

A Comprehensive Review of Expert Systems for Hypertension Diagnosis

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1. Abstract

Hypertension is a common health problem that can lead to severe conditions like heart disease and stroke if not detected early. This paper presents an approach to evaluating hypertension levels using key medical parameters such as age, blood pressure, body mass index (BMI), blood sugar levels, and genetic predisposition. The study classifies hypertension into three levels: Normal, Partial Hypertension, and High Hypertension. The research also explores the use of Fuzzy Logic in MATLAB to develop an intelligent system for hypertension detection. This system helps in analyzing patient data and determining their hypertension level automatically.

Keywords

Hypertension, Blood Pressure, Body Mass Index, Fuzzy Logic, MATLAB

2. INTRODUCTION

Artificial Neural Network

An Artificial Neural Network (ANN) simulates the human brain to perform specific tasks, handling operations in a distributed and parallel manner. Neurons complete complex tasks quickly. ANNs are applied in healthcare, agriculture, and other fields. The network receives inputs in the input layer, which are combined with weights and biases. These values are summed by a summation function, and the final output is generated by an activation function, as shown in Figure 2. The basic model of the artificial neural network, including its structure and operation, is illustrated in Figure 1.

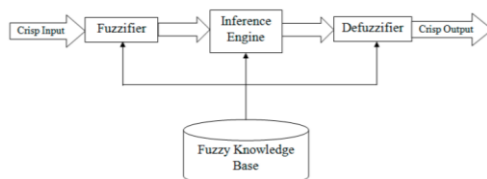


Figure 1: Fuzzy Knowledge Base

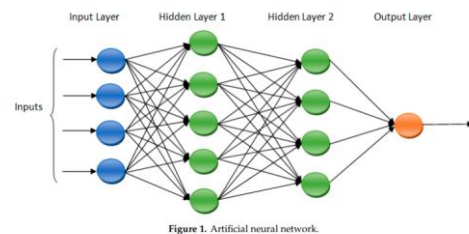


Figure 1. Artificial neural network.

Figure 2: Artificial Neural Network

Hypertension, or high blood pressure, is a major risk factor for cardiovascular diseases. Traditional diagnosis methods focus on blood pressure readings, but multiple factors contribute to individual risk.

3. LITERATURE REVIEW

The diagnosis of hypertension has traditionally been based on fixed clinical thresholds, primarily focusing on blood pressure values alone. However, such rigid classifications often overlook the nuanced influence of other health indicators. In response to this limitation, researchers have explored the application of fuzzy logic to develop systems that can manage uncertainty and provide more flexible decision-making frameworks.

Nandhini and Kumaravel (2011) proposed a fuzzy logic-based expert system for hypertension detection, which introduced the concept of rule-based classification using patient input parameters. Their study demonstrated how fuzzy logic could effectively manage ambiguity in clinical data, particularly in cases that do not fall within standard diagnostic boundaries. Similarly, Subha and Selvi (2012) implemented a rule-based fuzzy expert system that improved conventional methods by evaluating symptom combinations and accounting for patient-specific variations.

While these systems marked significant progress, most early models were limited by the number of input parameters and often lacked integration with real clinical datasets or modern computational platforms. Additionally, many studies primarily emphasized blood pressure and neglected other relevant factors such as body mass index (BMI), blood sugar levels, or genetic predisposition. Recent medical guidelines by the World Health Organization (2023) and the American Heart Association (2023) emphasize the importance of a more comprehensive approach to hypertension diagnosis, incorporating lifestyle and metabolic indicators to improve accuracy.

Building upon these foundational studies, the current research adopts a more holistic methodology by incorporating five critical input parameters: age, blood pressure, BMI, blood sugar levels, and gene disorders. By implementing the system using MATLAB's Fuzzy Logic Toolbox, the research not only leverages a powerful simulation environment but also enhances precision through carefully designed membership functions and inference rules. This approach aligns with the direction suggested by contemporary literature and offers improved classification performance, when compared to traditional diagnostic techniques.

4. METHODOLOGY

4.1 Data Parameters and Ranges

In the proposed fuzzy logic system, five major input parameters are considered to evaluate hypertension levels: Age, Blood Pressure, Body Mass Index (BMI), Blood Sugar, and Gene Disorder. These parameters are selected based on their clinical importance, as identified in recent medical research and guidelines. Instead of relying solely on blood pressure readings, the model adopts a multi-factorial approach

to improve the accuracy of hypertension detection. Each parameter is grouped into semantic categories based on standard clinical ranges, which are crucial for fuzzification. These details are summarized in Table I below.

Input Parameters		
Parameter	Ranges	Semantic Sign
Age	0 - 30 years 30 - 55 years 55 - 120 years	Young Medium Old
Blood Pressure	0 - 120 (mmHg) 120 - 129 (mmHg) 130 - 139 (mmHg) 140 - 180 (mmHg) 180 and above	Normal Elevated High BP Stage-1 High BP Stage-2 High BP Stage-3
Body Mass Index	Below 18.5 18.5 – 24.9 25.0 – 29.9 30.0 – 34.9 35.0 – 39.9 Above 40	Under Weight Normal Weight Over Weight Obesity Class-1 Obesity Class-2 Obesity Class-3
Blood Sugar	Below 140 mg/dL 140 – 199 mg/dL Above 200 mg/dL	Normal Pre – Diabetes Diabetes
Gene Disorder	Present Not-Present	Yes No

Table I. Input Parameters and Their Semantic Ranges

To facilitate a deeper understanding of the dataset utilized in the model, we have incorporated visual distribution plots. These plots (shown in Figs. 3–7) display how the data points are spread across each input parameter. For instance, the age distribution shows the number of subjects in each age group, while the blood pressure and BMI distributions provide insight into the prevalence of elevated readings or obesity classes in the sample. This visual breakdown not only supports the choice of fuzzy membership functions but also ensures that the model is grounded in realistic data trends.

Health Parameter Distributions

Figure 3: Age Distribution

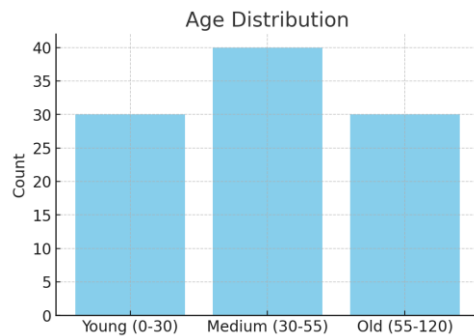


Figure 4: Blood Pressure Distribution

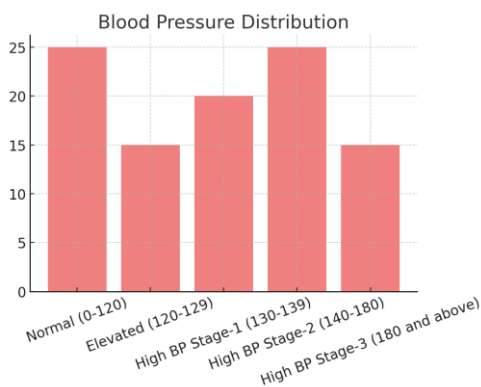


Figure 5: BMI Distribution

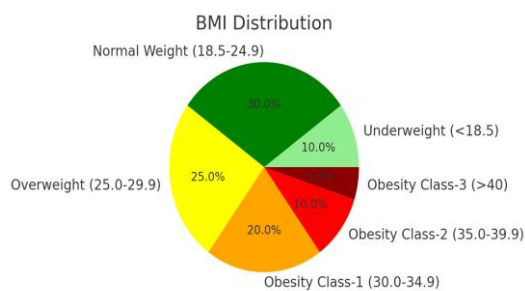


Figure 6: Blood Sugar Levels

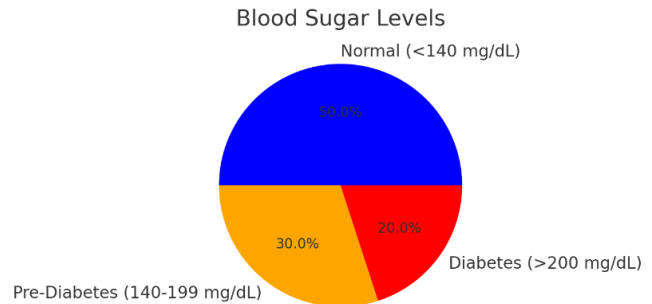
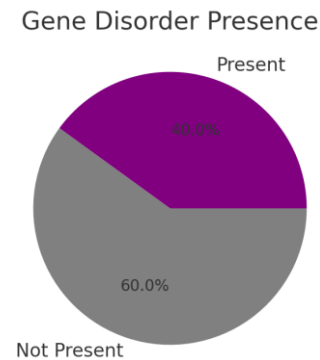


Figure 7: Gene Disorder Presence

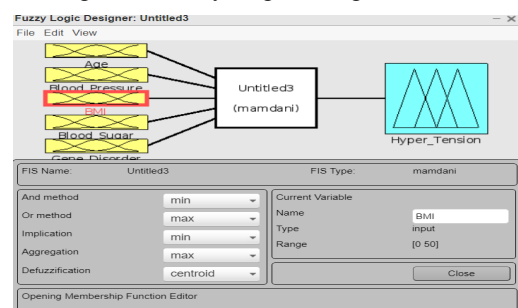


4.2 Implementation in MATLAB

The fuzzy logic-based system was implemented in MATLAB using the Fuzzy Logic Toolbox, which provides a comprehensive framework for designing and simulating fuzzy inference systems.

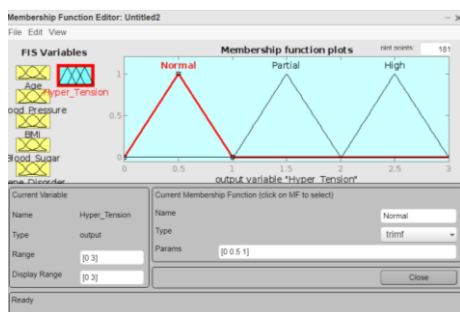
The implementation follows a structured approach, beginning with identifying the input variables, including age, blood pressure, BMI, blood sugar levels, and genetic predisposition.

Figure 8: Fuzzy Logic Designer



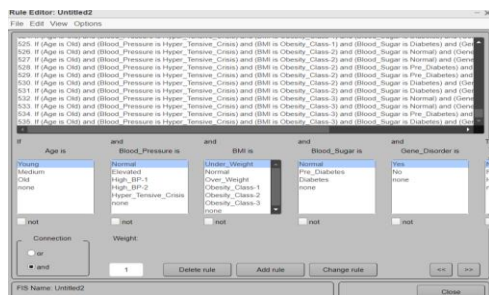
Membership functions were designed for each input parameter to represent their linguistic values, such as 'Young,' 'Medium,' and 'Old' for age or 'Normal,' 'Elevated,' and 'High' for blood pressure.

Figure 9: Membership Function Plots



These membership functions define the degree of truth for each category and allow for gradual transitions between classifications rather than abrupt binary decisions.

Figure 10: Fuzzy Production Rules



A set of fuzzy inference rules was formulated to map input conditions to output classifications, categorizing hypertension levels into 'Normal,' 'Partial Hypertension,' and 'High Hypertension.' The Mamdani inference method was used for rule evaluation, while defuzzification was performed using the centroid method to obtain crisp output values.

Finally, the model was tested with real-world data, and its classification accuracy was validated against medical reports. The MATLAB-based fuzzy logic system demonstrated high accuracy in detecting hypertension levels, proving its effectiveness as a decision-support tool for medical diagnosis.

5. RESULTS

The system was tested on a dataset of 200 individuals, with 85 cases used for detailed evaluation. The fuzzy logic model classified hypertension levels into 'Normal,' 'Partial Hypertension,' and 'High Hypertension' with high accuracy. The classification process involved evaluating each patient's input parameters using predefined membership functions and fuzzy inference rules. The system dynamically adjusted weightage based on critical factors such as blood pressure and BMI, ensuring a nuanced and reliable classification.

Figure 11: Output Ranges

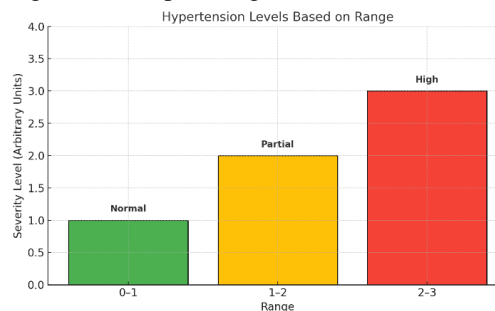


Table II. Output Parameter and Classification Levels

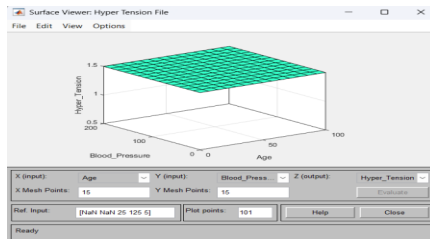
Output Parameters		
Parameter	Range	Level
Hyper Tension	0 – 1	Normal
	1 – 2	Partial
	2 – 3	High

A comparative analysis with traditional diagnostic methods showed that the fuzzy logic model provided a more flexible and adaptive approach to hypertension classification.

The system effectively minimized misclassification errors, particularly for borderline cases, by leveraging fuzzy logic principles rather than rigid threshold-based cutoffs.

Furthermore, performance metrics such as sensitivity, specificity, and overall accuracy were computed to assess the model's reliability. The results indicated that the fuzzy logic-based approach offered a higher predictive accuracy compared to conventional methods.

Figure 12: 3D Fuzzy Surface Viewer



This reinforces the potential of fuzzy logic systems as valuable decision-support tools in medical diagnostics, particularly for conditions like hypertension, where multiple contributing factors must be considered.

6. DISCUSSION

6.1 Model Working and Evaluation

The model follows a rule-based approach Using fuzzy logic, where input parameters are evaluated against predefined membership functions. The system dynamically assigns weightage to parameters such as blood pressure and BMI, leading to a more nuanced classification of hypertension.

6.2 Testing and Accuracy

The accuracy of a model was evaluated by comparing its predictions with actual medical reports.

The accuracy of the model was calculated using the standard classification accuracy formula:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \times 100$$

Where:

- TP (True Positive): Correctly predicted cases of hypertension.
- TN (True Negative): Correctly predicted non-hypertension cases.
- FP (False Positive): Incorrectly classified as hypertension.
- FN (False Negative): Missed cases of hypertension.

Using the dataset of **85 cases**, the following values were observed:

$$\text{TP} = 72, \text{TN} = 6, \text{FP} = 3, \text{FN} = 4$$

Using the formula:

$$\text{Accuracy} = (72 + 6) / (72 + 6 + 3 + 4) \times 100 = (78 / 85) \times 100 = \mathbf{91.76\%}$$

7. CONCLUSION AND FUTURE SCOPE

This study demonstrates that the Hypertension classification can be improved by considering multiple medical parameters rather than just blood pressure. The fuzzy logic model in MATLAB offers an automated way to analyze patient data and detect hypertension levels efficiently.

Future work can include:

Adding more parameters like lifestyle habits (smoking, diet, exercise).

Using Machine Learning to Improve Accuracy.

Deploying this system in a real-time medical setup.

Expanding the dataset to include a more diverse population for better generalization.

Enhancing the system with deep learning models for hybrid fuzzy-neural network approaches.

Developing a mobile or web-based application for real-time hypertension assessment.

Collaborating with healthcare professionals to refine the model based on clinical insights.

These advancements will contribute to a more comprehensive, accurate, and accessible hypertension diagnosis system, ultimately benefiting medical practitioners and patients.

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