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Expert system for diagnosing diabetes disease using the dempster-shafer method based on patient symptoms

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Abstract

Diabetes is a chronic disease that can cause serious complications and increase mortality risk if not detected and treated early. Therefore, an accurate and systematic diagnostic approach is needed to support early detection of diabetes. This study aims to implement the Dempster-Shafer method for classifying diabetes based on patients' symptoms and clinical conditions. The dataset used in this research was obtained from Kaggle and consists of 768 patient records containing several clinical attributes related to diabetes diagnosis. The original numerical attributes were transformed into binary symptom representations to simplify the reasoning process in the expert system. Each symptom was assigned a confidence value or mass function representing the level of belief in the presence of diabetes. Furthermore, these confidence values were combined using the Dempster-Shafer combination rule to produce a final diagnostic decision while handling uncertainty in the available evidence. The performance of the proposed method was evaluated using several classification metrics, including accuracy, precision, recall, and F1-score. The experimental results show that the Dempster-Shafer method achieved an accuracy of 68.23%, a precision of 53.31%, a recall of 72.01%, and an F1-score of 61.27%. The relatively high recall value indicates that the method is effective in identifying patients who are potentially affected by diabetes, which is important in early diagnosis applications. Based on these findings, the Dempster-Shafer method can be considered a feasible alternative approach for expert systems in supporting diabetes diagnosis and assisting medical decision-making in a more systematic and uncertainty-aware manner.

1. Introduction

Diabetes is a chronic disease caused by insulin deficiency, which leads to blood glucose levels rising above normal limits. Glucose that is not properly absorbed can cause various disorders in body organs [1]. This disease is also triggered by unhealthy eating habits, weight gain, lack of awareness, and limited early detection tools [2]. Therefore, a healthy lifestyle, increased awareness, and the use of early detection systems are necessary to prevent more serious impacts.

Advances in information technology, particularly in the field of Artificial Intelligence (AI), have had a significant impact on healthcare, especially in improving the effectiveness of disease diagnosis processes [3]. In artificial intelligence, one of the technologies frequently utilized is the expert system, which is designed to represent the knowledge of experts in assisting diagnostic decision-making based on symptoms experienced by users [4]. Expert systems help make disease diagnosis faster, more systematic, and knowledge-based. However, uncertainty often arises in diabetes diagnosis because symptoms may indicate several possible diseases. To address this issue, the Dempster-Shafer method is used because it can combine various symptom evidence to determine the level of confidence in a diagnosis.

The Dempster-Shafer method is one of the approaches widely used in artificial intelligence to handle and measure uncertainty in decision-making processes [5]. The method was introduced by Dempster through the concept of uncertainty based on probability intervals and later developed by Shafer in 1976 in the book *A Mathematical Theory of Evidence* [6]. The Dempster-Shafer method is recognized as an effective approach for handling uncertainty in decision-making processes, particularly in AI-based systems. In several previous studies, this method demonstrated satisfactory results in processing information derived from various symptoms to generate confidence levels for diagnoses. Nevertheless, the application of the Dempster-Shafer method for diabetes diagnosis is still relatively underexplored. This condition indicates opportunities for further research in developing systems capable of producing more accurate diagnoses and supporting decision-making processes. Several studies in Indonesia have applied the Dempster-Shafer method for diabetes diagnosis. Wardani et al. developed a web-based expert system utilizing patient data and symptoms, achieving an accuracy of 86.7% [7]. Another study by [8] also applied the Dempster-Shafer method for diagnosing diabetes and assessing the severity of diabetic wounds. The results showed high accuracy, although the values were strongly influenced by the characteristics of the data and rules used in the system [8]. Husna et al. compared the Certainty Factor and Dempster-Shafer methods in diagnosing Type 2 Diabetes Mellitus, showing that inference results may differ depending on the rules, symptom weights, and test data used [9].

Several previous studies have shown that the Dempster-Shafer method has considerable potential for implementation in healthcare expert systems. [10] applied it in Diabetes Mellitus diagnosis with an accuracy of 86.7%, proving its effectiveness in combining confidence values from symptoms to assist disease identification [11]. Furthermore, [12] utilized the Dempster-Shafer method to interpret user complaints and classify conditions into diabetes, prediabetes, or normal categories before the system provided further recommendations. Research by [13] applied the Dempster-Shafer method in an expert system for diabetes mellitus diagnosis, demonstrating the method’s capability in managing uncertainty by combining symptoms into confidence values and supporting systematic decision-making.

Research by [14] developed an expert system using the Dempster-Shafer method to diagnose ENT diseases based on patient symptoms, showing the method’s ability to determine confidence levels in diagnostic results. [15] developed a web-based expert system using the Dempster-Shafer method for diagnosing drug addiction, which proved capable of processing combinations of symptoms into diagnostic confidence levels and supporting the determination of initial treatment. Another relevant study was conducted by [16], who developed a web-based expert system using the Dempster-Shafer method for diagnosing stunting in children and toddlers. The results showed that the method could process symptoms into measurable diagnostic confidence values, with testing results reaching 71.2% [17]. This is also supported by research published in the Indonesian Informatics Journal, which indicates that the application of the Dempster-Shafer method in expert systems for disease diagnosis still has limitations in accuracy levels, potentially leading to decision-making errors if not supported by adequate data and knowledge bases.

Based on the explanation above, this study aims to develop an expert system for diagnosing diabetes based on patient symptoms using the Dempster-Shafer method. This method is used to manage uncertainty by combining confidence values from each symptom that appears. It is expected that the results of this study will contribute to producing more accurate diagnoses and support more effective decision-making processes in the healthcare field.

2. Research Methodology

This study uses a quantitative approach with an experimental method by applying a classification method based on Dempster-Shafer theory for diabetes disease classification. This method is chosen because of its ability to handle uncertainty and combine various pieces of evidence in the decision-making process. The classification results are then analyzed to determine the accuracy and effectiveness of the method in diagnosing diabetes.

2.1 Research Dataset

The dataset used in this study was obtained from the Kaggle platform, namely a diabetes dataset consisting of 768 records with 8 numerical attributes and 1 class label (Outcome). The attributes used include Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Diabetes Pedigree Function, and Age. Clinically, these attributes represent the following:

1. Pregnancies: Number of pregnancies, which is associated with the risk of gestational diabetes.
2. Glucose: Plasma glucose concentration measured during a 2-hour oral glucose tolerance test.
3. BloodPressure: Diastolic blood pressure (mm Hg).
4. SkinThickness: Thickness of the triceps skinfold (mm).
5. Insulin: 2-hour serum insulin level (mu U/ml).
6. BMI: Body Mass Index (body weight in kg/(height in meters)^2).
7. Diabetes Pedigree Function: A function that measures the likelihood of diabetes based on family history.
8. Age: Patient’s age (years).

The Outcome label has two classes, namely value 0 for non-diabetic patients and value 1 for diabetic patients. This dataset was selected because it is widely used in diabetes classification research and contains attributes that are relevant for medical analysis.

2.2 Research Stages

This study was conducted through several structured stages designed to achieve optimal results in the diabetes disease classification process. The research procedures carried out in this study consist of the following stages:

- Data Collection Stage
  At the initial stage, data collection was carried out to obtain the data used as the object of the study. The data were obtained from the Kaggle platform in the form of a diabetes dataset consisting of a total of 768 records. The dataset contains several attributes used as parameters in the analysis process.
- Data Processing Stage Using the Dempster-Shafer Method
  At this stage, the Dempster-Shafer method was applied to process the data. Each attribute was treated as a source of information with a certain level of confidence. These confidence values were then combined to produce a decision based on the available evidence.
- Result Evaluation Stage
  The results of the data processing were then evaluated to determine the effectiveness of the method in performing classification. The evaluation was conducted by examining the suitability of the classification results with the existing data.
- Interpretation and Conclusion Stage
  The final stage involved interpreting the results obtained. Based on these results, conclusions can be drawn regarding the performance of the Dempster-Shafer method in classifying diabetes disease, Figure 1. Shown

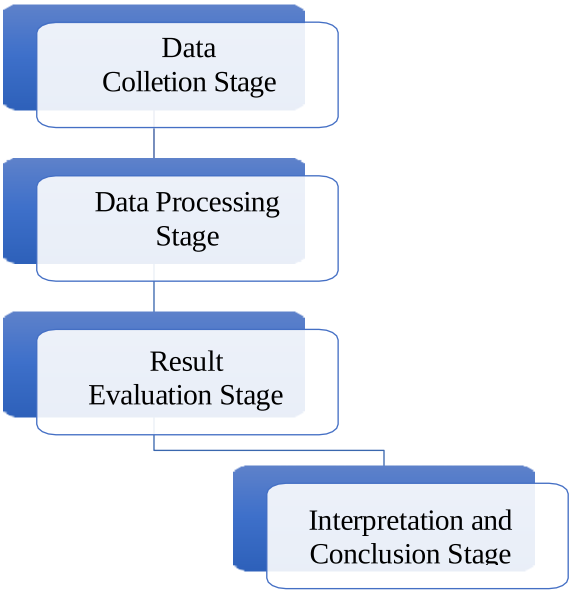

Figure 1. Research Method Flowchart

2.3 Dempster-Shafer Method

The Dempster-Shafer method is a classification method based on evidence theory that is used to determine a decision through the combination of various pieces of evidence. This method is capable of handling uncertainty by assigning a degree of belief to a hypothesis based on the available information. In this study, the Dempster-Shafer method is used to classify whether a data instance belongs to the diabetes or non-diabetes category. In this method, each attribute or symptom is considered as a source of evidence that has a certain level of confidence in a hypothesis. This level of confidence is expressed in a mass function, denoted by (m). The mass function value indicates the degree of belief in a particular set of hypotheses.

The process of combining evidence in the Dempster-Shafer method is carried out using Dempster's combination rule. The formula used to combine two mass functions is as follows:

$$m_1 \oplus m_2(Z) = \frac{\sum_{X \cap Y = Z} m_1(X) \cdot m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X) \cdot m_2(Y)}$$

- m1oplus2(Z) = the result of combining two mass functions
- m1(X)m_1(X)m1(X) dan m2(Y)m_2(Y)m2(Y) = the mass value of each piece of evidence
- X,Y,ZX, Y, ZX,Y,Z = hypothesis set
- The denominator indicates the level of conflict between the pieces of evidence

In addition, the Dempster-Shafer method also uses the measures of Belief (Bel) and Plausibility (Pl) to determine the level of confidence in a hypothesis. The Belief value represents the minimum degree of confidence in a hypothesis, while Plausibility represents the maximum possible degree of confidence. The formulas used are as follows:

$$Bel(A) = \sum_{B \subseteq A} m(B)$$

$$Pl(A) = 1 - Bel(\neg A)$$

In its application in this study, each symptom such as high glucose levels, obesity, risky age, high blood pressure, and abnormal insulin levels is assigned a confidence value toward the diabetes hypothesis based on the dataset processing results. These confidence values are then combined using the Dempster-Shafer rule to obtain the final confidence value. The final result of this combination process is used to determine whether a patient belongs to the diabetes or non-diabetes category based on the highest confidence value.

2.4 Model Evaluation Scenario

The Confusion Matrix is used to describe the distribution of classification results, which consists of four main components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). In the context of this study, these four components are explained as follows:

- **True Positive (TP):** The number of patient data correctly identified as having diabetes (Outcome = 1 and predicted result = 1).
- **True Negative (TN):** The number of patient data correctly identified as not having diabetes (Outcome = 0 and predicted result = 0).
- **False Positive (FP):** The number of patient data that actually do not have diabetes but are predicted as having diabetes (Outcome = 0 but prediction = 1).
- **False Negative (FN):** The number of patient data that actually have diabetes but are predicted as not having diabetes (Outcome = 1 but prediction = 0).

Based on these values, several evaluation metrics were calculated to determine the performance of the Dempster-Shafer method in classifying the data, as follows:

1. Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
2. Precision = $\frac{TP}{TP+FP}$
3. Recall = $\frac{TP}{TP+FN}$
4. F1 = 2. $\frac{Precision\,.\,Recall}{Precision+Recall}$

3. Result and Discussion

3.1 Implementation of the Dempster-Shafer Method

The data consist of several clinical attributes, namely Pregnancies, Glucose, Blood Pressure, Skin Thickness, Insulin, BMI, Diabetes Pedigree Function, and Age, along with one target variable, namely Outcome. The values in the Outcome column indicate the patient's condition, where the value "1" indicates that the patient has diabetes, while the value "0" indicates that the patient does not have diabetes.

The data in the table are still in numerical form and therefore cannot be directly used in the DempsterShafer method. Therefore, a data transformation process was carried out by converting the clinical attributes into symptoms in binary form (0 and 1). For example, the Glucose value was categorized as a high glucose symptom, BMI as obesity, Age as risky age, Blood Pressure as high blood pressure, and Insulin as abnormal insulin. This process aims to transform raw data into evidence that can be used in the Dempster Shafer method.

After the conversion process, each symptom is assigned a confidence value in the form of a mass function, namely m(Diabetes) and m(θ). These values indicate the degree of belief in the hypothesis that the patient has diabetes as well as the state of uncertainty. For each patient record, symptoms with a value of "1" are used as the basis for determining the belief values from the predefined belief table.

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Furthermore, the confidence values from each identified symptom are combined using the Dempster-Shafer rule to produce the final confidence value. The result of this combination is used as the basis for determining the classification, namely if the value of m(Diabetes) is greater than m(θ), then the patient is classified as having diabetes; otherwise, the patient is classified as non-diabetic.

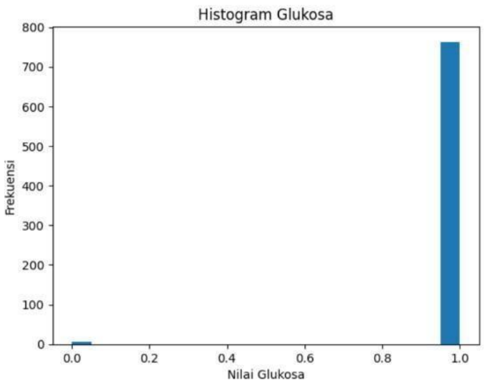

Figure 2. Histogram of Glucose Symptom Distribution (Binary)

Figure 2 shows a histogram illustrating the distribution of glucose symptoms in binary form within the dataset used. On the horizontal axis, the symptom values are displayed, where the value 0 indicates the absence of high glucose symptoms, while the value 1 indicates the presence of high glucose symptoms. Meanwhile, the vertical axis represents the frequency of data occurrences in each category. From the graph presented, it can be observed that most of the data are concentrated at the value 1, indicating that the majority of patients in the dataset exhibit high glucose symptoms. In contrast, the number of data points with the value 0 is relatively smaller. This condition shows that the data distribution tends to be imbalanced, with a dominance in the high glucose symptom category. This visualization provides an initial understanding of the characteristics of the data before it is used in further analysis processes. This information is important because it may influence the classification results, particularly in the application of the Dempster-Shafer method, which utilizes symptoms as the basis for decision-making in diagnosis.

3.2 Classification Model Evaluation Using Confusion Matrix and Classification Metrics

The evaluation of the expert system's performance in diagnosing diabetes was conducted using a confusion matrix as the primary instrument to measure the algorithm's ability to classify data accurately. The confusion matrix provides a comprehensive overview of the distribution of the model's predictions, which consists of four main components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These four components serve as the foundation for calculating the evaluation metrics used in this study, including accuracy, precision, recall, and F1-score.

The integration of these four metrics is essential because accuracy alone is often biased and unable to fully represent the reliability of the system, especially in healthcare datasets that tend to have class imbalance. In the implementation of the Dempster-Shafer method for diabetes classification, the clinical consequences caused by false negative predictions on patients who are actually positive are far more critical than other types of errors. Therefore, this study places particular emphasis on the recall value as a crucial indicator that demonstrates the method's capability to correctly identify all positive cases.

In addition, the precision aspect is also taken into account to verify the level of confidence in the positive predictions generated by the system. Meanwhile, the F1-score is applied as a balanced measure that harmonizes precision and recall, thereby providing a holistic overview of the model's performance. All evaluation results from the application of the Dempster-Shafer evidence theory are presented in detail to provide an objective comparison. This analysis is expected to reveal the strengths and limitations of the algorithm in managing uncertainty and data ambiguity in the process of diabetes diagnosis.

3.3 Analysis and Evaluation Result of the Dempster-Shafer Method

In the implementation of the Dempster-Shafer method, the effectiveness of diagnosis is highly influenced by the determination of confidence weight values (mass functions) for each symptom and the evidence combination rules. The following performance results were obtained:

Table 1. Recapitulation of the Evaluation Results of the Dempster-Shafer Method

Metrik	Capaian Performa
Akurasi	68,23%
Presisi	53,31%
Recall	72,01%
F1-Score	61,27%

Based on the data presented in Table 1, it can be observed that the Dempster-Shafer method demonstrates an advantage in the Recall aspect, reaching 72.01%. In the medical context, this achievement is highly important because it indicates that the system is sufficiently sensitive in identifying patients who are truly positive for diabetes, thereby minimizing the risk of undetected sick patients (False Negatives). However, the Precision value of 53.31% indicates that the system still faces challenges in distinguishing similar symptoms between diabetic and non-diabetic patients. As a result, the system tends to produce positive diagnoses for some cases that are actually negative (False Positives). This uncertainty is managed by the Dempster-Shafer method through the value of θ (theta), which represents the ambiguity of clinical data.

Overall, the system accuracy of 68.23% indicates that although the system does not undergo an iterative training process like conventional machine learning models, the use of evidence combination rules in this theory is capable of producing stable and objective results. These findings provide an important foundation for the further development of expert systems, particularly in optimizing the confidence weights (mass functions) for each symptom parameter in order to improve the accuracy of the final diagnosis.

3.5 Analysis of Feature Characteristics and Data Scale

A crucial factor influencing the effectiveness of diagnosis in this study lies in the characteristics and value ranges of the medical parameters used. This study utilizes the Kaggle Diabetes Dataset, which contains attributes with highly varied numerical scales, ranging from binary attributes such as obesity status and risky age to clinical parameters with wide numerical ranges such as glucose levels and insulin concentration.

In the Dempster-Shafer method, this scale variability is not measured based on the geometric distance between data points, but rather through the transformation of feature values into mass functions or confidence weights. The main advantage of this approach lies in its ability to evaluate each feature independently. Through the evidence combination rule, the system is able to balance the influence of each attribute without allowing features with large numerical ranges to automatically dominate the diagnostic results, as long as the confidence weights assigned by experts are equivalent. These data management characteristics enable the algorithm to achieve an optimal recall value (72.01%) even when working with raw clinical data. This method inherently accommodates information ambiguity through the uncertainty value (θ), which represents the limitations of evidence in features within the dataset. Therefore, the inference engine remains capable of producing stable decisions without requiring complex data normalization stages, making it highly adaptive for integration into expert systems based on medical data.

3.6 Analysis of Computational Complexity and System Efficiency

In addition to accuracy, evaluating the computational efficiency of the algorithm is essential to ensure that the clinical decision support system can operate in real time. The Dempster-Shafer method has different characteristics compared to conventional machine learning algorithms in terms of processor workload. This method does not require a time-consuming training phase to build a statistical model. Instead, the main complexity in Dempster-Shafer lies in the evidence combination rule (Dempster's Rule of Combination). Computationally, this process involves multiplying mass functions between the input symptoms. If there are n symptoms being combined, the system performs sequential calculations to integrate the evidence into a single final confidence value.

Although it involves matrix operations or set multiplications, the computational burden of Dempster-Shafer in this system is relatively low because the number of diagnostic classes is limited to only two (Diabetes and Non-Diabetes). This makes the system execution phase very fast and memory-efficient. This efficiency advantage makes the Dempster-Shafer method highly scalable and ideal for implementation in web-based and mobile healthcare applications with limited hardware resources. Therefore, the system is capable of providing instant diagnostic results immediately after medical practitioners or users input the clinical symptom data.

3.7 Clinical Implications of Diagnostic Result

From a clinical perspective, the implementation of the Dempster-Shafer method functions as an initial screening tool rather than an absolute diagnostic mechanism. The achieved accuracy of 68.23% provides a strong basis for identifying potential diabetes in patients based on non-invasive or routine data, such as body mass index, age, and blood pressure. In medical diagnostics, the risk of False Negatives (failing to identify diabetic patients) is significantly more dangerous than False Positives (diagnosing healthy patients as diabetic), because it may delay critical medical intervention. In this regard, the Dempster-Shafer method demonstrates an advantage through its recall value of 72.01%, indicating high sensitivity in identifying high-risk patients.

The integration of this predictive model into hospital information systems can assist medical practitioners in prioritizing high-risk patients for further laboratory examinations, such as the HbA1c test. The theoretical characteristics of the Dempster-Shafer method also provide a unique advantage because it is capable of generating a Degree of Belief value. Unlike rigid binary classifications such as "Yes/No," this method provides confidence scores that reflect the accumulation of symptom evidence, enabling doctors to make more measured decisions based on the strength of the available clinical evidence.

4. Conclusion

Based on the results of the study that has been conducted, the Dempster-Shafer method can be applied to classify diabetes disease based on the symptoms experienced by patients. The testing results show that the proposed method achieved an accuracy of 68.23%, with a precision value of 53.31%, recall of 72.01%, and an F1-score of 61.27%. The relatively high recall value indicates that the system has a good capability in detecting patients who truly suffer from diabetes, thereby reducing the risk of failing to identify positive cases (False Negatives). In the context of medical diagnosis, this aspect is highly important because undetected diabetes cases may lead to delayed treatment and more serious health complications. However, the precision value, which is still relatively moderate, indicates that the system occasionally classifies non-diabetic patients as diabetic (False Positives). This condition suggests that the diagnostic performance can still be improved, particularly through the optimization of belief values (mass functions) assigned to each symptom and through the refinement of evidence combination rules. In addition, the quality and balance of the dataset also play an important role in influencing the final classification results.

The Dempster-Shafer method has the advantage of handling uncertainty without requiring a complex training process like machine learning algorithms. This method is also computationally efficient and capable of producing real-time diagnostic results, making it suitable for implementation in web-based and mobile healthcare applications. From a clinical perspective, this system can be used as an initial screening tool to assist medical personnel in identifying the potential of diabetes based on patient symptoms. Overall, the Dempster-Shafer method shows good potential as a decision support system for early diabetes diagnosis and can still be further developed to achieve more optimal accuracy.

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