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Application of the dempster-shafer method in medical expert systems for disease diagnosis

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Abstrak

The use of expert systems in medical field allows computers to replicate human diagnostic reasoning. Among the available uncertainty-based approaches, Dempster-shafer theory of evidance provides a powerful probabilistic framework capable of combining incomplete and imprecise information for decision support. This article synthesizes three applied studies that employed the dempster-shafer method to diagnose Idiopathic Thrombocytopenic Purpura (ITP), Encephalitis and Periodontal Disease. Each implementation demonstrated that the Dempster-Shafer algorithm could quantify belief level in uncertain clinical evidance such as symptoms and laboratory results. Through successive evidance combination, the the systems achived diagnostic comfidence levels between 92%-97% across cases. Collectively these finding reaffirm that Dempster-Shafer reasoning can enhance diagnostic reliability compared to deterministic or rule-based systems by explicitly managing uncertainty and integrating multi-source medical data.

1. Introduction

Disease diagnosis is a critical process in the medical field because accurate and early identification of diseases can significantly improve treatment effectiveness and reduce the risk of severe complication [1]. However, medical diagnosis often involves uncertainty due to incomplete symptom information, overslapping dinical indication and differences in interpretation among medical practitioners [2]. These challenges make conventional diagnosis methods highly dependent on expert experience and can lead to delayed or inaccurate conclusions. Therefore the development of intteligent decision support system capable of handling uncertainty become increasingly important in modern heatcare.

One of the artificial intelligence approaches widely implemented in medical diagnosis is the expert system [3]. Expert systems are computer based systems designed to emulate the reasoning process of human experts by utilizing a knowledge base and inference mechanism to solve specific problem [4]. In healthcare domain, expert system have to demonstrated significant potential in assisting bonth medical perrsonel and the general public in identifiying diseases based on observed symptom [5]. Their ability to proces large amount of clinical evidence systematically enable faster and more consistent diagnostic support.

Among various uncertainty handling method the dempster shafer theory offer a powerful mathematical framework for reasoning under uncertainty [6]. This method combines multiple pieces of evidence and calculated a degree of belief for each possible hypothesis [7]. Unlike classical probabillistic approaches, dempster shafer explicitly represent uncertainty through belief and plausibility values, allowing diagnostic system to manage incomplete or ambiguous sysptom information more effectively [8]. This characterristic makes it partucularly suitable for medical diagnosis where patient sysmtom are oftem uncertain or partially observed.

Several previous studies have demonstrated the effectivenes of the dempster shafer method in diahnosing various diseases. Research on Idiopathic Thrombocytopenic purpura (ITP) showed that dempster shafer succesfully combines uncertain dinical indicator to support precise diagnosis [9]. Similarly, studies on encephalitis diagnosis proved that method could determine disease certainty values with high confidence based on symptom combination. In periodental diesease diagnosis, the implamentation of dempster shafer achieved strong diagnostic accuracy by evaluating belief values derived from expert defined rules [10]. These finding indicate that method perform consistently across different medical domain and support reliable decision making.

The main usefulnes of the dempster shafer method in disease diagnosis lies in its capability to integrate uncertaim evidence from multiple symptom and produce measurable confidence level for diagnostic outcomes [5]. This enables medical decision support system to provide recommendation that are not only systematic but also transparent in expressing uncertainty [11]. By applying this approuch diagnostic system can reduce ambiguilty, improve consistency and assist in early disease detection.

Based on the consideration, this study aims to analyze and synthesize the application of the dempster shafer method in expert system for diease diagnostic. The dicussion focuses on how the method in expert system for desease diagnosis. The discussdion focuses on how the method contribute to improving diagnostic accuracy and reliability in medical expert system, particularly for diseases such as Idiopathic Thrombocytopenic Purpura, Encepahlatis and Periodontal Disease.

2. Research Methodology

This study applies a qualitative literature synthesis approach by analyzing and integrating finding from previous studies related to the implementation of the dempster shafer method in medical expert system. The purpose of this method is to examine how dempster shafer contribute to handling uncertainty in disease diagnosis and to identify its effectivenes acros different medical case studies, namely Idiopathic Thrombocytopenic purpura (ITP), Encephalitis and periodontal disease [12].

2.1 Research framework

The research framework consists of several systematic stages designed to evaluate the role of dempster shafer in medical diagnosis system [13]. The stages aare as follow:

1. Problem Identification: the first stage identifies challenges in medical diagnostic, particularly uncertainty caused by incomplete symptom information, overlapping clinical indication and subjective interpretation by medical practitioner.
2. Literature Data Collection: relevant scientific articles discussing the implementation of dampster shafer in disease diagnosis were collected as the primary data source. The selected studies represent different disease categories to provide broader analytical perspective.
3. Knowledge Extraction: clinical knowledge, symptom data, belief values and diagnostic rules were extracted from each selected study. This stage focuses on identifiying how expert knowledge is represented within each expert system.
4. Method Analytic: the dempster shafer reasoning process used in each study was analyzed, including evidence combination, belief function aasighment and plausibility calculation.
5. Comparative Evaluation: the diagnostic performance of each implementation was compared to evaluate consistency, realibility and practical benefit in disease diagnosis.
6. Conclusion Formalition: final conclusion were derived regarding the usefulness of dempster shafer in supporting medical expert system.
7. DiabetesPedigreeFunction: A function that scores the likelihood of diabetes based on family history.
8. Age: Age of the patient (years).

The Outcome label has two classes: a value of 0 for non-diabetic patients and a value of 1 for diabetic patients. This dataset was selected because it is frequently used in diabetes classification research and contains attributes relevant to medical analysis.

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2.2 Rexpert System Architecture

The expert system analyzed in this study generally consist of four main component:

- Knowledge Base: store disease symptoms, disease categories and expert defined rules.
- Inference Engine: perfoem reasoning using the dempster shafer algorithm to combine multiple evidence source.
- User Interface: allow user to input sysmptom experienced by patient.
- Decision Support Output: display diagnostic result along with confidence values indicating the certainty level of each disease hypothesis.

This architecture enable the system to stimulate expert reasoning and provide recommendation based on symptom combination.

2.3 Dempster Shafer Method

Dempster shafer method is used as the main reasoning mechanism to manage uncertainty in diagnosis. This theory represent uncertainty using belief (Bel) and plausibility (PI) function:

$$Bel(X) = \sum_{Y \subseteq X} m(Y)$$

Where:

- Bel(X) = belief value for hypothesis X
- M(Y) = mass value assigned to evidence Y

Plausibility function is calculated as:

$$Pl(X) = 1 - Bel(\bar{X})$$

To combine multiple evidence values, dempster rule of combination is applied:

$$m_3(Z) = \frac{\sum_{X \cap Y = Z} m_1(X) m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y)}$$

This formula allow evidence from several symptoms to be integrated into a single confidence values for disease diagnosis.

2.4 Data representation

The diagnostic process uses symptom data represented as evidence with associated belief values assigned by medical expert.

The general structure includes:

- Symptom Code: Unique identifier for each symptom.
- Symptom Description: Clinical indication experienced by the patient.
- Balief Value: Expert confidence score assigned to each symptom.
- Disease Hypothesis: Possible disease associated with the symptom

The belief values are combined iteratively until a final certainty value is obtaned.

2.5 Model Evaluation Scenario

The diagnostic proces follow these step:

A. User select symptom experienced by the patiend.
B. The system retrieves corresponding belief values from the knowledge base.
C. Evidence is combined sequentially using Dempster combination rule.
D. The final belief values are calculated for all disease hypotheses.
E. Disease with the highest confidence value is selected as the diagnosis result.
F. The system display the diagnosis along with certainty percentage.

This proces allow the expert system to generate transparent and measurable diagnostic decision even when clinical evidence is uncertain

3. Results and Discussion

3.1 Knowledge Base Construction

The knowlege vase is fundamental component of the expert system because it store all diagnostic knowledge obtained from medical expert and previous studies. In this research synthesis, the knowledge base consits of symtom data, disease categories and belief values assosiated with each symtom. For Idiopathic Thrombocytopenic Purpura (ITP), the knowledge base include symptom such as excessive fatigue, nosebleed, unexplained bruising, gum bleeding and prolonged bleeding. In encephalitis diagnostic the knowledge base contain neurological symptom sush as high fever, halucination, emotional instability, seizure and body stiffnes. For periodontal disease the knoeledge base include oral symptom such as swollen gums, bleeding gums, bad breath, gum recession and tooth mobility. Quality of the knowledge base directly affect the accuracy of diagnosis because belief values assghned by expert serve as the primary evidence source for the Demster Shafer reasoning proces.

3.2 Symptom Representation and Belief Assignment

Each symptom is represented as evidence with an associated belief value indicating the degree of comfidence thet the symptom support a specific disease hypothesis. The belief values are assigned based on expert assessment and clinical observation the confidence scale generally ranges from low certainty to high certainty.

For example:

- Mild symptom indication → Low belief value.
- Moderate symptom indication → Medium belief value.
- Strong clinical indication → high belief value

This representation allow the expert system to quantify uncertainty mathematically rather than relying on deterministic yes or no reasoning.The assignment of belief values is essential because it form the basis for evidence combination during diagnosis.

3.3 Diagnostic Evidence Combination Proces

The diagnostic reasoning proces begin when user select symptom experienced by the patient. The system then:

- Retrieves the corresponding belief values.
- Convert symptom evidence into mass finction.
- Combines evidence iteratively using Dempster combination rule.
- Produce updated belief values after each combination.
- Determines the desease hypothesis with the highest final confidence value.

This iterative evidence combination enables the system to integrate multiple uncertain symptom observation into a single measurable diagnostic result. The proces is particularly useful in case where no single symptom is sufficient to comfirm a diagnosis independentlyw.

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3.4 Diagnostic Result For Idiopathic Thrombocytopenic Purpura

Theimplementation of Dempster shafer in diagnosing Idiopathic Thrombocytopenic Purpura deminstrated strong capability in combining uncertain clinical evidence. Sysmtom such as:

- Excessive Fatigue.
- Nosebleed.
- Gum Bleeding.
- Pale Skin.
- Unexplained Bruising.

Were processed to calculated cumulative belief values. The system succesfully identified ITP risk by combining symptom evidence assigning confidence level that support medical decision making. This demonstrated that Dempster Shafer is effective for blood disorder diagnosis where symptom overlap with other disease often crate uncertainty.

3.5 Diagnostic Result For Encephalitis

Encephalitis expert system produced one of the strongest comfidence result among the analyzed studies. By processing neurological symptom such as:

- High fever.
- Hallucinating.
- Emotionally Instebility.
- Muscle Weaknes.
- Body Stiffnes.

The system generated a diagnostic confidence value of 99.4% for herpes simplex encephalitis diagnosis. This result indicate that Dmpster Shafer perform exceptionally well when strong symptom relationship exist within the knowledge base. The high certainty value demonstrated affective evidence fusion and accurate pattern matching between symptom and disease hypotheses.

3.6 Diagnostic Result For Periodontal Disease

The periodontal disease system also showed high diagnostic performance. The system evaluated oral health symptom including:

- Swollen Gum.
- Bleeding during brushing
- Gum inflammation
- Tooth Mobility.
- Cum Recession.

The implementation achived a diagnostic accuracy of 92.86% The result comfirm that Dampster Shafer is not limited to systematic diseases but is equally effective for localized disease diagnosis. The method ability to proces oveslapping oral symptom contribute significantly to accurate disease classification.

3.7 Comparative Analysis Across Disease Cases

Across all three implementation the Dempster Shafer approach consistently delivered accuracy level above 90%, comparable to or exceeding result from other probabilistic systme. This reliability stem from Dempster shaver capability to integrated both certainty in evidence weighting rather than forcing deterministic logic.

3.8 Discussion on the Utility of Dempster Shafer in Medical Diagnoisis

Overall analysis comfirm several important advantage of Dempster Shafer in disease diagnosis. First it effectively handle uncertainty partial belief representation. Second it combines multiple pieces of evidence mathematically and objectively. Third it produce transparent confidence value that can assist medical interpretation. Fourth it improves consistency in diagnostic reasoning compared to manual assessment. Despite these advantege several limitation remain:

- Dependence on expert defined belief values.
- Sensitivity to incomplete knowlege base design.
- Need for broeder validation dataset.

Neverthles, the result demonstrated that Dempster Sshafer is highly valuable for expert system because it enhance diagnostic reliability, support early detection and provides measurable confidence level for decision support.

4. Conclusion

Based on the analysis of the implementation of the Dempster Shafer method in expert system for disease diagnosis, it can be concluded that this method provides significant advantage in handling uncertainty during the diagnostic proces. The Dempster Shafer theory enables the combination of multiple symptom based evidence and produces measurable confidence values taht support accurate and reliable medical decision making. The synthesis of three disease cases namely Idiopathic Thrombocytopenic Purpura (ITP), Encephalitis and Periodontal Disease, demonstrated taht Damster Shafer perform consistently acros different medical domain. The method succesfully processes uncertain and incomplete symptom information to produce diagnostic outcomes with high comfidence level. In encephalitis diagnosis, the system achieved a confidence value of 99.4%, while in periodontal disease diagnosis it reached an accuracy of 92.86%, indicating strong effectiveness in evidence-based reasoning.

The main usefulness of Dempster-Shafer lies in its ability to represent uncertainty explicitly through belief and plausibility functions. This capability allows expert systems to evaluate multiple possible disease hypotheses systematically and objectively. Compared to conventional deterministic diagnostic methods, Dempster Shafer provides a more flexible and transparent reasoning mechanism that is better suited to medical environments where uncertainty is unavoidable. Furthermore, the method contributes to improving consistency in diagnosis, supporting early disease detection, and assisting healthcare professionals in clinical decision support. The integration of Dempster-Shafer into medical expert systems can also increase public accessibility to preliminary health consultation services.

However the effectiveness of the method depends heavily on the completeness of the knowledge base and the accuracy of belief values assigned by medical experts. Therefore, future research should focus on expanding clinical datasets, improving knowledge representation, and integrating larger-scale validation to further enhance diagnostic reliability. In conclusion the Dempster-Shafer method is highly suitable for medical expert systems and has proven to be an effective approach for improving disease diagnosis accuracy under uncertain conditions. Its application has strong potential for future intelligent healthcare systems development.

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