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Gum Disease Identification Using Fuzzy Expert System

Muhammad Nasir[1*], Tri Basuki Kurniawan[2], Deshinta Arrova Dewi[3], Mohd Zaki Zakaria[4], Nurul Shaira Binti Bujang[5]

[1,2]*Faculty of Science Technology, Universitas Bina Darma, Palembang, Indonesia*

[3]*Faculty of Data Science and Information Technology, INTI International University, Malaysia*

[4, 5]*Faculty of Computer & Mathematics Sciences, University Technology Mara, Malaysia*

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Abstract

Gum disease, including Gingivitis and Periodontitis, is among the most common dental conditions, primarily caused by dental plaque, a bacterial biofilm. These conditions are strongly linked to various systemic illnesses, including cancer, atherosclerosis, hypertension, stroke, and respiratory and cardiovascular conditions like aspiration pneumonia, as well as adverse pregnancy outcomes. Gum inflammation is typically characterized by symptoms such as increased redness, swelling (edema), and a loss of surface texture (stippling; gum fiber attachment). These symptoms are site-specific, meaning that an individual can have both healthy and diseased areas within their mouth. In this research, we developed a fuzzy expert system using MATLAB to identify gum diseases. The system was tested on various cases and produced an output value of 0.133, which successfully identified Gingivitis. This value was derived using a fuzzy logic system that processes input data through predefined rules within the Fuzzy Expert System (FES). The system utilizes several input variables such as the frequency of gum bleeding, the extent of plaque accumulation, the depth of gum recession, and the degree of tooth mobility. The key contribution of this study lies in the integration of fuzzy logic to handle the inherent uncertainties in clinical diagnosis, providing a more nuanced assessment compared to traditional methods. The novelty of this research is the application of a fuzzy expert system in dental diagnostics, offering a promising tool for improving the accuracy and efficiency of gum disease identification in clinical settings. This system has the potential to assist dentists in making more informed decisions, ultimately leading to better patient outcomes.

Keywords: Gum Diseases, Dental Plaque, Fuzzy Expert System, MATLAB, Public Health

1. Introduction

As the global population continues to grow rapidly, surpassing 7.7 billion in 2019 according to Worldometers, health challenges are also on the rise. Chronic diseases such as heart disease, diabetes, hypertension, and various forms of cancer are becoming increasingly prevalent, often leading to severe health outcomes, including death. Alongside these major health issues, a myriad of minor diseases, including allergies, bronchitis, conjunctivitis, and dental diseases, pose significant threats to public health, particularly when left untreated [1]. Early prevention is widely recognized as more effective than later treatment, as addressing health issues before they escalate can significantly reduce the complexity and impact of subsequent care [2].

Dental diseases, in particular, represent a significant but often underestimated health concern worldwide. These conditions, caused by bacteria in the mouth, range from cavities to severe forms of gum disease, and in extreme cases, can even progress to oral cancer. Poor oral hygiene is a leading contributor to these conditions, which not only affect physical health but also have social and psychological consequences, such as diminished self-confidence due to poor oral appearance [3]. There are six primary types of periodontal diseases: Gingivitis, Periodontitis, Aggressive Periodontitis, Chronic Periodontitis, Systemic Periodontitis, and Necrotizing Periodontitis. Each of these conditions, though varying in severity, underscores the importance of maintaining oral health [4].

Research indicates that a lack of awareness and education regarding dental health is a primary factor contributing to the prevalence of these diseases globally [5]. Additionally, unhealthy lifestyle choices, such as smoking, excessive alcohol consumption, and neglect of oral hygiene, exacerbate these problems [6]. Common dental issues like cavities

***Corresponding author: Muhammad Nasir (nasir@binadarma.ac.id)**
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and gum disease affect nearly everyone at some point in their lives, emphasizing the critical need for improved public health initiatives and preventive care [7]. Dental and oral health are vital components of overall well-being. Dentistry, as defined by the American Dental Association (2011-2012), involves the evaluation, diagnosis, prevention, and treatment of diseases and conditions affecting the oral cavity. Dentists, the professionals specializing in this field, play a crucial role in addressing and managing these health challenges [8].

2. Literature Review

2.1. Overview of Gum Diseases

Gum diseases, commonly referred to as periodontal diseases, encompass a range of inflammatory conditions affecting the supporting structures of the teeth, including the gums, periodontal ligament, and alveolar bone. These conditions are primarily caused by bacterial plaque accumulation on the teeth and gums, leading to an inflammatory response. The mildest form of gum disease, gingivitis, is characterized by redness, swelling, and bleeding of the gums. If left untreated, gingivitis can progress to periodontitis, a more severe condition that involves the destruction of the tissues that support the teeth, potentially leading to tooth loss. According to the American Academy of Periodontology, gum disease is one of the leading causes of tooth loss in adults, affecting approximately 50% of the adult population to varying degrees [9].

The progression of gum disease is typically slow and often asymptomatic in the early stages, which contributes to its underdiagnosis and undertreatment. Many individuals may not realize they have a gum disease until significant damage has occurred, making early detection and intervention crucial [10]. The risk factors for gum disease include poor oral hygiene, smoking, diabetes, and genetic predisposition [11]. The chronic nature of gum disease and its potential impact on overall health, such as its association with cardiovascular disease and diabetes, underscores the need for improved diagnostic tools and preventive measures [12]. This has driven research into more accurate, early, and non-invasive diagnostic techniques to combat the global burden of periodontal disease [13].

2.2. Traditional Methods of Gum Disease Diagnosis

Traditional diagnostic methods for gum diseases are primarily clinical and rely on the physical examination of the oral cavity. These methods include visual inspection of the gums to detect signs of inflammation, such as redness and swelling, and probing to measure the depth of periodontal pockets—spaces that form between the teeth and gums due to disease [14]. Radiographic imaging is also commonly used to assess the extent of bone loss around the teeth [15]. While these methods are standard in dental practice, they often depend heavily on the clinician's expertise and experience, leading to potential variability in diagnosis and treatment planning [16].

The subjectivity inherent in traditional diagnostic techniques can result in inconsistencies, particularly in borderline cases where the symptoms are not pronounced. Moreover, these methods may not detect the disease until it has progressed to a more advanced stage, when irreversible damage has already occurred [17]. This highlights a critical need for diagnostic tools that can identify gum disease earlier and with greater accuracy, reducing the reliance on clinician judgment and improving patient outcomes [18]. Advances in technology, such as the development of digital imaging and analysis tools, are beginning to address some of these limitations, but the integration of more sophisticated diagnostic systems, such as those based on artificial intelligence, holds even greater promise [19].

2.3. Introduction to Fuzzy Expert Systems

Fuzzy Expert Systems (FES) represent a significant advancement in artificial intelligence, offering a powerful tool for decision-making in environments characterized by uncertainty and imprecision. Developed from the concept of fuzzy logic introduced by Lotfi Zadeh in the 1960s, FES allows for reasoning that accommodates degrees of truth rather than a binary true/false paradigm [20]. This capability makes FES particularly suitable for complex and ambiguous situations where traditional binary logic systems might fall short. In FES, inputs are mapped to outputs using a set of rules that reflect the expertise of human specialists, allowing the system to make nuanced decisions even in the presence of incomplete or unclear data [21].

The application of FES in various domains has demonstrated its versatility and effectiveness. In engineering, FES has been used to manage complex control systems, while in finance, it helps model market behaviors that are too intricate for conventional algorithms [22]. In healthcare, FES has been applied to diagnostic systems, treatment planning, and patient monitoring, offering a more adaptive approach to medical decision-making [23]. The ability of FES to integrate multiple inputs and provide a comprehensive assessment makes it an ideal candidate for enhancing medical diagnostics, particularly in fields like dentistry where patient symptoms and disease progression can vary widely [24].

2.4. Application of Fuzzy Expert Systems in Healthcare

In healthcare, the adoption of Fuzzy Expert Systems has been steadily increasing, particularly in diagnostic applications where the complexity and variability of symptoms present significant challenges [25]. FES allows for the incorporation of a wide range of patient data—such as clinical symptoms, patient history, and risk factors—into the decision-making process, leading to more accurate and personalized diagnostic outcomes [20]. For example, FES has been successfully implemented in diagnosing diabetes, where it evaluates a combination of symptoms and laboratory results to determine the likelihood of the disease [21]. Similarly, in cardiology, FES has been used to assess the risk of heart attacks by analyzing patient data that includes lifestyle factors, genetic predispositions, and clinical indicators [22].

The success of FES in these areas has opened the door for its application in dental diagnostics, where it can address the challenges posed by the variability and subjectivity of traditional methods. By using fuzzy logic, these systems can interpret ambiguous clinical signs and symptoms, providing a more refined and accurate diagnosis of conditions like gum disease [23]. Moreover, FES can assist in predicting disease progression and recommending appropriate treatment options, which is particularly valuable in managing chronic conditions like periodontal disease [24]. The integration of FES into dental practice could significantly enhance the quality of care by offering a more reliable and objective approach to diagnosis and treatment planning [25].

2.5. Fuzzy Expert Systems for Gum Disease Identification

Recent studies have explored the potential of Fuzzy Expert Systems in the identification and diagnosis of gum diseases, with promising results. These systems utilize a combination of clinical signs, patient-reported symptoms, and risk factors such as smoking or diabetes to assess the likelihood of different types of gum disease. For instance, a study by [26], developed a fuzzy logic-based system that could diagnose gingivitis and periodontitis with high accuracy [26]. The system used fuzzy rules derived from expert knowledge to evaluate the severity of symptoms and suggest a diagnosis, demonstrating the potential of FES to enhance traditional diagnostic methods [27].

The key advantage of FES in gum disease diagnosis lies in its ability to manage the inherent uncertainties associated with periodontal assessments. Traditional diagnostic methods often struggle with the subjective nature of symptoms and the variability in disease progression among patients [28]. FES addresses these challenges by providing a more nuanced evaluation, which can lead to earlier detection and more effective treatment. Furthermore, FES can be continuously updated with new clinical data and expert insights, making it a dynamic tool that evolves with advancements in periodontal research. This adaptability ensures that FES remains relevant and effective in the rapidly changing landscape of dental healthcare [29].

Despite the significant potential of Fuzzy Expert Systems in the diagnosis of gum diseases, there are still several challenges that need to be addressed. One of the primary challenges is the requirement for large and diverse datasets to train these systems effectively. FES relies on extensive input data to accurately model the complexities of gum disease, and obtaining such data can be difficult, particularly when it comes to standardized and high-quality datasets [30]. Additionally, the development of fuzzy rules requires significant expertise and can be time-consuming, making the initial setup of these systems resource-intensive.

Integrating FES into clinical practice poses its own set of challenges. Dentists and healthcare providers may be hesitant to adopt new technologies, particularly those that require a shift from traditional diagnostic methods. Overcoming this resistance requires robust evidence of the effectiveness of FES, as well as training and education to ensure that practitioners are comfortable using these systems. Future research should focus on refining FES models, expanding their diagnostic capabilities, and conducting large-scale clinical trials to validate their effectiveness. Moreover, the development of user-friendly interfaces and standardized protocols will be crucial in facilitating the integration of FES into everyday clinical practice, ultimately improving patient outcomes in the diagnosis and management of gum diseases [27].

3. Methodology

The research methodology used for this project is illustrated in figure 2 This methodology consists of six primary phases: preliminary study, knowledge acquisition, knowledge representation, system design, system development, and finally, testing and evaluation.

3.1. Preliminary Study

The main activity is to find a suitable topic and domain for this research. The title chosen is "Gum Diseases Identification Using Fuzzy Expert System," as found out through some research papers that people affected by dental problems do not have awareness and good care of their dental health because of their unhealthy lifestyle. The method chosen for this research is the fuzzy expert system. Figure 2 shows the research methodology framework used in this research.

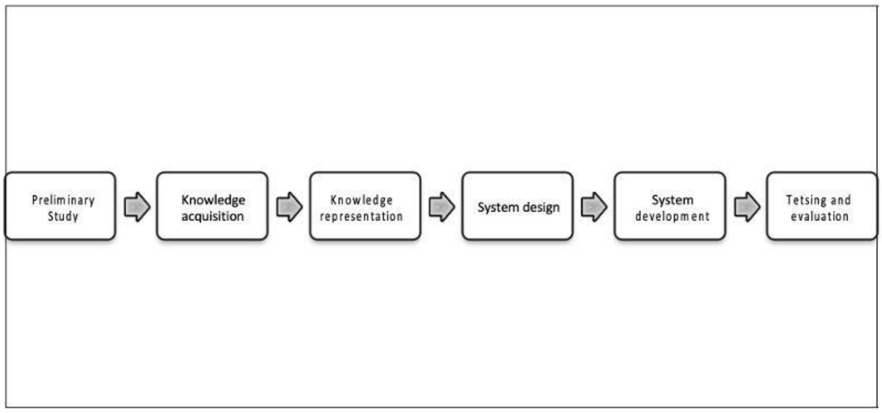


Figure 2. Research Methodology Framework.

3.2. Knowledge Acquisition

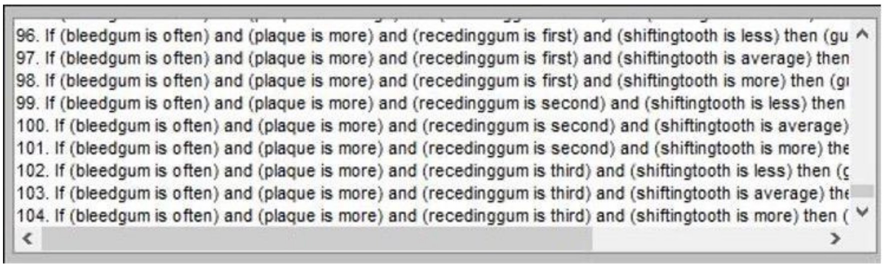
From the preliminary study, articles and journals that are found must be sorted into two categories: the gum diseases and the method used, which is the fuzzy expert system. The research articles and journals will be read and analyzed in this phase. The information needed from the articles and journals is being extracted for this research as guidelines. The deliverable for this phase is knowledge about gum diseases and the fuzzy expert system. For this research, based on previous research papers by [26] and a paper by [29], the chosen variables are the symptoms of gum diseases, which are the occurrence of gum bleeds per day, the number of teeth affected by plaque, the receding gum depth, and the number of shifting teeth. In this phase, I also had some discussions with the supervisor regarding the chosen topic and domain to fit the criteria needed for the research [30].

Articles and journals that are found must be sorted into two categories: the gum diseases and the method used, which is the fuzzy expert system. The research articles and journals will be read and analyzed in this phase. There are four input variables for this research. Each has its range and linguistic values. The range and linguistic values for each input variable are shown in table 1 below.

Table 1. The range and linguistic values for each input variable.

Input variables	Range	Linguistic value
The occurrence of gum bleeds per day	1-10 times	Rare Moderate Often
The number of teeth affected by plaque	1-32 teeth	Less Average More
The receding gum depth	1-10 mm	Less Moderate More
The number of shifting teeth	1-32 teeth	Less Average More

The input and output values in the designed fuzzy expert system and some created rules are presented. Figure 3 shows the total number of fuzzy rules created using the MATLAB software. MATLAB is software that helps solve problems using fuzzy logic [10].


96. If (bleedgum is often) and (plaque is more) and (recedinggum is first) and (shiftingtooth is less) then (gu
97. If (bleedgum is often) and (plaque is more) and (recedinggum is first) and (shiftingtooth is average) then
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99. If (bleedgum is often) and (plaque is more) and (recedinggum is second) and (shiftingtooth is less) then
100. If (bleedgum is often) and (plaque is more) and (recedinggum is second) and (shiftingtooth is average)
101. If (bleedgum is often) and (plaque is more) and (recedinggum is second) and (shiftingtooth is more) the
102. If (bleedgum is often) and (plaque is more) and (recedinggum is third) and (shiftingtooth is less) then (ç
103. If (bleedgum is often) and (plaque is more) and (recedinggum is third) and (shiftingtooth is average) the
104. If (bleedgum is often) and (plaque is more) and (recedinggum is third) and (shiftingtooth is more) then (

Figure 3. Fuzzy Rules created.

A total of 104 rules were written due to the general nature of the disease. Rules are steadily distributed in general, but according to output values, the disease stage was higher in patients with periodontitis. Figure 4 shows the fuzzy graph for variable gum bleed. This variable needs the user to input the number of occurrences of gum bleeding per day. The range is from one to ten times only. There are three linguistic values consisting of different ranges for each of them. Figure 5 shows the fuzzy graph for variable plaque. This variable needs the user to input the number of teeth the plaque affects. The range is from one to 32 teeth. There are three linguistic values consisting of different ranges for each of them.

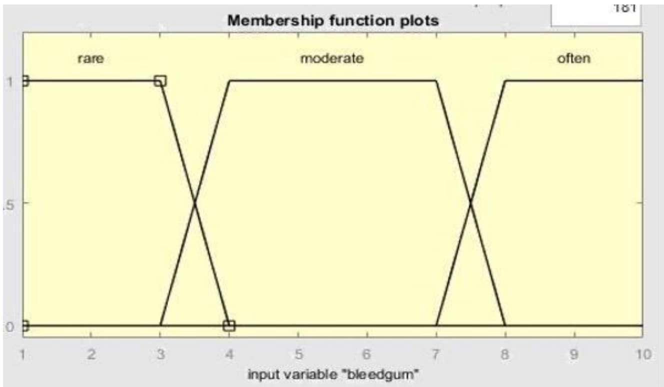

Figure 4. Fuzzy graph for variable gum bleed.

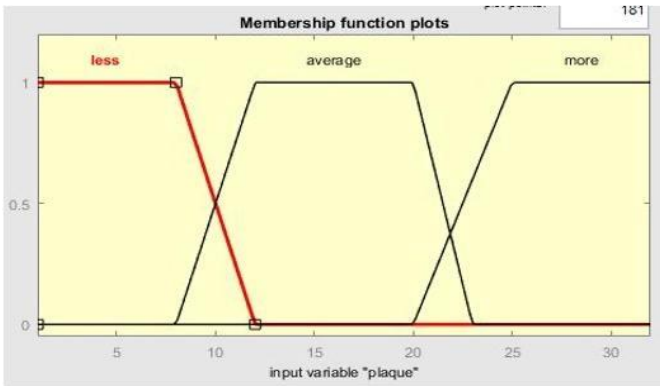

Figure 5. Fuzzy graph for variable gum plaque.

Figure 6 shows the fuzzy graph for variable receding gum. This variable needs the user to input the depth of the gum. The range is from one to ten millimetres (mm) only. There are three linguistic values consisting of different ranges for each of them. Figure 7 shows the fuzzy graph for variable shifting teeth. This variable needs the user to input the number of moving teeth. The range is from one to 32 teeth. There are three linguistic values consisting of different ranges for each of them. As for the results, the output will be the three different types of gum diseases. There are three gum disease types: Gingivitis, periodontitis, and advanced periodontitis. Figure 8 below shows the output's fuzzy graph/membership function plots. Figure 8 shows the fuzzy graph for the output of the three types of gum diseases. The range is from zero to one. There are three gum disease values of different ranges for each of them. This research uses MATLAB software to create fuzzy rules and graphs from the data collected.

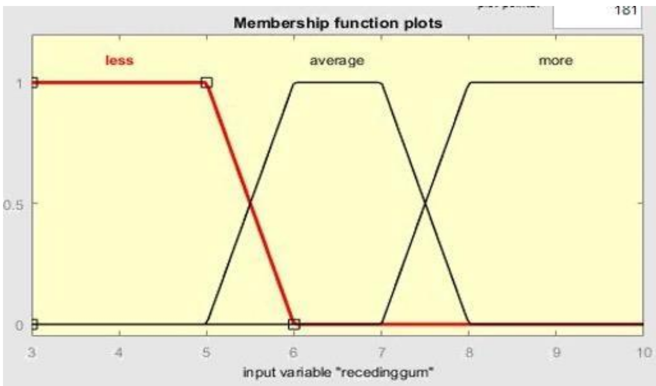

Figure 6. Fuzzy graph for variable receding gum.

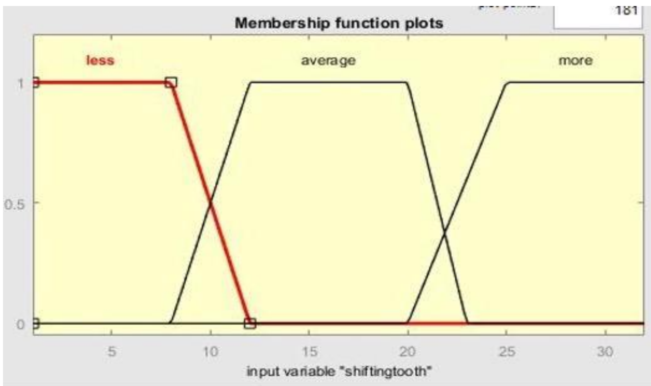

Figure 7. Fuzzy graph for variable shifting teeth.

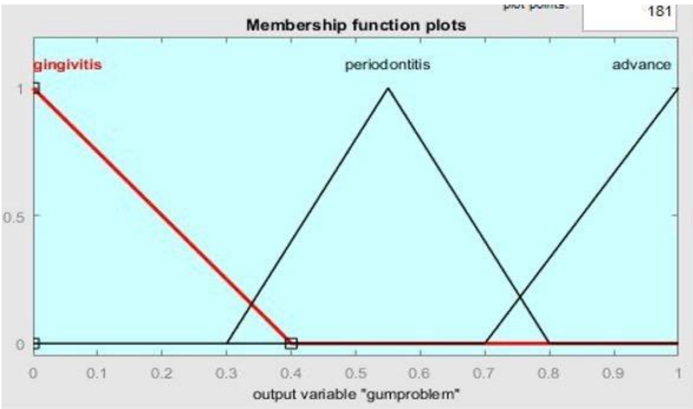

Figure 8. Fuzzy graph for variable gum problems.

The system architecture will show how the system works, as shown in figure 9. The system architecture shows how this research system flows from the beginning of the system.

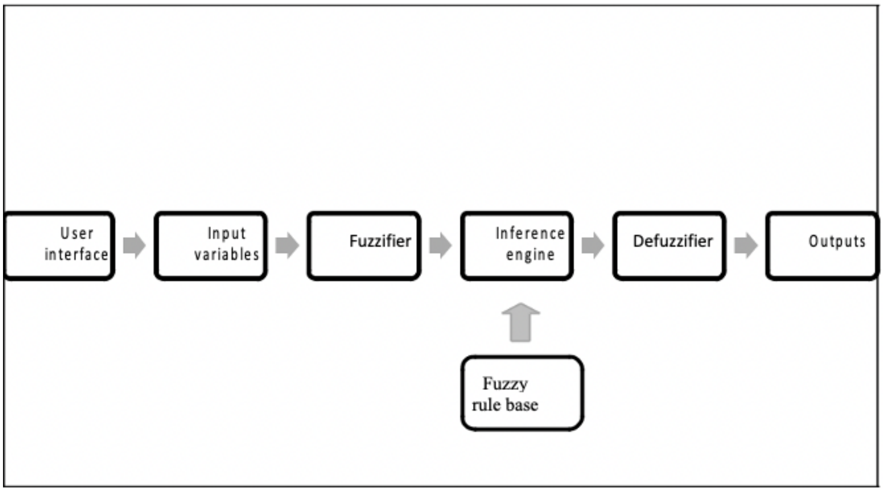

Figure 9. System Architecture.

Users must input values for each of four variables (the occurrence of gum bleeds per day, the number of teeth affected by plaque, the receding gum depth, and the number of shifting teeth). Then, the system will automatically generate the results and show which type of gum disease based on the inputs made by users. Figure 10 shows the first proposed interface for this fuzzy expert system. The interface design needs to be improved to be user-friendly and allow users to understand how to use the system.

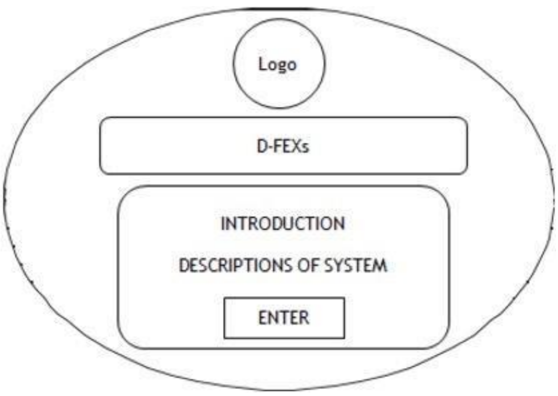

Figure 10. The proposed User interface (UI) for the Application.

The development of the system will use MATLAB, and the selected coding language will be based on the design from the system design phase. The output will be the type of gum disease based on the input values. Testing will be done to maintain the system's efficiency and accuracy. The application system and the flow of the application system are shown in figure 11 and figure 12.

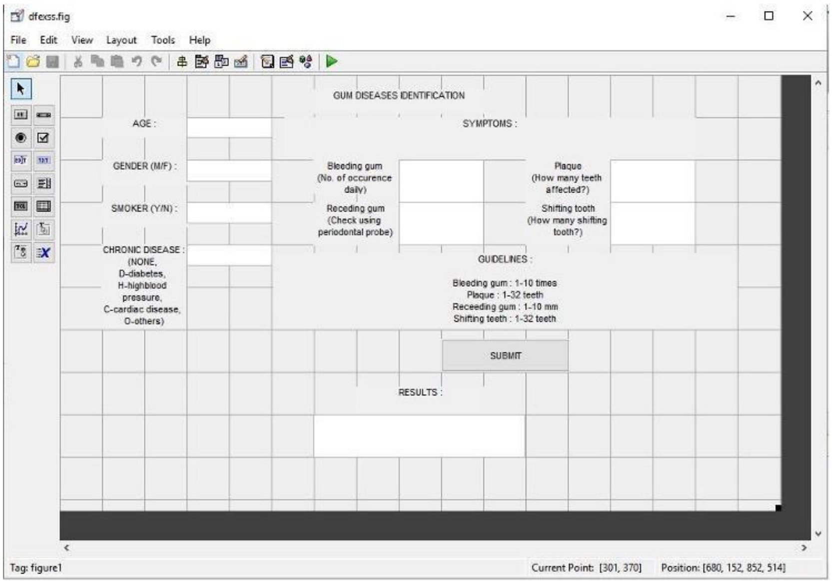

Figure 11. The Application System.

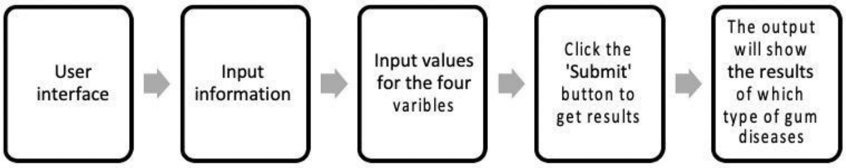

Figure 12. The flow of the Application System.

The flow of this system starts when users see the system interface, as shown in figure 12. On the left side of the user interface, users need to input information such as age, gender, smoker or non-smoker, and chronic diseases if related.

4. Result and Discussion

Upon completion of the system development, a thorough testing phase was conducted to ensure that the system's functionality aligned with the predefined objectives and specifications. The primary functionality of the system is its capability to accurately identify and diagnose various types of gum diseases, such as gingivitis, periodontitis, and other related conditions, based on user-provided input data. The system is designed to operate within the framework of a Fuzzy Expert System (FES), utilizing fuzzy logic to handle the uncertainties and variabilities commonly associated with medical diagnoses.

The testing process involved several key steps to validate the system's performance. Initially, the system was subjected to a series of test cases, each representing different scenarios of gum disease conditions. These test cases were carefully designed to cover a broad spectrum of potential inputs, ranging from mild symptoms, such as occasional gum bleeding, to more severe conditions, like significant gum recession and multiple loose teeth. For each test case, the system processed the input values provided by the user, including parameters such as the frequency of gum bleeding, the number of teeth affected by plaque, the depth of gum recession, and the degree of tooth mobility. The system then applied the fuzzy rules, which were predefined during the system's development phase, to generate a diagnosis. These rules were crafted based on expert knowledge and were intended to mimic the decision-making process of a dental professional.

The results produced by the system for each type of gum disease were meticulously evaluated. This evaluation involved comparing the system's output against expected outcomes, which were determined by consulting with dental experts and reviewing relevant medical literature. The primary objective was to ensure that the system's diagnoses were both

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accurate and reliable, reflecting the true nature of the gum disease based on the input data. A critical aspect of the evaluation was the use of fuzzy rules graphs, which were generated by MATLAB software. These graphs visually represented the fuzzy logic process, showing how the system arrived at its conclusions. By analyzing these graphs, testers were able to verify that the fuzzy logic was correctly implemented and that the system's reasoning process was transparent and logical. For instance, if a user input indicated frequent gum bleeding and significant plaque accumulation, the system would generate a diagnosis of moderate to severe gingivitis. The corresponding fuzzy rules graph would illustrate the logic used to reach this conclusion, showing how the input values interacted with the fuzzy rules to produce the final diagnosis.

To further validate the system's effectiveness, the generated fuzzy rules graphs were cross-referenced with clinical data from actual patient cases. This step served as a proof of concept, demonstrating that the system could replicate real-world scenarios and provide diagnoses that were consistent with those made by dental professionals. Moreover, the system's performance was tested for its robustness in handling borderline cases, where symptoms might be ambiguous or overlap between different types of gum diseases. The system's ability to accurately distinguish between similar conditions, such as mild periodontitis versus severe gingivitis, was crucial in establishing its practical utility in a clinical setting.

In addition to technical performance, the user interface was also evaluated to ensure that it was intuitive and user-friendly. The system was designed to guide users through the input process, making it straightforward for them to enter the required data. The feedback provided by users during testing indicated that the system was easy to navigate, with clear instructions and a logical flow from input to diagnosis. Overall, the testing phase confirmed that the system functions as intended, accurately identifying types of gum diseases based on user input and providing clear, reliable diagnoses. The use of fuzzy logic and MATLAB-generated graphs not only enhanced the system's diagnostic capabilities but also provided a transparent and verifiable method for understanding how each diagnosis was reached. This transparency is essential for building trust in the system's outputs, especially in a medical context where accuracy and reliability are paramount. Future work may focus on expanding the system's capabilities by incorporating more complex fuzzy rules, integrating additional input parameters, and conducting large-scale validation studies to further ensure its accuracy across diverse patient populations. For each type of gum disease, the results are evaluated based on the input values by the user, as shown in figure 13. These results can be proved by the fuzzy rules graphs generated by the MATLAB software based on the rules created.

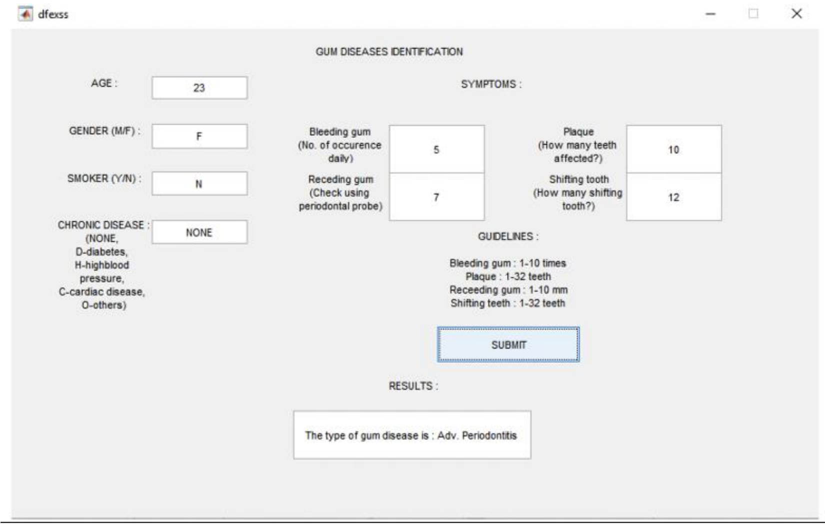

Figure 13. The first input value for the Application.

The test was conducted as follows. Figure 13 shows the input values for the four variables. For bleeding gum, the input value is 2. For plaque, the input value is 8. For receding gum, the input value is 5; for shifting tooth, the input value is 1. Figure 14 below shows the fuzzy rules graphs with each input value for all variables and the output values. If the output value is from 0 to 0.4, then the type of gum disease is Gingivitis. If the output value is from 0.3 to 0.8, then the type of gum disease is periodontitis. If the output value is from 0.7 to 1, then the type of gum disease is advanced periodontitis. All the processes involved were discussed in detail from their input, process, and output that was achieved. The techniques used are to process the system work and produce accurate results. From the results, all strengths and weaknesses of this system were identified.

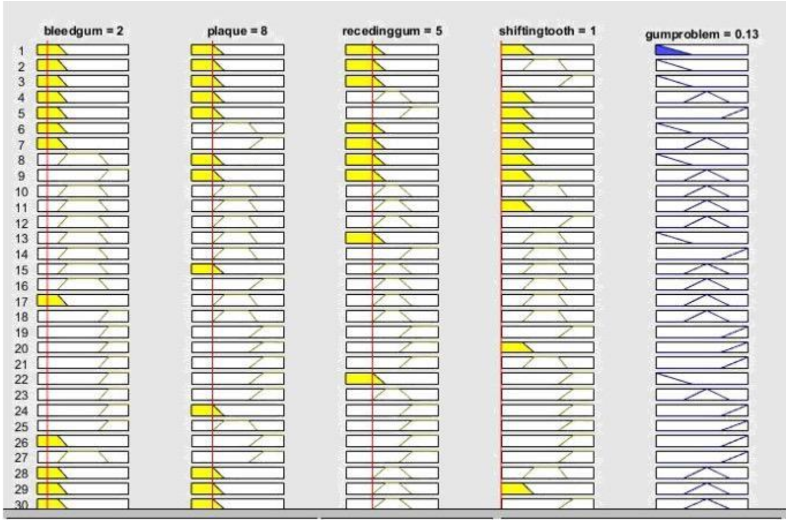

Figure 14. The first input value for the Application.

From figure 14, the output result shows a value of 0.133, which indicates that the identified type of gum disease is Gingivitis. This value is derived from the fuzzy logic system that processes the input data through a series of predefined rules within the Fuzzy Expert System (FES). In this particular scenario, the FES utilizes several input variables such as the frequency of gum bleeding, the extent of plaque accumulation, the depth of gum recession, and the degree of tooth mobility. These variables are initially fuzzified, meaning they are transformed from crisp numerical values into fuzzy sets that represent degrees of membership across different linguistic categories, such as "low," "medium," and "high."

Once the input values are fuzzified, the system applies a set of if-then rules that have been developed based on expert knowledge and previous clinical research. For instance, a rule might state, "If the frequency of gum bleeding is high, and the plaque accumulation is significant, then the likelihood of Gingivitis is high." These rules are critical as they guide the inference process, where the fuzzy logic system combines the different fuzzy inputs to evaluate the likelihood of each type of gum disease.

The inference process leads to an intermediate fuzzy output, which is then defuzzified to obtain a crisp numerical value, in this case, 0.133. The defuzzification process involves converting the fuzzy output back into a specific, actionable value, which can be interpreted by the clinician or the system as a diagnosis. The value 0.133 falls within a predefined range that corresponds to Gingivitis, confirming the diagnosis. This process highlights the flexibility and accuracy of Fuzzy Expert Systems in handling the inherent uncertainties in medical diagnosis. Unlike traditional diagnostic methods that rely on binary outcomes, the FES allows for a more nuanced understanding of the patient's condition by considering the degrees of severity across multiple factors.

The output value of 0.133 reflects the system's integrated assessment of the input variables according to the fuzzy rules. It determines that Gingivitis is the most likely diagnosis. This result not only aids in the accurate identification of the disease but also provides a foundation for subsequent treatment planning, as the severity of Gingivitis can be quantified and monitored over time using similar assessments. The ability to generate such detailed and precise outcomes underscores the potential of FES as a valuable tool in dental diagnostics, enhancing the quality of care by enabling early and accurate disease detection.

5. Conclusion

Gum problems, also known as periodontal diseases, can originate from various causes such as poor oral hygiene, genetic predisposition, and lifestyle factors like smoking and diet. These issues often present with a diverse array of symptoms, including gum bleeding, plaque accumulation, gum recession, and tooth mobility. Due to the complexity and variability of these conditions, timely and accurate diagnosis is critical to prevent progression to more severe stages, such as periodontitis, which can ultimately lead to tooth loss. Regular visits to a dentist are therefore essential for early detection and intervention.

This research focuses on utilizing a fuzzy inference engine with a rule-based system and the Center of Gravity (COG) method to identify and diagnose gum problems more efficiently. In the study, the system was tested with various input parameters related to gum health, and it generated an output value of 0.133. This specific output was found to correspond to the diagnosis of Gingivitis, a mild but common form of gum disease characterized by inflammation, redness, and bleeding of the gums. The accuracy of this result highlights the potential of the system in supporting dental professionals by providing a preliminary diagnosis based on quantifiable input data.

The fuzzy expert system developed in this research offers several advantages. By automating the diagnostic process, it provides a time-saving tool that can help guide dentists in quickly identifying the type of gum problem a patient may be experiencing. This can be particularly beneficial in busy clinical settings where time and resources are often limited. However, while the system offers a useful preliminary diagnosis, it should be emphasized that it is not a replacement for professional clinical judgment. The role of the dentist remains crucial in confirming the diagnosis, interpreting the broader clinical context, and determining the appropriate treatment plan.

Despite the promising results demonstrated in this study, the system still requires further development to enhance its effectiveness and reliability. One of the primary challenges identified is the need for a more extensive and diverse dataset. The accuracy of the fuzzy inference system is heavily dependent on the quality and breadth of the input data it processes. Therefore, gathering more comprehensive data on gum diseases from various dental experts across the globe would be instrumental in refining the system's rule base and improving its diagnostic accuracy. This continuous data collection and updating process would ensure that the system remains relevant and accurate in the face of evolving medical knowledge and changing patient demographics.

Additionally, the current system may face limitations due to the variability in the values of each diagnostic variable over time. Factors such as changes in patient health status, advancements in dental technology, and new research findings can all influence these variables, potentially leading to inaccuracies if the system is not regularly updated. To address this, implementing a dynamic updating mechanism within the system would allow it to adapt to new data and maintain its diagnostic accuracy over time.

Moreover, integrating additional or hybrid methods, such as machine learning algorithms or neural networks, could further enhance the system's capabilities. These methods could allow the system to analyze more complex patterns and relationships within the data, providing more nuanced and accurate diagnoses. For example, combining fuzzy logic with neural networks could enable the system to learn from new data inputs and improve its performance over time, making it more robust in handling a wider range of gum diseases and patient scenarios.

The potential for this system extends beyond its current application. With further development, it could be transformed into a mobile application, offering even greater accessibility and convenience for both dentists and patients. A mobile platform could include additional features such as patient history tracking, real-time data input, and integration with electronic health records (EHRs). This would not only streamline the diagnostic process but also enhance patient engagement and compliance with treatment plans. The development of a user-friendly interface and standardized protocols would be crucial in facilitating the adoption of such a system in everyday clinical practice.

In conclusion, this research demonstrates the potential of fuzzy expert systems in the field of dental diagnostics, particularly for identifying and managing gum diseases. The system’s ability to provide a preliminary diagnosis, such as identifying Gingivitis with an output value of 0.133, illustrates its utility in supporting clinical decision-making. However, to fully realize its potential, ongoing improvements are necessary, including expanding the dataset, incorporating hybrid methods, and developing a mobile application platform. These advancements would ensure that the system remains an effective, efficient, and widely accessible tool in modern dental practice, ultimately leading to better patient outcomes.

6. Declarations

5.1. Author Contributions

Conceptualization: M.N., T.B.K., D.A.D., M.Z.Z., and N.S.B.B.; Methodology: T.B.K. and N.S.B.B.; Software: M.N.; Validation: M.N., T.B.K., D.A.D., M.Z.Z., and N.S.B.B.; Formal Analysis: M.N., T.B.K., and D.A.D.; Investigation: M.N.; Resources: M.Z.Z. and N.S.B.B.; Data Curation: N.S.B.B.; Writing Original Draft Preparation: M.N., T.B.K., and D.A.D.; Writing Review and Editing: T.B.K., D.A.D., M.Z.Z., and N.S.B.B.; Visualization: M.N.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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