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Detection of Cardiovascular Disease Using AI

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Abstract- **Detecting illnesses in their early stages can help prevent serious complications and improve treatment outcomes. Early diagnosis is critical because it reduces the risk of severe consequences, as prevention is better than cure. A high death rate often occurs when diseases are not detected early.**

Expert systems can bridge this gap by diagnosing diseases automatically in their initial phases. These systems use fuzzy, rule-based engines to analyze patient data and apply forward-chaining techniques for diagnosis.

In this study, data such as age, gender, blood sugar levels, blood pressure, and ECG results were collected from various sources, including hospitals, to evaluate patients' health conditions.

For example, the expert system might analyze the risk of heart disease and classify it as "low," "high," or "critical." Based on the system's diagnosis, a doctor determines the appropriate treatment and prescribes medication according to the risk level.

The study shows that this approach significantly improves the accuracy of detecting heart disease risk levels and supports doctors in providing effective treatment to patients.

Keywords: expert system; fuzzy logic; ECG; heart disease; blood sugar; cholesterol.

INTRODUCTION

The primary goal of this research is to assess the accuracy of existing expert systems and enhance their efficiency using fuzzy logic. The proposed system offers improved accuracy and efficiency for diagnosing various medical conditions. In the past, manual methods were prone to errors, but fuzzy logic enables precise estimations, leading to better diagnosis and treatment outcomes even at early stages.

The research in [2] focused on creating a specialized system to automatically diagnose diseases in people. They used a fuzzy logic-based inference engine to identify symptoms of the disease. The system worked by gathering knowledge from experts through a knowledge base and using predefined rules for diagnosis and treatment. It also incorporated information from general medical databases [3,4].

In [5], the authors developed a detailed system to identify different stages of heart disease in humans. Heart disease is increasingly common due to unhealthy lifestyles and a lack of physical activity.

The study in [6] shifted focus to Parkinson's disease, one of the most critical global health issues. It proposed a genetic algorithm as a powerful tool for treating Parkinson's and other conditions in healthcare systems [7-11]. Researchers gathered data for studying neurons using genetic algorithms and evaluated system performance with statistical methods like classification accuracy, sensitivity, and more.

In [12], the authors introduced a method for diagnosing heart disease using a combination of genetic algorithms and fuzzy logic. They designed a hybrid system that selects key factors—like serum levels, gender, cholesterol levels, and maximum heart rate—from the dataset to help diagnose the disease. The rules for this system were created using genetic algorithms.

Additionally, the study in [13] encouraged researchers to use data mining techniques to develop mathematical models. These models aid in making clinical decisions by analyzing patterns in medical datasets. The authors employed a Back Propagation Neural Network (BPNN) to identify diseases early by comparing different attributes from the dataset.

PURPOSE AND SCOPE

The proposed system describes the system workflow, as shown in Figure 1. How the system would work for getting input from the user after diagnosis on given medical diseases symptoms and suggest the physician take necessary action against the disease is depicted in Figure 1. This study examines the expert system working for heart disease diagnosis and treatment**.**

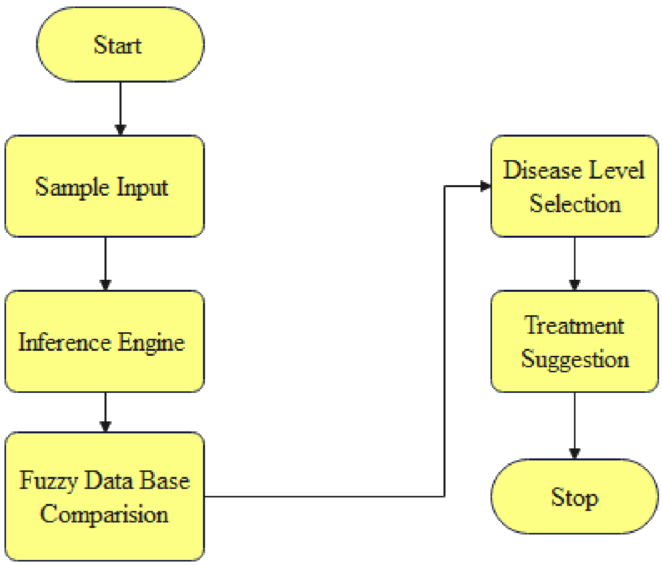

Figure 1. The system flow diagram.

The proposed expert system for medical diagnosis can identify even the mildest disease levels and suggest effective treatments for various illnesses, including heart diseases. During diagnosis, the hospital collects input data, processes it, and feeds it into the expert system.

This system converts crisp input data into fuzzy values (a process called fuzzification), compares the results with its database using an inference engine, and generates fuzzy outputs. These outputs are then converted back into clear, readable values through defuzzification.

LITERATURE SURVEY

The authors' study [1] described an online system for diabetes diagnosis. They have focused on the causes of how diabetes and a stroke can affect different diseases in the human body. The focus of this study is to identify five major complications that arise from a diabetes attack. The proposed model contains the fuzzy-based model, which has been used to classify the five most significant risks due to diabetes, such as blindness, kidney damage, heart attack, stroke disease, and other heart problems. The correct prediction rate performed by the system is 92.5%. The patients can enter their symptoms of diabetes attack online; their models are then matched with the database and required action is accurately recommended against the submission of a diabetes sample.

The authors of [14] found that a multi-layered Mamdani fuzzy inference system (MI-MFIS) can be used to diagnose different stages of hepatitis B, such as no hepatitis acute HBV or chronic HBV. This system has II input variables in stage 1 and VII input variables in stage 2. In the first layer, they examined the condition of the liver to be healthy or infectious. Intier 2, multiple variables were used to determine no hepatitis, acute HBV, or chronic HBV due to enzyme vaccination. All the data sets have been collected by the pathology department, which must be examined in this research paper.

Moreover, ref. [15] provided a method for practical applications and clinical sugges- tions regarding which type of decision should be considered for the study of the research regarding therapy. RCTs are the foremost important factor to consider in the clinical de- cision about treatment. However, the doctor should also know how to use this study adequately. The main work of RCTs is in the aspects of validity, results, and applications. Clinicians can use these practices for the best results in their practices and experience.

The authors of [16] proposed three main stages: pre-processing, feature extraction, and feature reduction with PCA and best classification. The experimental results and analysis show that the described method is best for elucidating the disease. The fuzzy-based expert system has some advantages of automation; it is speedy, cheap, and easy to diagnose the disease in the clinical application. The system is best for the early survey of the population. The authors of [17] investigated some problems in creating fuzzy logic rules, such as speed and accuracy. They proposed a precise and fast fuzzy rule expert system to minimize these issues. In this system, rules are made from numeric data using an agreed approach based upon a selection–reduction method. Lastly, they created a redundancy index method

for making rules for the expert system.

Similarly, authors in [2] investigated an expert system for the automatic diagnosis of diseases in humans. They used an automatic, fuzzy, rules-based inference engine for the detection of the symptoms of the disease. The expert system has examined the diagnosis by getting the user's knowledgebase information from an expert system through the rules formed for the inference engine and from the databases used worldwide for disease diagnosis and treatment. The fuzzy-based expert system increases the system's work by reducing the physician's workload. After diagnosing the disease, the investigated system recommended that the doctor prescribe the medicine for the detected disease. In addition, a variety of approaches related to Alzheimer's disease using neuroimaging are presented by the researchers to investigate such diseases [18–20].

The researchers of [20] encourage us through their work to detect disease using Enzyme-Linked Immune-Sorbent Assay (ELISA). As time goes on, medical research advances. Many bio marks have been used to detect different conditions at a different level, but many have no practical applications. The authors developed a technique to measure the glucose level in humans by using an Enzyme-Linked Immune-Sorbent Assay (ELISA). This includes the biological conversion of analyses into inverts, after which the glucose level can be examined. An ELISA kit produces quicker and more efficient results than other methods used for this purpose.

Authors in [18] described that they could manage diabetes by adding glucose and data of insulin pumping. They found that many variables have been defined for data collection, such as hours of sleep, heartbeat rate, daily walking routine, etc. This can be helpful for a doctor to make the right decision as regards the patient. A system has been developed using an

AI scenario to assist the doctor in making decisions for the patient.

Similarly, authors in [13] concluded that about 45 million people all around the world have diabetes. Many applications of artificial intelligence (AI) and cognitive computing have been developed for disease cures. These systems have been helpful for persons with diabetes (PWDs), their families and their caregivers. These systems have been divided into four main areas: automated retinal screening, clinical decision support, predictive population risk stratification, and patient self-management tools.

ALGORITHMS

In the proposed research, all input is taken from the patient and then evaluated by the expert doctor at Hospital, who verified all the test results. The evaluation of the system is designed very effectively, and the system is more reliable and beneficial for the doctor and the patient, reducing the rush at the hospital to avoid continuous patient monitoring. A fuzzy expert system is helpful and useful for all patients and doctors to diagnose heart disease patients. Fuzzy member functions and fuzzy rules have been made by fuzzy logic.

The flow of the proposed expert system is given and described in the following steps.

Step 1: Input chest pain level and heart electrical signal in the body;

Step 2: Input the blood sugar level;

Step 3: Input the heart rate;

Step 4: Input blood pressure;

Step 5: Input the gender and age of the patient;

Step 6: Input the cholesterol value;

Step 7: The doctor starts the diagnosis on the fuzzy-based expert system;

Step 8: Diagnosis report is generated;

Step 9: The doctor advises the patient on the proper dose of medicine to cure heart disease;

Step 10: Then, the system is terminated.

Fuzzy Rules Member Functions

Fuzzy rules have been developed by applying the following formula for all fuzzy set's member functions

Formula = mn

M is the membership function, and n are input

For ECG: there are 3 membership (m) functions, and input (n) is 1 31 = 3

For Chest Pain: there are 3 membership (m) functions, and input (n) is 1 31 = 3

For Blood Sugar: there are 4 membership (m) functions, and input (n) is 1 41 = 4

For Cholesterol: there are 3 membership (m) functions, and input (n) is 1 31 = 3

For Blood Pressure: there are 3 membership (m) functions, and input (n) is 1 31 = 3

For Heart Rate: there are 3 membership (m) functions, and input (n) is 1 31 = 3

For AGE: there are 4 membership (m) functions and input (n) are 1 41 = 4

Thus, it has calculated the total number of fuzzy rules by multiplying all the outputs of the fuzzy set member function by applying the above-cited formula = mn

= mn × mn

= 31 × 31 × 41 × 31 × 31 × 31 × 41

= 35 × 42

= 3888

Total number of 3888 rules by given input

Fuzzy Inputs and Output

Fuzzy-Based Expert System Workflow

- Set the result to false;
- Input the ECG Value;
- Input Chest pain level;
- Input the Blood Sugar level;
- Input the Cholesterol value;
- Input the Blood Pressure level;
- Input the Age of the patient;
- Input the Heart Rate of the patient;
- Then, the system will start the diagnosis of the given values, such as blood pressure and sugar levels;
- Then select the Recommendation level;
- And recommend the proper dose to the patient;
- Setup 2 is complete;
- Display true;
- Exit.

Table 1. The fuzzy input/output rule.

ECG	Chest Pain	Blood Sugar	Cholesterol	Blood Pressure	Age	Heart Rate	Disease Level
Medium	Typical Angina	Normal	Medium	High	Young	Medium	High
Normal	Normal	Medium	Medium	Medium	Young	Medium	Medium
Medium	Normal	Medium	Medium	Medium	Young	Medium	Medium
Normal	Normal	Normal	Normal	High	Young	Medium	Low
Medium	A Typical Angina	Normal	Medium	High	Aged	Medium	High
High	A Typical Angina	Normal	Medium	High	Aged	Medium	High
Medium	Normal	Medium	Medium	High	Aged	Medium	Medium

RESULT ANALYSIS

Fuzzy logic is used to create all the rules, which are then processed in MATLAB to generate results.

Data for the system is collected from various sources, including hospitals, by testing factors such as patient age, gender, blood sugar levels, heart rate, and ECG results. After the tests are completed, the system calculates and generates a crisp (precise) value, which is then converted into a fuzzy value as input for the expert system.

The expert system starts by **fuzzifying** the input, turning crisp data into fuzzy data to work with fuzzy logic rules. Once this is done, the system moves to the **defuzzification** step, where the fuzzy results are converted back into a crisp value that is easier for humans to understand.

The system uses these values to determine the level of heart disease risk—classified as low, high, or critical. After this diagnosis, the system provides the doctor with the results. Based on the diagnosis, the doctor decides on the appropriate treatment and prescribes the correct dose of medicine according to the identified risk level.

Simulations and results show that this approach improves the accuracy of diagnosing heart disease risk levels. It also ensures the treatment provided meets the needs of heart disease patients effectively. Simulation outcomes clearly indicate the system's ability to classify heart disease risk levels accurately. Rule 1: If the chest pain is atypical, the HbA1c level is high, the HDL level is low, the LDL level is very high, the heart rate is very healthy, the age is mid-range, and the blood pressure is normal, Then the status is medium risk. Rule 2: If the chest pain is atypical, the HbA1c level is high, the HDL level is low, the LDL level is very high, the heart rate is very healthy, the age is mid-range, and the blood pressure is high, Then the status is high risk. For Rule 1: Medium Risk was identified as a heart disease state by our expert system with a membership value of 0.7. Medium Risk = MIN (1,1,1,1,1,1,0.7) = 0.7. For Rule 2: High Risk was identified as a heart disease state by our expert system with a membership value of 0.3 High Risk = MIN (1,1,1,1,1,1,0.3) = 0.3. After defuzzification (average of weighted average, sum of area, and mean of maxima) was applied, the output variable resulted in a crisp value of 6.44, which denotes a medium risk for heart disease. We used 260 datasets of input variables from the Cleveland Clinic Foundation database to do benchmark testing on the functionality of our system. It is available at the UCI machine learning Repository. Only five input variables combinations were classified wrongly by our expert system, and 255 are classified accurately, which are in the Cleveland database. That results in 5 variable input combinations wrongly classified by our system but close to the classification value. It might be overcome if we combine our present five heart disease detection input factors with one or more input variables acquired from the Cleveland database.

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