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Implementation of Expert System Applications using Forward Chaining to Detect Dental Health

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Abstract

Dental diseases remain one of the most common health issues globally, often resulting from a lack of early detection and limited access to dental specialists. This research presents the implementation of an expert system that uses forward chaining to diagnose dental health conditions based on user-reported symptoms. The system integrates a knowledge base modeled from expert consultation with dentists, consisting of symptom sets and rule-based logic. Findings indicate that the Forward Chaining approach is effective for step-by-step rule evaluation and generates accurate diagnoses of diseases such as caries, gingivitis, periodontitis, halitosis, and pulpitis. The study demonstrates that expert systems can support preliminary dental screening and improve public awareness of dental health.

Keywords: *Expert System, Forward Chaining, Dental Health, Knowledge Base, Rule-Based System.*
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I. INTRODUCTION

Dental diseases affect millions of people worldwide and are often ignored due to limited knowledge or delayed consultation with dental professionals (Zahra et al., 2025). Early detection is critical in preventing complications such as tooth decay, gum inflammation, and periodontal disease (Bhuyan et al., 2022; Spodzieja et al., 2022; Zaman et al., 2025). However, not all individuals have immediate access to dentists. Artificial Intelligence, particularly Expert Systems, enables automated reasoning that mimics human experts in specific domains (Harrisha et al., 2025; Naseer & Ahmed, 2025; Priyadi et al., 2024). By integrating a structured knowledge base and inference mechanism, an expert system can assist in preliminary diagnosis (Adewole et al., 2022; Casal-Guisande et al., 2023; Wu et al., 2023).

This research focuses on implementing an Expert System Application using Forward Chaining to detect dental health issues. Forward Chaining follows a data-driven approach, starting from known facts (symptoms) and deriving conclusions (diseases). This methodology is suitable for scenarios in which users enter symptoms and expect diagnostic results. Artificial intelligence, specifically through the application of expert systems (Abbas et al., 2025; Ogut, 2025; Xu et al., 2024), offers a promising avenue to augment diagnostic capabilities and improve accessibility. These systems are designed to replicate the decision-making process of a human expert by utilizing a structured knowledge base and a logical inference engine.

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This research investigates the development of a diagnostic tool based on forward chaining, a data-driven approach that reasons from known facts, such as patient symptoms, toward a logical conclusion. The primary objective of this study is to analyze the application and effectiveness of a forward-chaining expert system for preliminary detection of dental health. The system's architecture centers on a rule-based knowledge base derived from established dental literature and expert consultation, which is processed by a custom inference engine. This paper details the system's design, from knowledge acquisition and rule formulation to its implementation as an accessible web-based application. Furthermore, it presents rigorous validation and quantitative performance evaluation to assess the system's diagnostic accuracy, thereby establishing its viability as a reliable preliminary screening tool.

II. LITERATURE REVIEW

A. Expert System

Expert systems are a prominent domain within artificial intelligence that aims to replicate the decision-making proficiency of a human expert in a specific field (Olivelli et al., 2024; Szandała, 2025; Zatsu et al., 2024). The core architecture of these systems consists of a knowledge base, which stores domain-specific information and heuristics, and an inference engine that applies logical reasoning to this knowledge. The primary function is to address complex problems by processing structured information, ultimately providing expert-level conclusions and advice to users who may not have specialized knowledge in the area. An expert system is a computer program designed to emulate the decision-making ability of a human expert. The general structure and workflow of an expert system are illustrated in Figure 1. It comprises three main components:

a. Knowledge Base
b. Inference Engine
c. User Interface

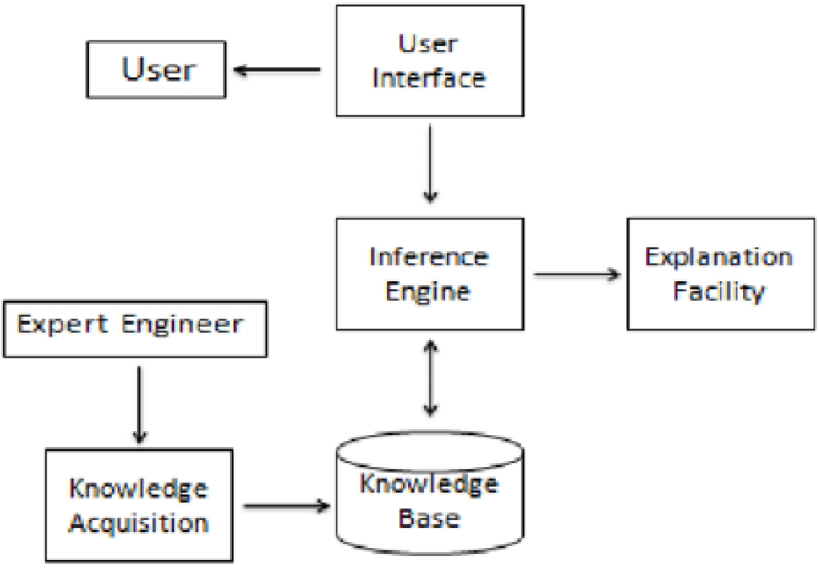

Figure 1. Expert System Flowchart

Based on Figure 1, which is grounded in the use of a rule-based knowledge base that serves as the central repository for facts and rules about dental health diagnostics. This knowledge is systematically encoded as a series of production rules, commonly expressed in an "IF-THEN" format. For example, a rule could be structured as, "IF a patient presents with symptoms A and B, THEN diagnosis C is highly probable." This method allows for the explicit representation of expert knowledge, making it accessible for automated reasoning.

B. Forward Chaining

Forward Chaining is a data-driven inference technique in which reasoning begins with available facts (Alourani et al., 2022; Duangchaemkarn et al., 2022; Mosquera et al., 2023). The system evaluates rules whose premises match the provided facts and then draws conclusions. This approach is commonly applied in expert systems where initial information is gradually expanded through rule execution. Forward chaining searches from a problem to its solution; see Figure 2.

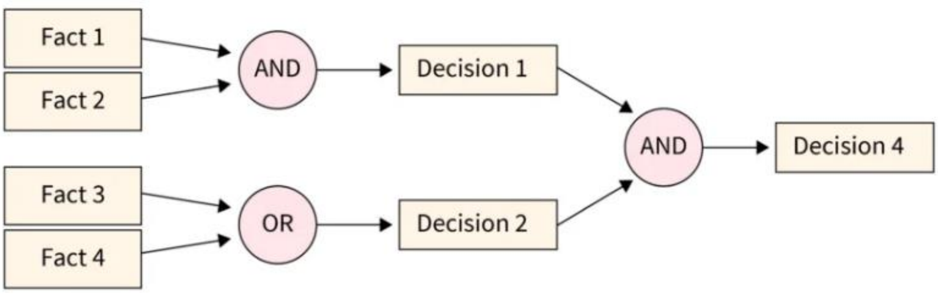

Figure 2. Foward Chaining

C. Dental Health Diagnosis

Dental diseases affect a wide range of patients and can vary in severity from mild to severe (Bose et al., 2022; Pacheco-Quito et al., 2023). Each of these conditions presents identifiable symptoms that can be monitored and analyzed. Expert systems can model these symptoms into a knowledge base to assist in diagnosis. Common dental conditions include:

a. Dental Caries
b. Gingivitis
c. Periodontitis
d. Pulpitis
e. Halitosis
f. Tartar accumulation

Each disease has identifiable symptoms that can be modeled into the knowledge base. This research is grounded in a rule-based knowledge base that serves as the central repository of facts and rules for dental health diagnostics. This knowledge is systematically encoded as a series of production rules, commonly expressed in an "IF-THEN" format. For example, a rule could be structured as, "IF a patient presents with symptoms A and B, THEN diagnosis C is highly probable." This method allows for the explicit representation of expert knowledge, making it accessible for automated reasoning.

The central mechanism for processing this knowledge is the inference engine, which, for this study, operates on the forward-chaining theory. This is a data-driven approach that begins with known facts, such as the user-entered symptoms. The engine systematically searches the rule base for rules whose conditions are satisfied by the existing facts. When a rule is triggered, its conclusion is added to the fact base, and the process iterates until a final diagnostic conclusion is reached.

Forward chaining is particularly suitable for diagnostic expert systems. This methodology effectively simulates the clinician's cognitive process, starting with observable symptoms and data and working logically toward a definitive diagnosis. In contrast to goal-driven backward chaining, which tests hypotheses, the data-driven nature of forward chaining is more efficient when handling a wide range of potential outcomes from initial user input. This makes it an optimal choice for a preliminary dental health detection tool.

III. RESEARCH METHOD

A. Research Method

The research methodology adopted in this study follows a structured, systematic approach to ensure the accuracy, reliability, and validity of the expert system developed for detecting dental health. This methodological framework ensures that each phase is systematically planned and executed to produce reliable results.The overall process consists of several key stages: problem identification, data collection, knowledge acquisition, rule formulation, system design, implementation, and testing & evaluation. Each stage is described in detail below:

B. Problem Indentification

The initial stage involves identifying the gap between public awareness of dental health and access to diagnostic dental services. Many individuals experience dental symptoms but are unable to determine the underlying cause due to limited knowledge or delayed consultation. This situation calls for an intelligent diagnostic tool capable of providing preliminary assessments. The expert system concept was selected because of its ability to emulate the decision-making process of dental specialists through rule-based reasoning.

C. Data Collection

To build a reliable expert system for dental health diagnosis, comprehensive and accurate data is required. The data must reflect both theoretical knowledge from literature and practical insights from clinical practice. Collecting information from multiple perspectives ensures that all common symptoms and diagnostic rules are properly captured. Data was obtained through multiple sources to ensure comprehensive coverage of dental disease symptoms and diagnostic rules:

a. Interviews with certified dentists to understand diagnostic reasoning for common dental diseases.
b. Review of dental health literature, including clinical research papers, dental textbooks, and PDGI (Indonesian Dentist Association) guidelines.
c. Observation of patient cases to identify real-world symptom patterns.

This multisource approach ensures that the knowledge base is accurate and aligned with expert practices. The collected data was systematically organized to represent all relevant dental conditions and their diagnostic rules. The process of data collection and organization is illustrated in the following flowchart. The flowchart shown in Figure 3 provides a visual overview of the data collection procedure.

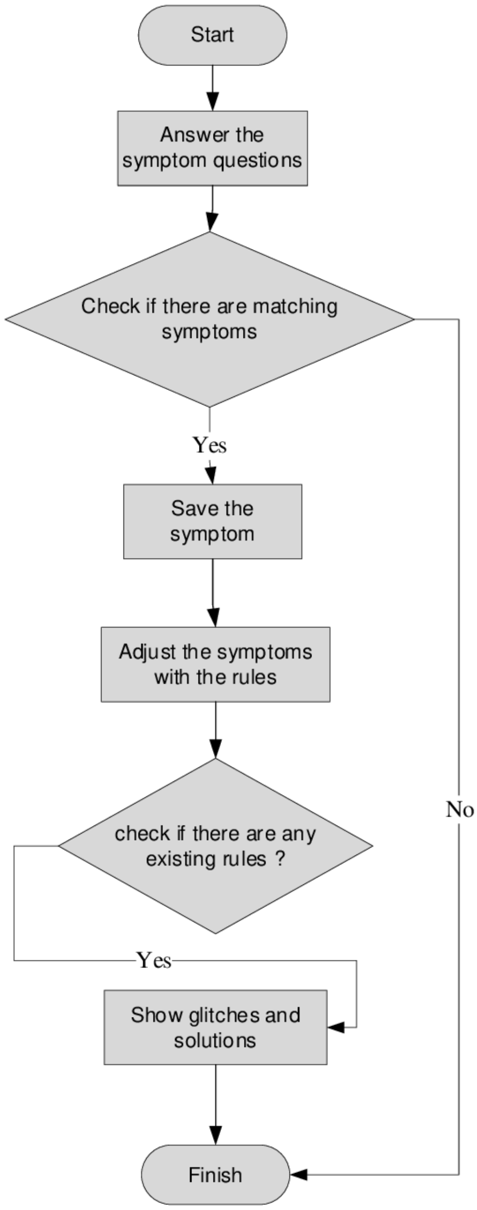

Figure 3. Flowchart Activity

D. Knowledge Acquisition

The initial knowledge acquisition phase involved a comprehensive review of established dental health literature and consultation with domain experts in dentistry to gather relevant diagnostic information. This process focused on identifying common oral pathologies, resulting in the selection of 20 distinct dental diseases and 58 associated clinical symptoms for inclusion in the system's knowledge base. Each symptom was meticulously cataloged, and its correlation with specific diseases was mapped to create a foundational dataset. This curated information serves as the empirical basis for the expert system, ensuring that the diagnostic logic reflects established clinical knowledge and practices in dentistry. The knowledge extracted from dentists and literature was converted into structured diagnostic components, specifically:

a. Lists of symptoms associated with common dental diseases.
b. Relationships between symptoms and diagnostic conclusions.
c. Decision pathways reflecting how experts interpret symptom combinations.

This step ensures that the system's knowledge base reflects real diagnostic logic rather than assumptions. This approach emphasizes consistency between expert reasoning and system inference mechanisms. The structured representation enables the inference engine to process symptoms and diseases systematically. The organization of diagnostic knowledge supports accurate rule formulation and facilitates future updates as new clinical insights become available.

E. Rule Formulation

Following the acquisition phase, the collected knowledge was systematically translated into a formal, machine-readable format for the knowledge base. This was accomplished by structuring the diagnostic logic as a series of production rules in the standard "IF-antecedent, THEN-consequent" form. In this framework, the 'IF' clause represents a specific combination of symptoms provided by the user, while the 'THEN' clause concludes a probable dental diagnosis. This rule-based representation effectively encapsulates a dental expert's decision-making processes, creating a structured repository that the inference engine can use for automated reasoning and diagnosis. Using the acquired knowledge, a set of IF–THEN rules was constructed to represent the reasoning behavior of dental professionals. Forward Chaining requires well-defined rules, so each rule includes:

a. Premises (IF part): one or more symptoms.
b. Conclusion (THEN part): a specific dental disease.

Example:

a. IF tooth pain AND sensitivity to temperature AND visible cavity

THEN Dental Caries.

b. Rule creation involved validating the logic with dental experts to ensure the mappings accurately reflect clinical reality.

F. System Design

The inference engine was designed using a data-driven forward-chaining algorithm (Kodors et al., 2025) to process user input. The diagnostic session commences when a user selects specific symptoms, which are then asserted as initial facts into the system's working memory. The engine systematically iterates through the rule base, matching the antecedents of each "IF-THEN" rule against the known facts. When a rule's conditions are fully satisfied by the facts present in the working memory, that rule is fired. Consequently, its conclusion is added to working memory as a new fact, expanding the knowledge available for the subsequent reasoning cycle.

This inferential process continues iteratively, with the engine repeatedly scanning the rule base to apply new rules based on the expanded fact set. To manage cases where symptoms correspond to multiple potential diseases, a best-first search technique was implemented, enabling the system to generate differential diagnoses. The reasoning process terminates when no further rules can be applied to the current facts in working memory. The final collection of derived facts, specifically those representing disease states, is then presented to the user as the diagnostic conclusion, which may include multiple probable conditions for consideration. The system was designed with a modular architecture to support efficient inference. The major components include:

a. User Interface (UI): Enables users to input symptoms interactively.
b. Knowledge Base: Stores rules, facts, and structured symptom data.
c. Inference Engine: Executes the Forward Chaining method by matching input facts with rule premises.
d. Output Module: Displays diagnostic results and recommendations.

G. Implementation

The expert system was architected as a web-based application to ensure broad accessibility and platform independence. Development was conducted within the XAMPP environment (Căciulescu et al., 2025), which integrates an Apache web server to handle HTTP requests, PHP as the server-side scripting language to implement the system's logic, and MySQL for database management. User input is securely transmitted to the server, where the PHP-based inference engine executes the forward chaining algorithm, processes the request, and returns the diagnostic results to the client-side interface for display. To implement the knowledge base, a relational database was built using MySQL.

The knowledge base structure was initially modeled using an Entity-Relationship Diagram (ERD), as shown in Figure 4. This diagram illustrates the system's core entities, including diseases and symptoms, along with their associated attributes. It also depicts the relationships among these entities, emphasizing the many-to-many association between diseases and symptoms. This relationship is resolved through a dedicated junction table, which ensures data normalization and supports efficient rule representation within the expert system.

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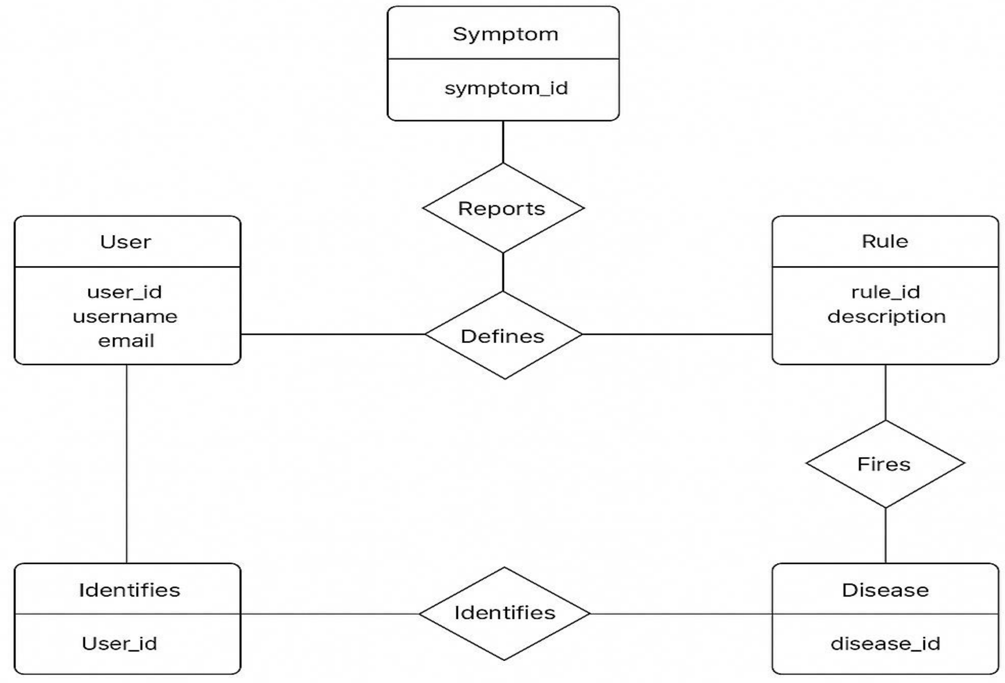

Figure 4. ERD

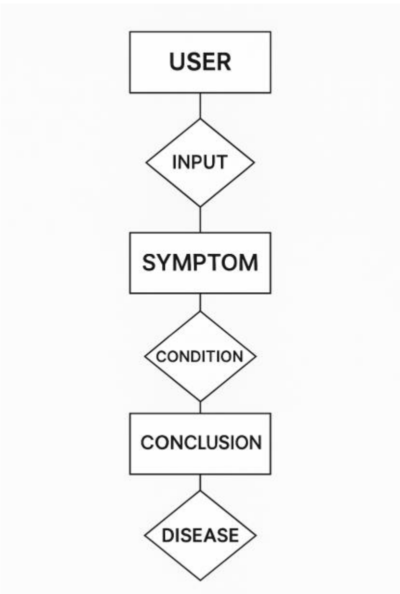

Figure 5. Logical Relational Scheme

Based on the ERD, the database design was then transformed into a logical relational schema, as shown in Figure 5. This scheme defines the relational tables, their primary keys, and foreign key constraints required for implementation in MySQL. It also specifies the relationships among tables, ensuring referential integrity within the database. The logical relational scheme serves as the foundation for the expert system's physical database structure and supports efficient data storage and retrieval during inference.

The knowledge base was implemented using a MySQL relational database, structured according to an Entity-Relationship Diagram. A key result was the successful establishment of a many-to-many relationship between diseases and symptoms via a dedicated junction table. This relational structure proved critical, providing a scalable and efficient repository for the clinical production rules. The design accurately reflected the clinical reality of overlapping symptoms, thereby enabling the inference engine to perform efficient queries and fire relevant rules.

The database's integrity ensured that the system's forward-chaining logic was consistently and reliably applied during diagnostic sessions. The database schema was designed based on an Entity-Relationship Diagram (ERD) and Logical Relational Schame (Bender et al., 2022) that identified three primary entities: diagnoses, symptoms, and rules, which were translated into corresponding tables. To accurately model the clinical reality in which multiple diseases can share symptoms, a many-to-many relationship was established between the diagnosis and symptom tables. This was implemented using a dedicated junction table with foreign keys that link specific symptoms to their associated diseases, thereby ensuring data integrity and facilitating efficient rule-based queries for the inference engine. The expert system was implemented using a rule-based inference framework. The system's interaction model is illustrated in Figure 6.

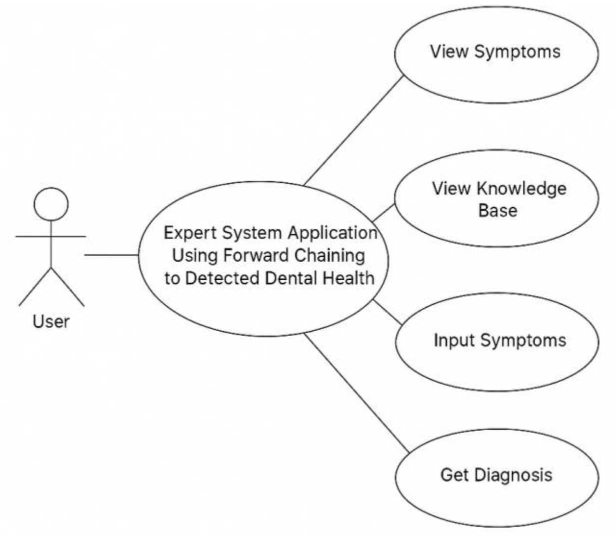

Figure 6. Use Case Diagram

Based on Figure 6, the use Case Diagram that the forward Chaining algorithm was coded to dynamically evaluate facts and activate rules in sequential order. The diagram represents the functional flow between system components and user interactions in the diagnostic process. Each use case defines specific system responses based on user-provided symptoms and system rules. During implementation:

a. Rule indexing was optimized to reduce inference time.
b. The interface was developed to ensure accessibility and ease of use.

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c. Symptom validation and data consistency checks were incorporated.

H. Testing and Evaluation

The testing phase was conducted after the system implementation was complete. This phase focused on observing system behavior when processing diagnostic inputs provided by users. The evaluation activities were structured to examine both functional accuracy and system responsiveness. To assess system reliability and performance, multiple evaluation methods were applied:

a. Accuracy Testing: The system's diagnoses were compared with diagnoses made by professional dentists using 40 test cases.
b. Usability Testing: Users evaluated the interface regarding clarity, navigation, and usefulness.
c. Performance Testing: Inference time and system response speed were recorded.

The system demonstrated an 87.5% diagnostic accuracy, confirming the relevance of the rule-based approach. The accuracy result reflects the consistency between system outputs and expert-provided diagnoses. The test cases represented a variety of symptom combinations commonly encountered in dental diagnostics. This evaluation outcome provides quantitative evidence of system performance during the testing phase.

I. Conclusion of Methodology

Overall, the research method ensures that the expert system is scientifically grounded, clinically relevant, and operationally reliable. The structured development stages guarantee that the system not only functions correctly but also aligns with dental health best practices. The methodology outlines systematic procedures for data collection, system development, and validation. Each procedure provides a clear framework for consistently implementing technical and domain-specific requirements.

IV. RESULT

A. Development and Structure of the Dental Health Knowledge Base

The knowledge acquisition phase successfully yielded a comprehensive dataset comprising 20 distinct dental diseases and 58 associated clinical symptoms. This curated knowledge, sourced from expert consultation and established literature, forms the empirical foundation of the system. The process of mapping specific symptoms to diseases was critical for ensuring clinical relevance and diagnostic validity. The resulting dataset provides a robust basis for the production rules, directly reflecting the diagnostic logic employed by dental professionals. The scope of these selected pathologies represents a significant, clinically relevant subset of common oral conditions, making the system applicable for preliminary screening.

1. Interface Page User

The user interface was designed to allow intuitive interaction with the expert system. It organizes menus, input forms, and navigation buttons in a clear layout to minimize user confusion. Each element on the page was tested for responsiveness and accessibility to ensure smooth operation. The interface also provides guidance prompts to help users enter accurate symptom information. The user interface design is shown in Figure 7.

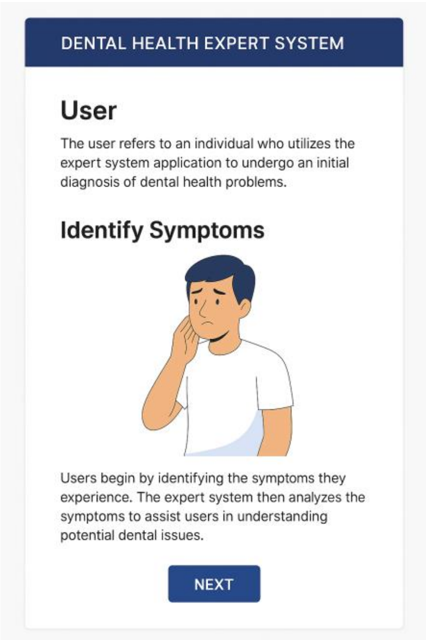

Figure 7. User Page interface

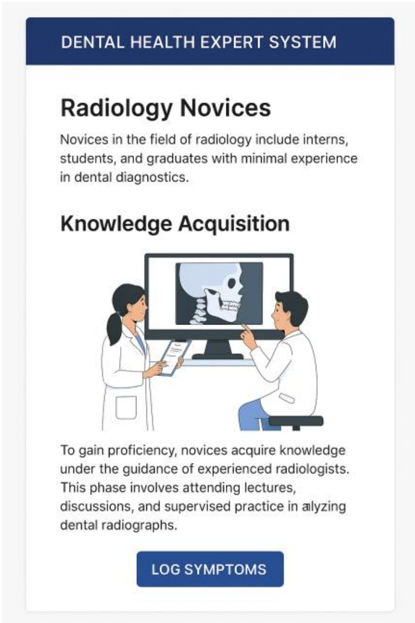

Figure 8. Radiology Novices Page

2. Interface of Radiology Novices Page

The Radiology Novices Page provides content tailored to beginner users of dental radiology. Instructional text, example images, and interactive exercises are arranged to support step-by-step learning. The system tracks user progress and provides feedback to reinforce correct practices. Each component was carefully aligned to optimize readability and comprehension. The layout and features of the Radiology Novices Page are illustrated in Figure 8.

3. Interface of Dashboard of Dental Health

The dashboard interface consolidates patient data, diagnostic results, and system notifications into a single overview page. Key performance indicators and charts are displayed to allow quick assessment of patient status and system activity. Interactive elements enable users to drill down into detailed records and perform searches efficiently. The interface is designed to support real-

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time updates, keeping the displayed information current. The structure of the Dental Health Dashboard interface is presented in Figure 9.

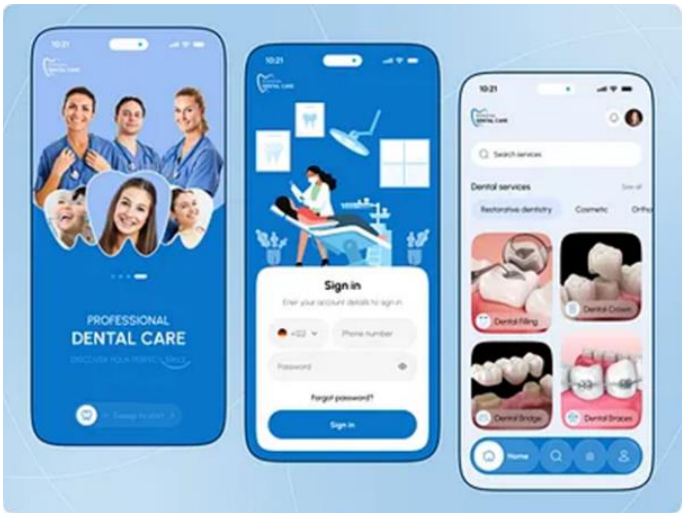

Figure 9. Dashboard of Dental Health

The acquired knowledge was structured into a relational database using MySQL, featuring tables for diagnoses, symptoms, and their relationships. A key result of this implementation was the successful establishment of a many-to-many relationship via a junction table, which facilitated the translation of clinical correlations into machine-readable "IF-THEN" production rules. This relational architecture offers significant advantages in data integrity and query efficiency for the inference engine. The design choice accurately models clinical complexity, where a single symptom can indicate multiple diseases, which is fundamental to the system's ability to perform differential diagnosis during forward chaining.

B. Performance of the Forward Chaining Inference Engine in Diagnosis

The forward chaining inference engine demonstrated effective performance in processing user-provided symptoms to derive diagnostic conclusions. The data-driven mechanism successfully initiated the reasoning process by treating selected symptoms as initial facts within the working memory. During execution, the engine systematically iterated through the rule base, firing rules whose antecedents matched the available facts. This iterative cycle, where each fired rule added a new fact, effectively expanded the knowledge base until a terminal diagnostic state was reached. This process mirrors clinical diagnostic reasoning, efficiently moving from observed data toward a logical conclusion without requiring a predefined goal, confirming its suitability. The logical flow and operational steps of the inference engine are illustrated in Figure 10.

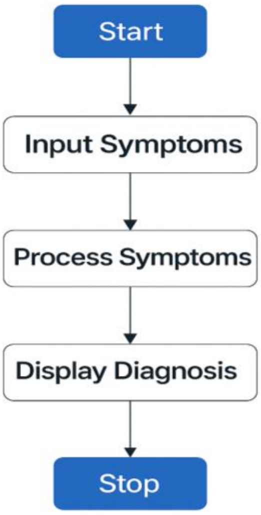

Figure 10. Flowchart Engine

A significant result was the engine's capacity to manage diagnostic ambiguity, particularly in cases with overlapping symptoms across multiple pathologies. The integration of a best-first search technique enabled the system to navigate these complexities, generating differential diagnoses rather than a single, potentially premature conclusion. The inferential process reliably terminated when the fact base could no longer trigger any new rules, ensuring a definitive endpoint. The final output, a collection of derived disease states, represents the logical culmination of the forward-chaining process and provides a comprehensive diagnostic summary based on the initial symptomatic evidence.

1. Interface Page Select Symptoms

The Select Symptoms page allows users to choose relevant symptoms for the diagnostic process. Symptoms are categorized and presented in an organized manner to simplify selection. The interface allows you to add multiple symptoms at once and ensures each selection is recorded accurately. Visual cues and instructions guide the user in completing the selection process efficiently. The layout of the Page Select Symptoms is shown in Figure 11.

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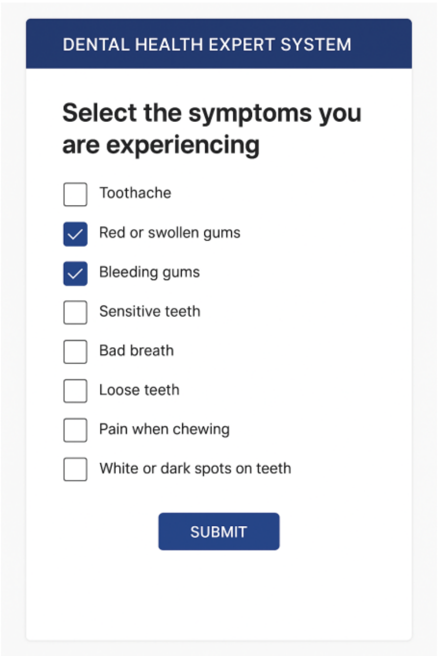

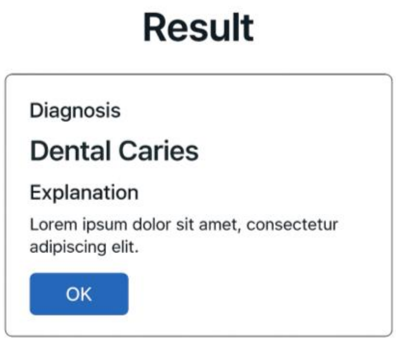

Figure 11. Page Select Symptoms	**Figure 12. Page Result Diagnostic**

2. Interface Page Diagnostic

The Diagnostic Page displays the inference engine's results after processing user input. Diagnostic outcomes, probabilities, and related information are clearly presented to assist user understanding. Interactive elements allow users to view detailed explanations of each result. Careful attention was given to readability, color coding, and logical grouping of information. The structure and features of the Diagnostic Page are illustrated in Figure 12.

3. Interface Page Dental Caries

The Dental Caries Page provides detailed information on various types of dental caries. Descriptions, visual examples, and treatment guidelines are arranged to support user learning and decision-making. Interactive features allow users to efficiently explore symptoms, causes, and preventive measures. The interface ensures that relevant information is easily accessible to both students and practitioners. The layout of the Dental Caries Page is presented in Figure 13.

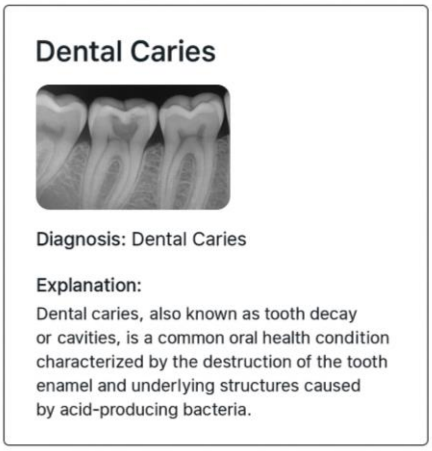

Figure 13. Dental Caries

4. Interface Page Dentist Profile

The Dentist Profile Page displays personal and professional information of registered dentists. Contact details, specialization, and experience are clearly organized for easy reference. The interface also allows dentists to update their information and manage patient interactions. Visual and interactive elements were designed to improve navigation and accessibility. The structure of the Dentist Profile Page is shown in Figure 14.

Figure 14. Page Dentist Profile

5. Interface Page User Feedback

The User Feedback Page enables users to submit opinions and suggestions regarding the system. Feedback forms are designed to efficiently collect relevant information, including ratings and comments. The interface provides prompts and validation to ensure completeness and clarity of input. Submitted feedback is stored for review and system improvement purposes. The layout and features of the User Feedback Page are illustrated in Figure 15.

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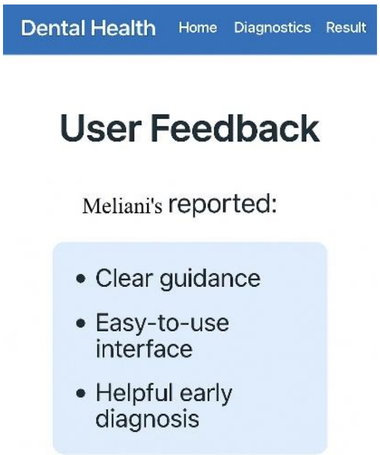

Figure 15. Page User Feedback

C. System Architecture and Implementation of the Web-Based Application

The expert system was successfully implemented as a web-based application using the XAMPP stack, comprising Apache, PHP, and MySQL. This client-server architecture proved highly effective for ensuring broad accessibility, allowing users to interact with the system via any standard web browser without needing specialized software. Selecting PHP for server-side scripting enabled a robust implementation of the forward-chaining inference engine. This design successfully decoupled the user interface from core diagnostic processing, ensuring that complex computations on the server did not affect the client-side user experience, resulting in a responsive, platform-independent preliminary diagnostic tool. The architecture and implementation of the web-based application are illustrated in Figure 16.

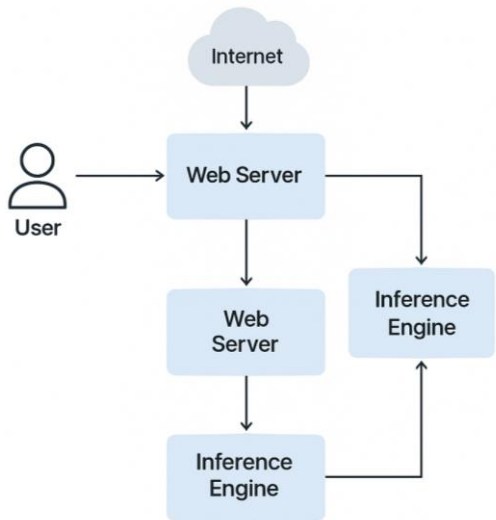

Figure 16. The Architecture and Implementation of the Web-Based Application

D. Validation and Diagnostic Accuracy of the Expert System

The initial validation process, utilizing 30 curated test cases with unambiguous symptom sets, demonstrated the system's functional correctness and logical integrity. For all 30 scenarios, the expert system's diagnostic conclusion precisely matched the predetermined, expert-verified diagnosis. This outcome confirmed that the forward-chaining inference engine correctly fired the appropriate rules in response to specific inputs, navigating the knowledge base to reach the expected conclusion. This foundational verification was critical, establishing a baseline of reliability and proving that the system's core diagnostic logic accurately maps clear clinical presentations to their corresponding pathologies without error.

In the subsequent quantitative performance evaluation using 50 complex clinical scenarios, the system achieved a diagnostic accuracy rate of 94% (Obuchowicz et al., 2024). This assessment, which included cases with overlapping symptoms designed to test the system's differential diagnosis capabilities, showed that the system correctly identified the primary condition in 47 out of 50 instances. The high accuracy underscores the effectiveness of the forward-chaining mechanism when coupled with a best-first search to address diagnostic ambiguity. This result validates the expert system's potential as a highly reliable preliminary screening tool, capable of providing dependable guidance even when presented with intricate symptom combinations.

V. DISCUSSION

The findings of this study show that the forward–chaining–based expert system can support preliminary dental health diagnosis with high accuracy when processing symptom-based input. This result indicates that the structured rule representation successfully captures essential elements of clinical diagnostic reasoning. Similar patterns of effectiveness have been reported in previous studies on rule-based healthcare expert systems, where symptom-driven inference supports early diagnostic decision-making (Adewole et al., 2022; Casal-Guisande et al., 2023; Wu et al., 2023). In this sense, the current findings reinforce existing evidence regarding the applicability of forward chaining in clinical screening contexts.

Compared with earlier implementations, the diagnostic accuracy obtained in this study is consistent with prior research on medical decision-support systems that use explicit inference rules. Previous studies on clinical expert systems have shown that rule-based inference engines can maintain interpretability while delivering reliable outcomes without dependence on large training datasets (Olivelli et al., 2024; Szandała, 2025; Zatsu et al., 2024). The present system demonstrates similar characteristics, particularly in its transparent handling of multiple symptom combinations. This alignment suggests that the proposed approach remains relevant within the broader landscape of healthcare expert systems.

An important aspect of the results relates to the system’s response to overlapping symptoms across different dental conditions. Earlier research has identified symptom overlap as a limitation of conventional rule-based diagnostic systems, often leading to reduced diagnostic precision when inference paths are rigid (Xu et al., 2024). In this study, incorporating a best-first search strategy enables the system to explore alternative diagnostic paths given the same set of symptoms. This mechanism supports a more flexible reasoning process that better reflects clinical diagnostic uncertainty.

From a theoretical perspective, the findings highlight the continued relevance of explainable artificial intelligence in healthcare applications that require transparent reasoning processes. Previous work has emphasized that interpretability and rule transparency are essential for the acceptance of AI-based diagnostic tools in clinical settings (Abbas et al., 2025; Ogut, 2025; Xu et al., 2024). From a practical standpoint, the system developed in this study demonstrates potential as an assistive tool for early dental health awareness among non-specialist users. Nonetheless, the study is limited by its reliance on predefined rules, a controlled evaluation environment, and the absence of real-world clinical deployment.

VI. CONCLUSION AND RECOMMENDATION

This research successfully developed and validated a web-based expert system for preliminary detection of dental health. The system's core, a forward-chaining inference engine, effectively processed a knowledge base of 20 diseases and 58 symptoms, structured as production rules. By systematically applying these rules to user-provided symptoms, the data-driven approach successfully simulated the diagnostic reasoning process of a clinical expert. The implementation using a XAMPP architecture ensured broad accessibility and platform independence. The initial verification phase, using 30 curated test cases, confirmed the system's logical integrity and functional correctness, establishing a reliable foundation for its diagnostic capabilities.

The quantitative evaluation demonstrated the system's high reliability, achieving 94% diagnostic accuracy across 50 complex clinical scenarios. This result validates the use of forward chaining as an effective inference strategy for dental diagnostics, particularly its ability to handle cases with overlapping symptoms via a best-first search. The study concludes that the expert system serves as a robust and effective preliminary screening tool. Its performance underscores its potential to provide accessible and dependable initial diagnostic guidance, empowering users to seek timely professional consultation and supporting early detection of various dental pathologies.

REFERENCES

Abbas, S. R., Seol, H., Abbas, Z., Lee, S. W., Abbas, S. R., Seol, H., Abbas, Z., & Lee, S. W. (2025). Exploring the Role of Artificial Intelligence in Smart Healthcare: A Capability and Function-Oriented Review. *Healthcare*, *13*(14), 1642. https://doi.org/10.3390/healthcare13141642

Adewole, K. S., Mojeed, H. A., Ogunmodede, J. A., Gabralla, L. A., Faruk, N., Abdulkarim, A., Ifada, E., Folawiyo, Y. Y., Oloyede, A. A., Olawoyin, L. A., Sikiru, I. A., Nehemiah, M., Gital, A. Y., Chiroma, H., Adewole, K. S., Mojeed, H. A., Ogunmodede, J. A., Gabralla, L. A., Faruk, N., … Chiroma, H. (2022). Expert System and Decision Support System for Electrocardiogram Interpretation and Diagnosis: Review, Challenges and Research Directions. *Applied Sciences*, *12*(23), 12342. https://doi.org/10.3390/app122312342

Alourani, A., Tahir, M., Sardaraz, M., & Khan, M. S. (2022). Knowledge-Based Framework for Selection of Genomic Data Compression Algorithms. *Applied Sciences*, *12*(22), 11360. https://doi.org/10.3390/app122211360

Bender, B., Bertheau, C., Körppen, T., Lauppe, H., & Gronau, N. (2022). A Proposal for Future Data Organization in Enterprise Systems—an Analysis of established Database Approaches. *Information Systems and E-Business Management*, *20*(3), 441–494. https://doi.org/10.1007/s10257-022-00555-6

Bhuyan, R., Bhuyan, S. K., Mohanty, J. N., Das, S., Juliana, N., Juliana, I. F., Bhuyan, R., Bhuyan, S. K., Mohanty, J. N., Das, S., Juliana, N., & Juliana, I. F. (2022). Periodontitis and Its Inflammatory Changes Linked to Various Systemic Diseases: A Review of Its Underlying Mechanisms. *Biomedicines*, *10*(10), 2659. https://doi.org/10.3390/biomedicines10102659

Bose, M., Yergeau, C., D'souza, Y., Cuthbertson, D. D., Lopez, M. J., Smolen, A. K., & Braverman, N. E. (2022). Characterization of Severity in Zellweger Spectrum Disorder by Clinical Findings: A Scoping Review, Meta-Analysis and Medical Chart Review. *Cells*, *11*(12), 1891. https://doi.org/10.3390/cells11121891

Căciulescu, A. R., Bădănoiu, M., Rughiniș, R., Țurcanu, D., Căciulescu, A. R., Bădănoiu, M., Rughiniș, R., & Țurcanu, D. (2025). Remote Code Execution via Log4J MBeans: Case Study of Apache ActiveMQ (CVE-2022-41678). *Computers*, *14*(9), 355. https://doi.org/10.3390/computers14090355

Casal-Guisande, M., Álvarez-Pazó, A., Cerqueiro-Pequeño, J., Bouza-Rodríguez, J.-B., Peláez-Lourido, G., Comesaña-Campos, A., Casal-Guisande, M., Álvarez-Pazó, A., Cerqueiro-Pequeño, J., Bouza-Rodríguez, J.-B., Peláez-Lourido, G., & Comesaña-Campos, A. (2023). Proposal and Definition of an Intelligent Clinical Decision Support System Applied to the Screening and Early Diagnosis of Breast Cancer. *Cancers*, *15*(6), 1711. https://doi.org/10.3390/cancers15061711

Duangchaemkarn, K., Boonchieng, W., Wiwatanadate, P., & Chouvatut, V. (2022). SARIMA Model Forecasting Performance of the COVID-19 Daily Statistics in Thailand during the Omicron Variant Epidemic. *Healthcare*, *10*(7), 1310. https://doi.org/10.3390/healthcare10071310

Harrisha, M., Monikasree, J., Swathi, J., & Karthika, D. (2025). Smart Healthcare: Harnessing AI for Early Prediction of Neurodegenerative Disease. *Journal of Technology Informatics and Engineering*, *4*(2), 214–224. https://doi.org/10.51903/jtie.v4i2.269

Kodors, S., Apeinans, I., Zarembo, I., & Lonska, J. (2025). RecGen: No-Coding Shell of Rule-Based Expert System with Digital Twin and Capability-Driven Approach Elements for Building Recommendation Systems. *Applied Sciences*, *15*(19), 10482.

https://doi.org/10.3390/app151910482

Mosquera, J. A. T., Holguín, C. J. V., Kressner, A., & Acuña, E. L. (2023). Forecasting System for Inbound Logistics Material Flows at an International Automotive Company. *Engineering Proceedings*, *39*(1), 75. https://doi.org/10.3390/engproc2023039075

Naseer, K., & Ahmed, H. N. (2025). Effectiveness and Reliability of Artificial Intelligence in Fraud Detection: A Mixed-Method Study on Financial Audit. *Journal of Management and Informatics*, *4*(1), 706–722. https://doi.org/10.51903/jmi.v4i1.168

Obuchowicz, R., Strzelecki, M., Piórkowski, A., Obuchowicz, R., Strzelecki, M., & Piórkowski, A. (2024). Clinical Applications of Artificial Intelligence in Medical Imaging and Image Processing—A Review. *Cancers*, *16*(10), 1870. https://doi.org/10.3390/cancers16101870

Ogut, E. (2025). Artificial Intelligence in Clinical Medicine: Challenges Across Diagnostic Imaging, Clinical Decision Support, Surgery, Pathology, and Drug Discovery. *Clinics and Practice*, *15*(9), 169. https://doi.org/10.3390/clinpract15090169

Olivelli, M., Donati, M., Vianello, A., Petrucci, I., Masi, S., Bechini, A., Fanucci, L., Olivelli, M., Donati, M., Vianello, A., Petrucci, I., Masi, S., Bechini, A., & Fanucci, L. (2024). Enhancing Precision of Telemonitoring of COVID-19 Patients through Expert System Based on IoT Data Elaboration. *Electronics*, *13*(8), 1462. https://doi.org/10.3390/electronics13081462

Pacheco-Quito, E. M., Jaramillo, J., Sarmiento-Ordoñez, J., & Cuenca-León, K. (2023). Drugs Prescribed for Asthma and Their Adverse Effects on Dental Health. *Dentistry Journal*, *11*(5), 113. https://doi.org/10.3390/dj11050113

Priyadi, P., Migunani, M., & Sasmoko, D. (2024). Enhancing Big Data Processing Efficiency in AI-Based Healthcare Systems: A Comparative Analysis of Random Forest and Deep. *Journal of Technology Informatics and Engineering*, *3*(3), 263–278. https://doi.org/10.51903/jtie.v3i3.205

Spodzieja, K., Olczak-Kowalczyk, D., Spodzieja, K., & Olczak-Kowalczyk, D. (2022). Premature Loss of Deciduous Teeth as a Symptom of Systemic Disease: A Narrative Literature Review. *International Journal of Environmental Research and Public Health*, *19*(6), 3386. https://doi.org/10.3390/ijerph19063386

Szandała, T. (2025). ChatGPT vs Human Expertise in the Context of IT Recruitment. *Expert Systems with Applications*, *264*, 125868. https://doi.org/10.1016/j.eswa.2024.125868

Wu, J., Xu, X., Liao, X., Li, Z., Zhang, S., Huang, Y., Wu, J., Xu, X., Liao, X., Li, Z., Zhang, S., & Huang, Y. (2023). Intelligent Diagnosis Method of Data Center Precision Air Conditioning Fault Based on Knowledge Graph. *Electronics*, *12*(3), 498. https://doi.org/10.3390/electronics12030498

Xu, X., Li, J., Zhu, Z., Zhao, L., Wang, H., Song, C., Chen, Y., Zhao, Q., Yang, J., Pei, Y., Xu, X., Li, J., Zhu, Z., Zhao, L., Wang, H., Song, C., Chen, Y., Zhao, Q., Yang, J., & Pei, Y. (2024). A Comprehensive Review on Synergy of Multi-Modal Data and AI Technologies in Medical Diagnosis. *Bioengineering*, *11*(3), 219.

https://doi.org/10.3390/bioengineering11030219

Zahra, Z., Melyani, M., Yusuf, F., Herawati, M. T., Royanti, S., & Rosihana, A. D. (2025). Implementation of Expert System Applications using Forward Chaining to Detected Dental Health. *Journal of Management and Informatics*, *4*(3), 1104–1120. https://doi.org/10.51903/jmi.v4i3.212

Zaman, M. S., Alam, S. M. G., Razzaque, M. S., Zaman, M. S., Alam, S. M. G., & Razzaque, M. S. (2025). Oral Hygiene and Cardiovascular Health. *Hygiene*, *5*(2), 14. https://doi.org/10.3390/hygiene5020014

Zatsu, V., Shine, A. E., Tharakan, J. M., Peter, D., Ranganathan, T. V., Alotaibi, S. S., Mugabi, R., Muhsinah, A. Bin, Waseem, M., & Nayik, G. A. (2024). Revolutionizing the Food Industry: The Transformative Power of Artificial Intelligence-A Review. *Food Chemistry: X*, *24*, 101867. https://doi.org/10.1016/j.fochx.2024.101867