	0.78	20
Bruxism (Menggeretak Gigi)	1.00	0.67	0.80	9
Erosi Gigi (Akibat Asam)	0.49	1.00	0.66	23
Fluorosis Gigi	1.00	1.00	1.00	14
Gigi Impaksi	1.00	1.00	1.00	10
Gigi Retak (Fraktur Gigi)	1.00	1.00	1.00	10
Gigi Sensitif	1.00	1.00	1.00	7
Gigi Tumbuh Tidak Rata (Maloklusi)	1.00	1.00	1.00	15
Gingivitis (Peradangan Gusi)	0.80	0.44	0.57	9
Kandidiasis Oral	1.00	0.50	0.67	6
Kanker Mulut	0.00	0.00	0.00	4
Karies Gigi (Gigi Berlubang)	1.00	0.58	0.73	19
Kerusakan Gigi Pasca Perawatan	1.00	0.89	0.94	9
Penyakit Gigi Infeksi Jamur	1.00	1.00	1.00	13
Penyakit Gusi Necrotizing	1.00	1.00	1.00	9
Penyakit Periodontal (Penyakit Gusi)	1.00	1.00	1.00	11
Periodontitis (Penyakit Gusi Lanjut)	0.00	0.00	0.00	6
Stomatitis (Radang Mulut)	0.00	0.00	0.00	6
accuracy			0.82	200
macro avg	0.77	0.73	0.73	200
weighted avg	0.82	0.82	0.79	200

Figure 5. Naïve Bayes Model Evaluation Metrics

Figure 5 shows that the overall accuracy of the Naive Bayes model is 82%, with a macro average f1-score of 0.73, and a weighted average f1-score of 0.79. Some categories such as Dental Fluorosis, Impacted Teeth, and Necrotizing Gum Disease showed perfect precision and recall values (1.00), indicating excellent model performance in these categories. In contrast, a low precision value was found in the Dental Abscess category (0.65), although the recall was perfect (1.00), indicating that the model tends to over-classify the class . The lowest f1-score values were found in some rare classes such as Oral Cancer (0.00) and Stomatitis (0.00), indicating the failure of the model to detect these cases.

3.4 1Implementation Results and System Interface Display

In the implementation stage, the system has been successfully developed and tested in the form of a web-based application. This application allows patients to self-diagnose the symptoms of oral diseases they feel, and provides prediction results based on the Certainty Factor and Naive Bayes methods. In addition, the system also provides data management features for admins to manage rules, users, and disease information.

3.4.1 Requirement Stage Results

In the initial stage, a requirement analysis was conducted to understand the problems and objectives of the system. The result is a clear requirement specification: the system must be accessible online, able to provide initial diagnosis of dental diseases for patients based on symptoms, and provide an administration panel for managers to maintain the system knowledge base.

3.4.2 Results of Design and Implementation Phase

The system interface is designed to be intuitive and easy to use by two types of users, namely patients and admins. Here are some of the main interfaces of the system that has been developed:

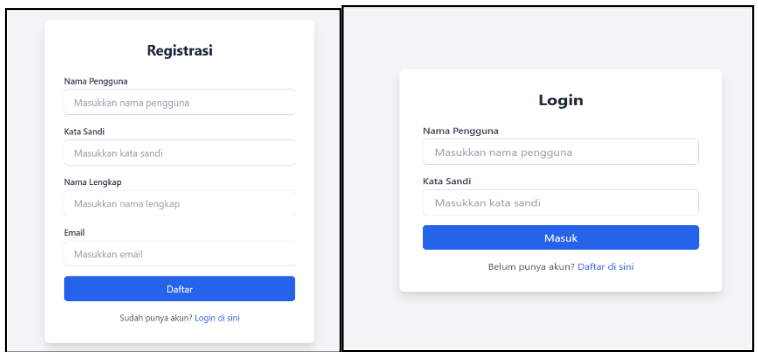

Figure 6. Registration and Login Page

Figure 6 shows the initial page of user interaction with the system. The registration page allows new users to create an account by filling in the required personal data. After that, users can log in to the system through the login page, which verifies credentials before granting access to the system's features. The interface is designed to be simple and clear to ease the user authentication process.

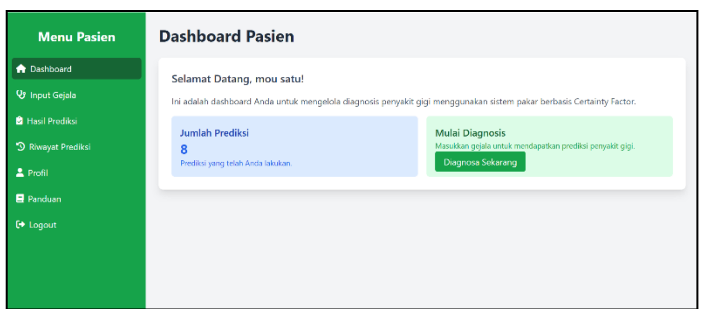

Figure 7. Patient Dashboard Page

Figure 7 shows the page after successfully passing the login process, the patient will be directed to the patient dashboard which presents a summary of information as well as the main navigation menu. This page becomes the user's control center to access the diagnosis feature, prediction history, profile, and usage guide.

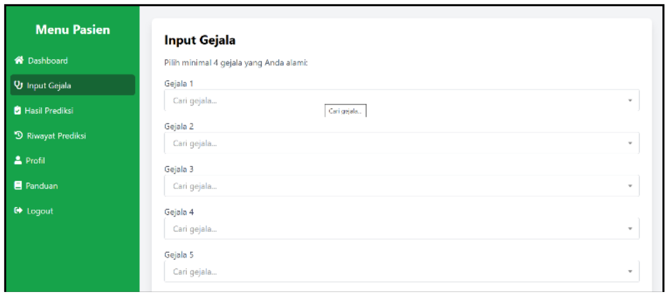

Figure 8. Symptom Input Page

Figure 8 shows the symptom input page which is the core component of the diagnosis system. Users can select their symptoms from the dropdown list, which will be processed by the system using the Certainty Factor method.

Figure 9. Prediction Results Page

Figure 9 shows the page after the user inputs symptoms, the system will display the results of disease predictions which include the name of the disease, certainty value, as well as additional information such as disease description and recommended actions.

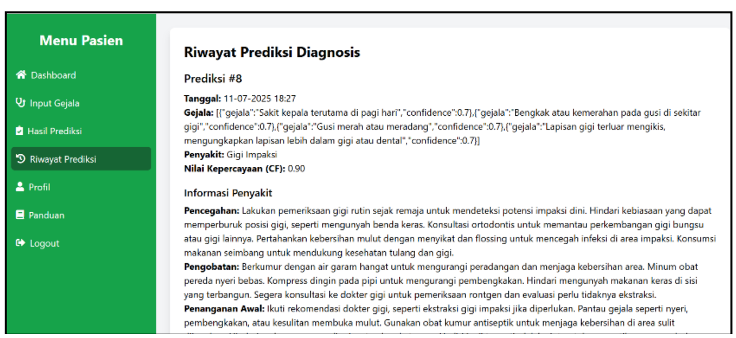

Figure 10. Prediction History Page

Figure 10 shows the prediction history page which is useful for improving traceability and continuity of information, the system provides a prediction history page that stores all the diagnosis results that have been made by the user. This page is equipped with dates, disease names, and other details, so users can monitor the development of their conditions over time.

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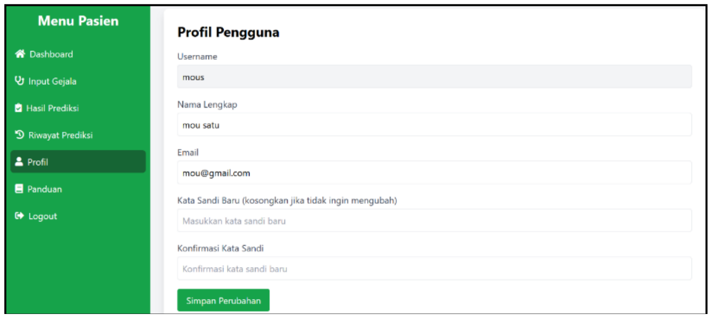

Figure 11. Profile Page

In Figure 11 shows the profile page, users can view and update account information such as name, email address, and password. This function is important for keeping user data up-to-date as well as providing flexibility in account management.

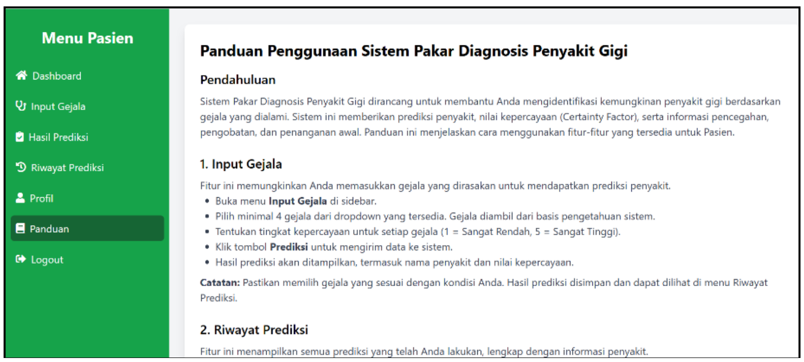

Figure 12. User Guide Page

Figure 12 shows the user guide page which functions to facilitate understanding, the system provides a guide page containing information on the steps for using the system. This feature helps new users and those who are not familiar with the system to make the most of the application.

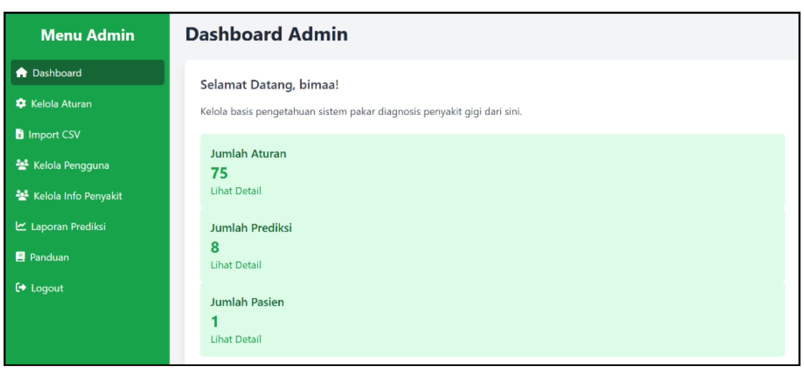

Figure 13. Admin Dashboard Page

P.ISSN: 2086 – 4981
E.ISSN: 2620 – 6390
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In Figure 13 shows a page for users with admin login status, there is an admin dashboard that presents prediction statistics, the number of users, and other system activities.

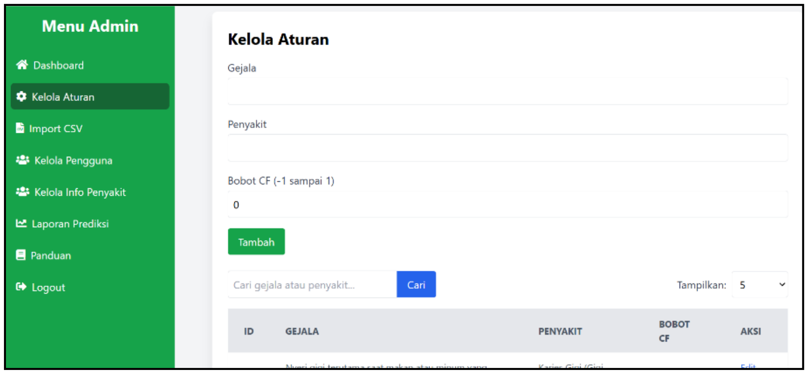

Figure 14. Rule Management Page

In Figure 14 shows the rule management page, it allows the admin to add, edit, and delete rules in the system knowledge base. This rule becomes the basis of diagnosis in the Certainty Factor method, so its existence is very important to maintain the accuracy of the system.

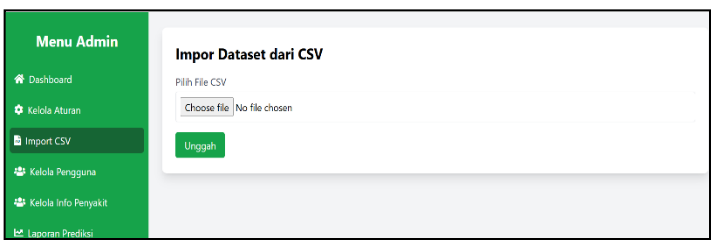

Figure 15. CSV Import Page

In Figure 15 shows the CSV import page for data management efficiency, there is a CSV import feature that allows admins to enter symptom, disease, and rule data in bulk. This feature speeds up the data update process compared to the manual data input method.

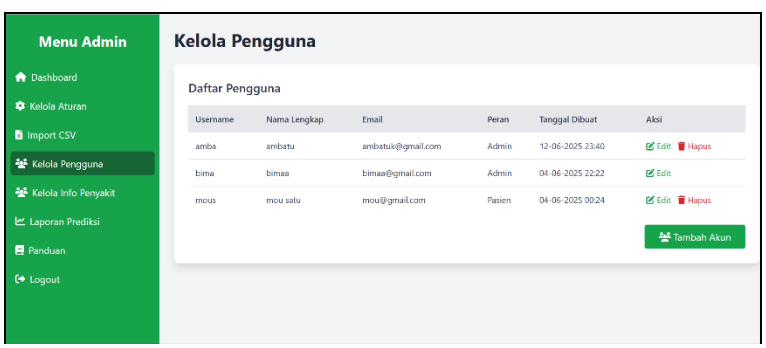

Figure 16. User Management Page

Figure 16 shows the user management page, through this page admins can monitor and manage user accounts, both patients and fellow admins. This feature includes activation, deletion, and modification of user information.

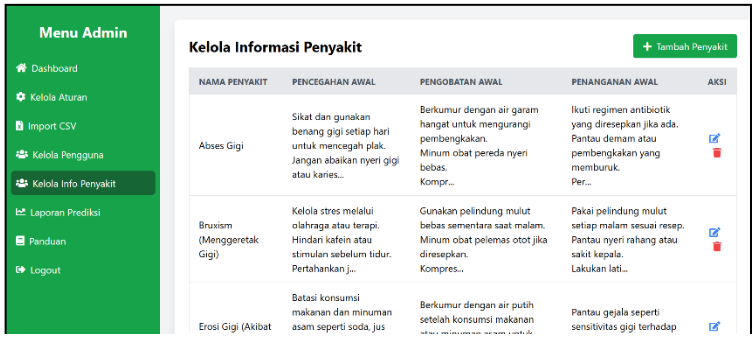

Figure 17 Manage Disease Info Page

Figure 17 shows the manage disease info page, this is used to manage disease-related information, such as name, description, and solution. Admins can ensure that disease data in the system is always accurate and relevant to the symptoms inputted by users.

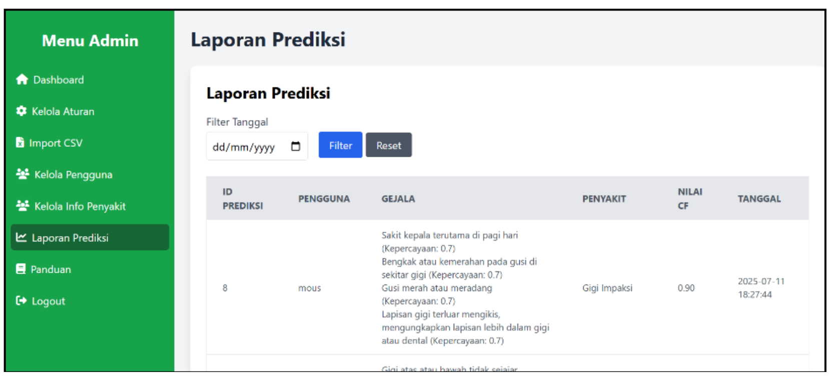

Figure 18 Prediction Report Page

Figure 18 shows the prediction report page, which is a recapitulation of the diagnosis results made by all users. Admins can use this information to analyze disease trends, conduct system evaluations, and make strategic decisions in service management.

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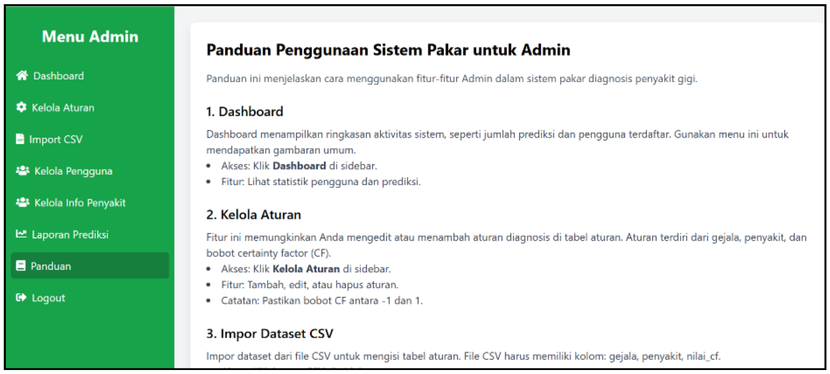

Figure 19. Admin Guide Page

Figure 19 shows the admin guide page, this page explains the functions of the system from the manager's side and helps the admin in carrying out his duties effectively.

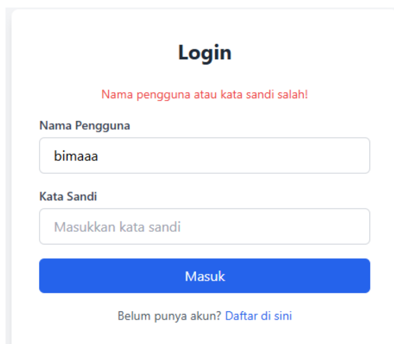

Figure 20. Admin Guide Page

Figure 20 shows the security of the system, the system implements login authentication to restrict access to registered users only. Additionally, input validation is used to ensure data is entered in the correct format, so that when a user enters an incorrect username or password, the system displays a login failure message as a security measure.

Figure 21. Negative Scenario

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Figure 21 shows a negative scenario where the disease diagnosis process fails because the API has not been executed. The system displays an error message as a form of handling, so that users are informed that the service cannot be accessed until the API is active.

Figure 22. Results of disease symptom input by patients

Figure 22 shows the results of disease symptom input by patients with an average diagnosis response time of ±3–4 seconds. This illustrates the system's performance in providing rapid diagnosis results, with testing conducted from the patient's perspective.

3.5 Verification Stage Results

After the implementation is complete, the system enters the verification stage to ensure all functions run without errors and in accordance with the needs. The testing method used is Black Box Testing, where each function is tested based on the input provided by the user and the output generated by the system, according to the scenarios in Table 4 and Table 5.

Table 4 Patient Side Testing

No.	Testing Scenario	Step-Steps	Result Expected Result	Testing Result
1.	Account Registration	Fill in the registration form & click "Register".	New account successfully created.	Success
2.	Account *Login*	Fill in *the login* form & click "Login".	Successfully *login* to the patient *dashboard*.	Successful
3.	Input Diagnosis Symptoms	Select at least 4 symptoms & process.	Diagnosis result page is displayed.	Success
4.	View Diagnosis History	Open the "Prediction History" menu.	The diagnosis history list is displayed.	Successful
5.	Change User Profile	Open the "Profile" menu, change data & save.	Profile data is successfully updated.	Successful
6.	Account *Logout*	Click the "*Logout*" menu.	Successfully *logout* & return to the *login* page.	Successful

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Table 5 Admin Side Testing

No.	Testing Scenario	Step-Steps	Expected Result Expected Result	Testing Result
1.	*Admin* Login	Fill in the *login* form & click "Login".	Successfully *login* to the *admin dashboard*.	Successful
2.	Add CF Rule	Fill in the form in "Manage Rules" & add.	New rule is saved & appears in the table.	Success
3.	Import Rules (CSV)	Select CSV file in "*Import* CSV" menu & upload.	Rules from CSV are imported successfully.	Successful
4.	Manage User	Edit or delete data in "Manage User".	User data is successfully edited/deleted.	Successful
5.	Manage Disease Info	Edit data in "Manage Disease Info".	Disease information is successfully updated.	Successful
6.	View Diagnosis Report	Open the "Prediction Report" menu.	A list of all patient diagnoses is displayed.	Successful

3.6 Maintenance Stage Result

The last stage is maintenance. The result of this stage is not a new feature, but rather the provision of tools for admins to maintain the system independently [23]. Like the features already mentioned in the implementation section which include: Manage Rules, Manage Disease Info, and Manage Users are specifically designed so that admins can update the knowledge base and manage data without having to change the core code of the program. This ensures the system can continue to be relevant and accurate over time.

4. CONCLUSION

This study successfully developed a web-based dental disease diagnosis expert system by applying the Certainty Factor method that can handle uncertainty in symptom data. This system provides convenience for patients in conducting initial consultations without having to come directly to the clinic, and helps clinics in the process of digitizing dental health services. The evaluation results show that the Certainty Factor method provides a high accuracy of 89% and is stable in classifying various dental diseases, outperforming the Naïve Bayes comparison method which only achieves 82% accuracy. The system is also equipped with data management features and a user-friendly interface, both for patients and admins. Thus, this system can be a practical solution in improving the efficiency and quality of dental health services, especially at Al-Fatah Primary Clinic, and has the potential to be implemented in other clinics with similar cases.

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