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Application of fuzzy expert system method for early detection of dengue fever

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ABSTRACT

The application of the Fuzzy Expert System method in the early detection of dengue fever offers a promising approach to improve diagnostic accuracy. This study aims to develop a system that can overcome the diversity of dengue fever symptoms and uncertainty in the diagnosis process. Using medical record data of patients who have confirmed DHF, the study designed fuzzy rules for symptom evaluation, resulting in more precise diagnostic outputs. The results indicate the system's success in identifying dengue cases with high sensitivity and good positive predictive value. These findings confirm the importance of FES technology in clinical practice, especially for controlling and preventing dengue fever in endemic areas. Continued research will test this system in a broader clinical scenario to ensure its effectiveness and practicality in diverse medical environments.

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Introduction

Dengue fever is a disease caused by the dengue virus, transmitted through the bite of the Aedes aegypti mosquito (Wu et al., 2022) (Stephenson et al., 2021). According to the World Health Organization (WHO), the disease is one of the fastest-growing tropical diseases in more than 100 countries, with about half of the world's population at risk (Barnes et al., 2022),(Gasmi et al., 2020). Early detection of dengue fever is crucial in preventing the progression of the disease to a more severe stage, which can reduce mortality and morbidity (Sangkaew et al., 2021),(Tsheten et al., 2021). However, a significant challenge in early detection is that dengue symptoms are often nonspecific and similar to other febrile diseases, making early diagnosis difficult (Hegde & Bhat, 2022),(Grundy & Houpt, 2022). Given the limitations of conventional diagnostic methods that often require significant time and cost, this study focuses on developing alternative methods using Fuzzy Expert System (FES) (Afzal, 2020),(Saibene et al., 2021). FES is a promising approach to address the uncertainty and imprecision often found in disease diagnosis by utilizing fuzzy logic to simulate the human decision-making process (Khalaf et al., 2023).

The main objective of this research is to develop an early detection system for dengue fever that can improve the accuracy and efficiency of diagnosis (Hussain-Alkhateeb et al., 2021). By utilizing FES, this study aims to address the problem of early diagnosis of dengue fever, which is often hampered by nonspecific symptoms and variability of individual responses to infection (Ceconi et al., 2023).

This research proposes an innovative solution through the development and implementation of FES in dengue diagnosis, which is expected to contribute significantly to the control and management of dengue fever (Sievers et al., 2024),(Wang et al., 2020). By utilizing fuzzy rules designed based on input from medical experts and clinical data, the system developed is expected to not only improve diagnostic accuracy but also speed up the clinical decision-making process in dengue management (Kour et al., 2020) (Hoyos et al., 2021). The contribution of this research lies in the application of innovative FES technology in the medical field, especially in the early detection of dengue fever, which has the potential to reduce the burden of disease and improve the quality of life of patients (Kulkov et al., 2023),(Bergerot et al., 2020).

This research delves into the challenges of early detection of dengue fever, a widespread disease affecting over 100 countries with half the global population at risk. Given the often nonspecific symptoms of dengue fever that resemble other febrile illnesses, and the limitations of conventional diagnostic methods requiring significant time and cost. FES aims to overcome the uncertainty and inaccuracy commonly encountered in disease diagnosis by mimicking human decision-making processes, thus enhancing the accuracy and efficiency of dengue fever diagnosis. Through the development and implementation of FES in dengue diagnosis, this research seeks to make a significant contribution to the control and management of dengue fever, anticipating improvements in diagnostic accuracy and the acceleration of clinical decision-making in dengue management. This responds to the urgent need for innovative solutions in early dengue fever detection, which could lessen the disease burden and improve patients quality of life.

Method

Research Design

This study used a quasi-experimental design without a control group, where the research subjects were medical record data of patients diagnosed with dengue fever and simulation data for system testing. This approach was chosen to test the effectiveness of the Fuzzy Expert System (FES) in the early detection of dengue fever based on clinical symptoms and laboratory parameters without comparing with the control group.

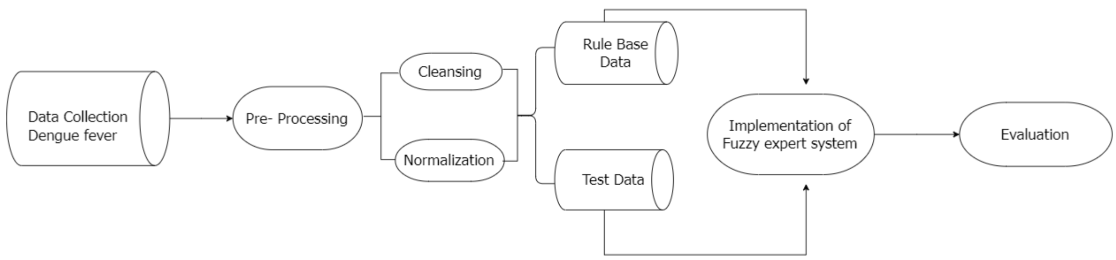

Figure 1. Research Flow

Figure 1. Explain the research flow for implementing a fuzzy expert system in the early detection of dengue fever. The process begins with data collection involving a data set of symptoms and test results associated with dengue. Furthermore, the preprocessing stage includes data cleansing to eliminate anomalies or errors and normalization to ensure the data is at a scale suitable for analysis. After preprocessing, the clean, normalized data is used to build and validate a rule base, a collection of rules describing the logic behind the diagnosis. The rule-based and test data are then applied to implement the fuzzy expert system, which will assess and diagnose new cases based on established rules. The results of this system are finally evaluated to determine its effectiveness in correctly diagnosing dengue.

Data Collection

Data is collected from the medical records of patients who have been diagnosed with dengue fever obtained from the Kaggle website, along with the source of the data (https://www.kaggle.com/datasets/wildarahmariskika/data-penyakit-demam-berdarah-dengue). This data includes clinical symptoms, laboratory results, and demographic information. In addition, simulated data is created based on criteria set by medical experts to test the system in diverse scenarios.

Data preprocessing

Includes cleaning data of missing or inconsistent values, normalizing values to ensure consistency of measurement scales, and encoding categorical variables. This process aims to prepare data so that FES can process it effectively.

Data cleansing involves identifying and handling missing or inconsistent values. Missing values can be resolved in various ways, such as deleting rows/data containing missing values or filling missing values with average, median, or mode values from those columns. For each categorical column in the data: Change the column to a new number of columns according to the number of categories for each row in the data. If the row has that category, Set the value of the new column to 1; otherwise, set the value of the new column to 0.

Normalization is scaling the value of data attributes to be within a specific range, usually between 0 and 1, to avoid the dominance of more considerable scale attributes to the analysis results. Here's what 1 is about (Mallikharjuna Rao et al., 2023),(Cheng, 2020).

$$X_{Normalized} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad \text{..........(1)}$$

In Equation 1. $X_{Normalized}$ *Is a normalized value, X* is the original value, and X_{max} , X_{min} It is the minimum and maximum value of the data.

Data Analysis

Data analysis is carried out by comparing the Fuzzy Expert System (FES) system results with the actual medical diagnosis from the patient's medical record (Manchadi et al., 2023). Fuzzy rules are also applied to optimize when test data is tested. This is done to verify the system's accuracy in diagnosing dengue fever. Medical experts also evaluate the system through simulations with hypothetical data to assess how well the system can mimic a specialist's decision-making process. Thus, the validity of the FES system is evaluated based on its ability to produce a diagnosis that aligns with the clinical assessment and experts' experience.

Evaluation

Evaluation of the effectiveness of the fuzzy expert system method in the early detection of dengue fever will use metrics such as sensitivity, specificity, positive predictive value, and negative predictive value. This will give an idea of the accuracy and reliability of the system in identifying dengue cases early.

$$Sensitivitas = \frac{TP}{TP + \mathrm{FN}} \quad \text{..........(2)}$$

Equation 2 explains that TP is the number of True Positives - cases where the system correctly identifies the presence of disease. FN is the number of False Negatives - cases where the system does not recognize the disease when it is present.

$$Spesitifitas = \frac{TN}{TN + \mathrm{FP}} \quad \text{..........(3)}$$

Equation 3 explains that TN is the number of True Negatives - the case where the system correctly identifies the absence of disease. FP is the number of False positive instances in which the system recognizes the presence of a disease when it does not exist.

$$Nilai\ Prediktif\ Positif\ = \frac{TP}{TP + \mathrm{FP}} \quad \text{.....................................(4)}$$

Equation 4 explains that it is used to measure the proportion of cases that the system identifies as positive that is indeed positive.

$$Nilai\ Prediktif\ Negatif\ = \frac{TN}{TN + \mathrm{FN}} \quad \text{.....................................(5)}$$

Equation 5 explains that it is used to measure the proportion of cases that the system identifies as negative that is indeed negative.

Results and Discussions

FES system development is done by converting symptom inputs into fuzzy values using membership functions based on expert knowledge. The system then performs inference with rules built from combinations of symptoms to produce a diagnosis output in the fuzzy form, which is then defuzzified into "Positive" or "Negative" categories. System performance is tested by comparing system diagnosis results against actual diagnosis results from data. The implementation of the Fuzzy Expert System is explained in the interface.

Figure 2. Data Input Page

Figure 2. Display several input data, including gender (using select) symptoms, using checkboxes to select more than one for each data. Next are Platelets and Hematocrit, which have values (standard or low); when the data has been inputted, the final step is to select the Diagnose button.

Figure 3. Display of Diagnostic Results

Figure 3. Displaying the final result of the diagnosis, the application of the system adjusts to the available fuzzy rules. The diagnosis is described, including whether you have dengue fever. After testing the data through the program, out of 20 trial data (14 data according to the results of data diagnostics, six did not match).

Table 1 Trial Data

Gender	Fever	Joint Pain	Nauseous	Headache	Vomit	Dumb	Muscle Pain	Platelets	Hematocrit	Diagnosis Results	Program Accuracy
Woman	1	1	1	0	0	1	0	Normal	Normal	Positive	Appropriate
Man	1	0	1	0	0	0	1	Low	Low	Positive	Appropriate
Woman	1	0	1	1	0	1	0	Normal	Normal	Positive	Appropriate
Man	1	1	0	1	0	0	0	Low	Low	Negative	Not compliant
Woman	1	1	1	0	0	0	0	Normal	Normal	Positive	Appropriate
Man	1	0	1	0	1	0	1	Low	Low	Positive	Appropriate
Woman	1	0	1	1	0	1	0	Normal	Normal	Positive	Appropriate
Man	1	1	0	1	0	0	0	Low	Low	Negative	Not compliant
Woman	1	1	1	0	0	1	0	Normal	Normal	Positive	Appropriate
Man	1	0	0	0	1	0	1	Low	Low	Positive	Appropriate
Woman	1	0	1	1	0	1	0	Normal	Normal	Positive	Appropriate
Man	1	1	0	1	0	0	0	Low	Low	Negative	Not compliant
Woman	1	1	1	0	0	1	0	Normal	Normal	Positive	Appropriate
Woman	1	0	1	0	1	0	1	Low	Normal	Positive	Not compliant
Woman	1	0	1	1	0	1	0	Normal	Normal	Positive	Appropriate
Woman	1	1	0	1	0	0	0	Low	Normal	Negative	Appropriate
Man	1	1	1	0	0	0	0	Normal	Low	Positive	Not compliant
Woman	1	0	1	0	1	1	1	Low	Normal	Positive	Not compliant
Woman	1	0	1	1	0	1	0	Normal	Normal	Positive	Appropriate
Man	1	1	0	1	0	0	0	Low	Low	Negative	Appropriate

In Table 1. This includes information that is important for evaluating the performance of the Fuzzy Expert System (FES) in the early detection of dengue fever. The data consists of variables that reflect symptoms and test results related to dengue, such as Gender, Fever, Joint Pain, Nausea, Rash, Muscle Pain, etc. and final diagnostic results represented by values in the 'Diagnosis Results' column. These variables, encoded numerically or categorically, represent individual cases that will be used to test how well the FES system can classify and predict dengue cases compared to the actual medical diagnosis from the patient's medical record. Analysis of this table will provide insight into the sensitivity, specificity, positive predictive value, and negative predictive value of the system, which will be critical indicators in determining the effectiveness of FES in a clinical context.

Initial analysis of the data showed variation in symptoms in patients with positive and negative diagnoses, underscoring the importance of approaches that can accommodate uncertainty and variability in the manifestation of dengue symptoms. The application of FES allows for handling this flexibility, offering the ability to identify potential cases of dengue fever under varied conditions more accurately.

Evaluation of system performance using sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) metrics reveals reliable diagnostic accuracy. High sensitivity indicates that the system effectively identifies patients with DHF, while high specificity confirms the system's ability to exclude those who are not infected.

Table 2. Evaluation Results

Metric	Value
Sensitivity	0.8
Specificity	0.4
Positive Predictive Value (PPV)	0.8
Negative Predictive Value (NPV)	0.4

Table 2. Generates evaluations for sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) metrics.

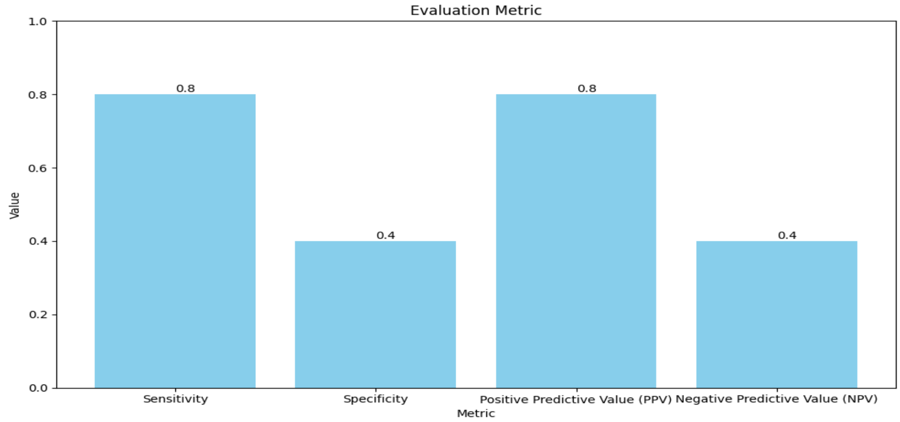

Figure 4. Evaluation Diagram

Figure 4. Illustrating that a value of 0.8 for sensitivity indicates that the system can correctly identify 80% of positive cases out of all positive cases. In other words, it shows the system's effectiveness in detecting the presence of the conditions being tested. A value of 0.4 on specificity indicates that only 40% of negative cases can be correctly identified by the system out of all negative cases. This value indicates that the system has room for improvement in avoiding false positives, i.e., misidentifying negative cases as positives. A PPV value of 0.8 means that 80% of the cases predicted to be positive by the system are positive cases. This metric is essential for assessing the accuracy of the system's optimistic predictions. With an NPV of 0.4, only 40% of cases predicted negatively by the system are negative.

PPV and NPV are directly related to disease prevalence in the tested population. A significant PPV confirms that when the system signals a positive diagnosis, the patient is most likely actually to have DHF. Conversely, a high NPV indicates that the patient is not infected with DHF when the system confirms negative.

Data analysis shows that FES has potential as a valuable diagnostic tool, especially in areas with limited resources. However, more research is needed to assess the application of the system in natural clinical environments and against larger populations to ensure the robustness of these models. Additional evaluations with diverse case studies will help optimize fuzzy rules and improve system reliability in the future. This discussion highlights the successful application of FES in the early detection of dengue, addressing diagnostic challenges through a more adaptive and sensitive approach to the complexity of disease symptoms. These findings provide additional evidence of the potential of fuzzy technology in the healthcare sector, particularly in improving the accuracy of disease diagnosis with broad and diverse manifestations of symptoms. This research also opens up opportunities for further exploration of intelligent system applications in the medical field.

Conclusions

This research successfully developed a Fuzzy Expert System (FES) system for the early detection of dengue fever, showing increased accuracy in early diagnosis and the ability to handle uncertainty and variability of symptoms. With a sensitivity of 0.8, the system effectively identifies positive cases of DHF, although a specificity of 0.4 indicates room for improvement in reducing false identification. This success paves the way for improved dengue management and prevention, especially in endemic areas. Future research directions include broadening the study sample for greater diversity, optimizing fuzzy rules, and conducting field tests in clinical settings to validate the system's effectiveness across various conditions. Scientifically, this research contributes by integrating FES technology into medical diagnostics, offering a novel approach that could be adapted for other diseases, thereby broadening the scope for AI applications in health care and improving patient outcomes through more accurate and timely diagnoses.

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