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A MEDICAL DIAGNOSTIC SUPPORT SYSTEM FOR THE MANAGEMENT OF HYPERTENSION (MEDDIAG)

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ABSTRACT
Hypertension is one of the silent killer diseases and the need to optimize the management using fuzzy logic approach is a dual need. Hypertension directly or indirectly concerns us in one way or the other. As far as hypertension is concerned, one can be a patient, a patient's relative or a wise counselor. A little more knowledge and understanding will make a wiser counselor. In this paper, a medical diagnostic support system for the management of hypertension (MEDDIAG) is presented. MEDDIAG diagnoses the possibility of the disease and its severity using fuzzy logic approach. Fuzzy logic technology provides a simple way to arrive at a definite conclusion from vague, ambiguous, imprecise or noisy data (as found in medical data) using linguistic variables that are not necessarily precise. In order to achieve this, a study of the knowledge base system for the management of hypertension was undertaken. MEDDIAG applied forward chaining method in making inferences and the Root Sum Square (RSS) of drawing inference was employed to infer the data from the rules developed. The defuzzification technique employed is the Centroid approach. MEDDIAG was implemented in the Fuzzy Logic Toolbox in MATLAB 7.10.0. Diagnostic data from 30 patients with confirmed diagnosis of hypertension were evaluated and the computed results were in the range of the predefine limits by the domain experts. Fuzzy diagnosis had 85% exact diagnosis. Based on the results obtained, fuzzy diagnosis resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution.
Keywords: Medical diagnosis, Fuzzy Logic, Knowledge-base, Hypertension

INTRODUCTION
Hypertension is one of the silent killer diseases and the need to optimize the management using fuzzy logic approach is a dual need. This is because, Fuzzy logic technology provides a simple way to arrive at a definite conclusion from vague, ambiguous, imprecise or noisy data (as found in medical data) using linguistic variables that are not necessarily precise. Hypertension is one of the known cardiac diseases believe to be the cause of the "sudden death" syndrome prevalent in Nigeria today. Complication arising from hypertension could lead to stroke or heart failure. Such complications may be caused by improper diagnosis and or improper management of the disease may be, due to inaccessibility experienced medical personnel at the time of need [7]. Hypertension has been reported to be a major problem of the blacks. The quickening speed of change and adoption of Western lifestyles by people in developing countries has led to a sharp rise in the incidence of hypertension. Hypertension is the medical illness most frequently diagnosed in elderly Nigerian. The prevalent of hypertension in Nigeria according to [14] was documented as 11.2% (based on blood pressure threshold of 160/95 mmHg). This translates into approximately 4.33 million Nigerian

hypertensive aged 25 years and above. However, with the currently published Joint National Committee on Prevention, Detection, Evaluation, and Treatment of high blood pressure (JNC VII) guidelines, many more Nigerians (20-25%) can be said to be hypertensive [14].

In recent time, research efforts have been concentrated on medical diagnostic support systems as complementary solution to conventional technique for finding solution to medical problems. Medical diagnosis process involves a complex mental exercise and a state space search of medical knowledge, which could become unwieldy and complicated especially when the variables involved are numerous and the patients presenting symptoms which are non-specific [2]. In order to improve the possibility of early and accurate diagnosis of hypertension, there is the need for the application of artificial intelligence techniques or other decision support systems in the diagnostic process, because these are known to improve patient outcomes [19]. A number of expert technology-oriented systems have attempted to address the subjects of knowledge acquisition, representation and utilization in medical diagnosis. However, the problem of managing imprecise knowledge still exists. Clinical decision support systems utilize patients' data and some inference procedures to generate case specific advice and suggestions to the practitioner [24]. [17] recognized that a very important task in achieving hospital efficiency is to optimize the diagnostic process in terms of the number and duration of patient examinations, with corresponding accuracy, sensitivity, and specificity, as this is known to reduce morbidity and mortality rates, control costs and improve both doctor–patient and community–facility relationships. The task of medical diagnosis, like other diagnostic processes, is made more complex because a lot of imprecision is involved. Patients may not be able to describe exactly what has happened to them or how they feel; doctors and other health care practitioners may not understand or interpret exactly what they hear or observe; laboratory reports are not instantaneous and may come with some degree of error; and medical researchers cannot precisely characterize how diseases alter the normal functioning of the body [20]. Fuzzy logic which is one of the soft computing techniques can render precise what is imprecise inherent in medical diagnosis [16]. Fuzzy set and fuzzy logic founded by [25] makes it possible to define inexact medical entities as fuzzy set. Fuzzy logic together with the appropriate rules of inference provides a power framework for managing uncertainties pervaded in medical diagnosis [8]. Fuzzy logic technology is adopted in this paper for the management of hypertension. This is because, fuzzy logic can adequately address the issue of uncertainty and lexical imprecision of knowledge [2] and [6], but fuzzy systems still requires human expert to discover rules about data relationship. The applications of fuzzy concepts to medical diagnosis of some diseases are discussed in [3, 4, 5, 9, 10, 11, 12, 13, 15, 18, 22, 23].

The study was aimed to design a medical diagnostic support system for the management of hypertension (MEDDIAG). Using MEDDIAG can assist medical experts in the tedious and complicated task of diagnosing hypertension and the designed system can provide a scheme that will assist medical personnel especially in rural areas, where there are shortage of doctors, in the process of offering primary health care to the patients.

RESEARCH METHODOLOGY

The proposed computer-based system, christened "a medical diagnostic support system for the management of hypertension (MEDDIAD)" has architecture for the fuzzy inference system presented in figure 1 below. Fuzzy logic methodology involves three main processes; fuzzification, inference engine and defuzzification processes. The designed system (MEDDIAG) is a rule based system that uses fuzzy logic approach. It has the following key components:

- MEDDIAG knowledge-base
- MEDDIAG Fuzzification
- MEDDIAG Inference Engine
- MEDDIAG Defuzzification

For the designed process, Systolic blood pressure (SBP), diastolic blood pressure (DBP), age, and body mass index (BMI) are taken as input parameters to the system and "hypertension risk" is the output parameter of the system. For fuzzification of these parameters, the linguistic variables mild, moderate, severe and very severe were used for SBP and DBP, the linguistic variables young, middle age, old, and very old for Age, and the linguistic variables low, normal, high and very high for BMI. The fuzzy inference system (FIS) mechanism use in this research is the Mamdani Inference. The developed FIS for MEDDIAG has the structure as shown in figure 1 below. The various membership functions for both input and output parameters with their linguistic variables are shown in figures (2 to 6) below.

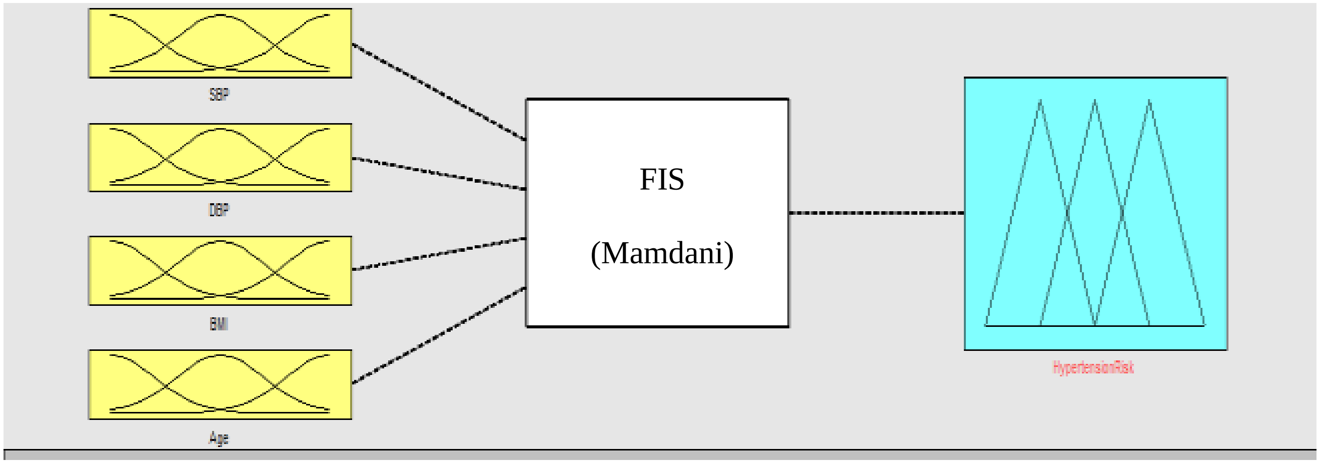

Figure 1: **Architecture of the Fuzzy Inference System (FIS) for MEDDIAG**

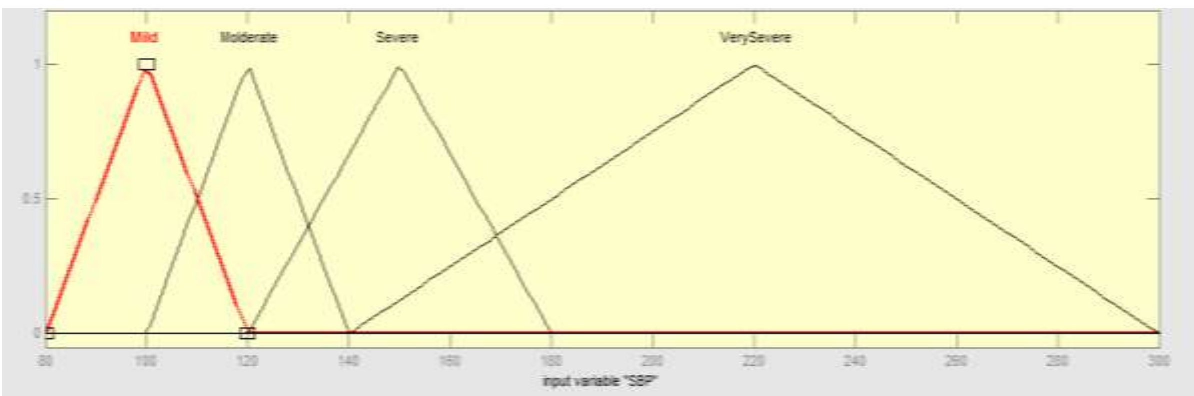

Figure 2: **Membership Function for SBP**

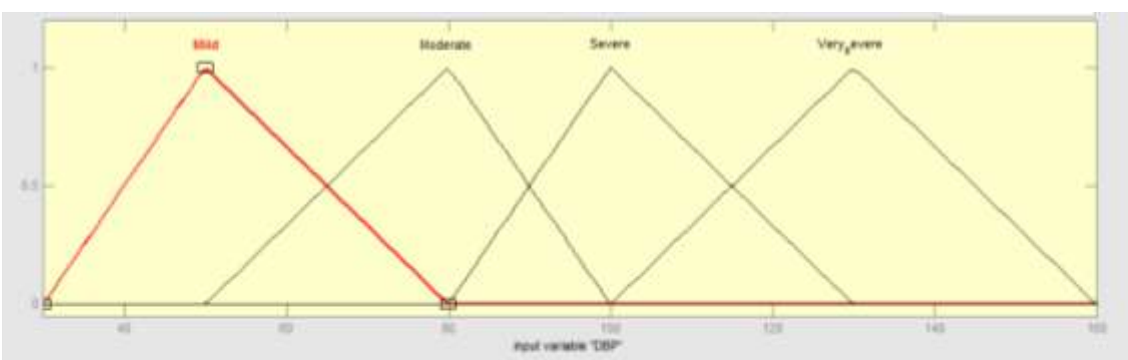

Figure 3: **Membership Function for DBP**

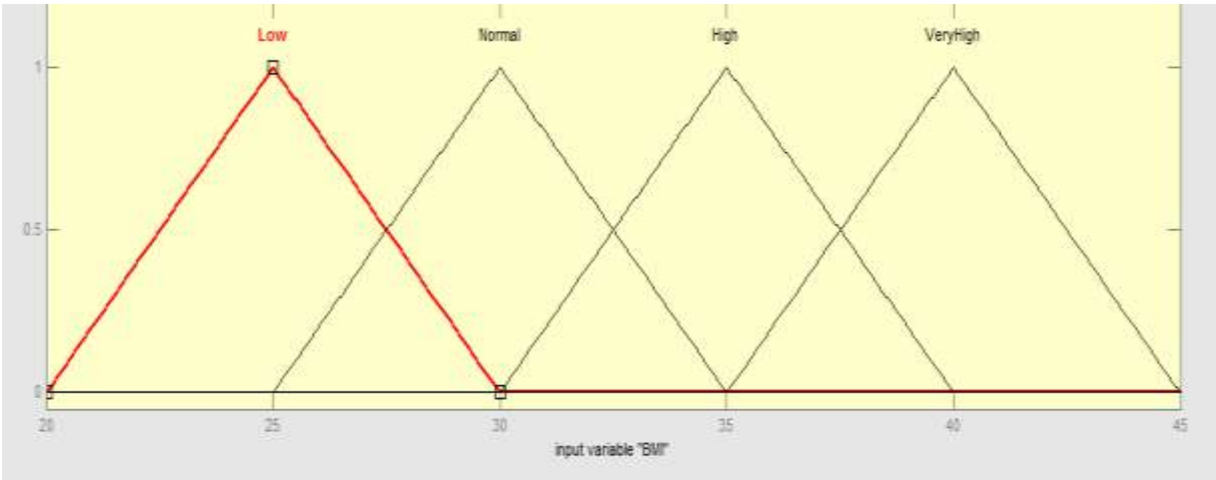

Figure 4 : Membership Function for BMI

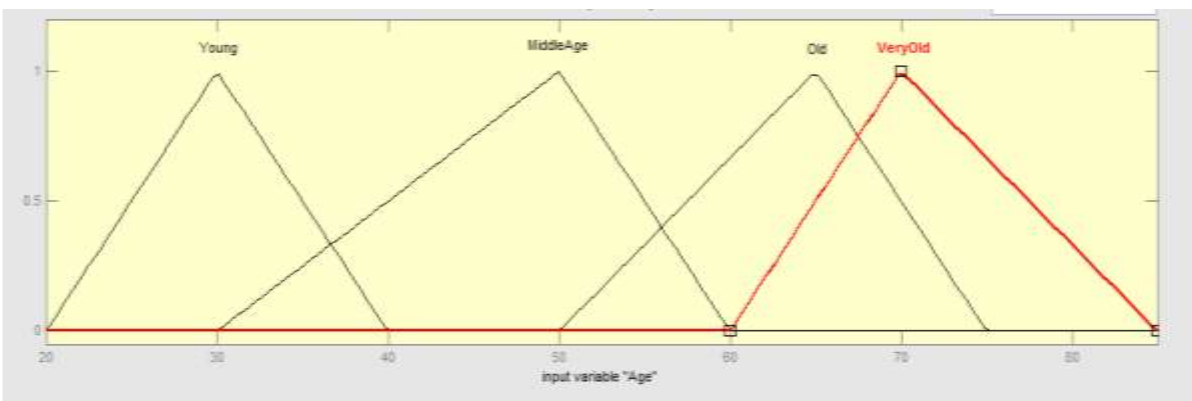

Figure 5: Membership Function for Age

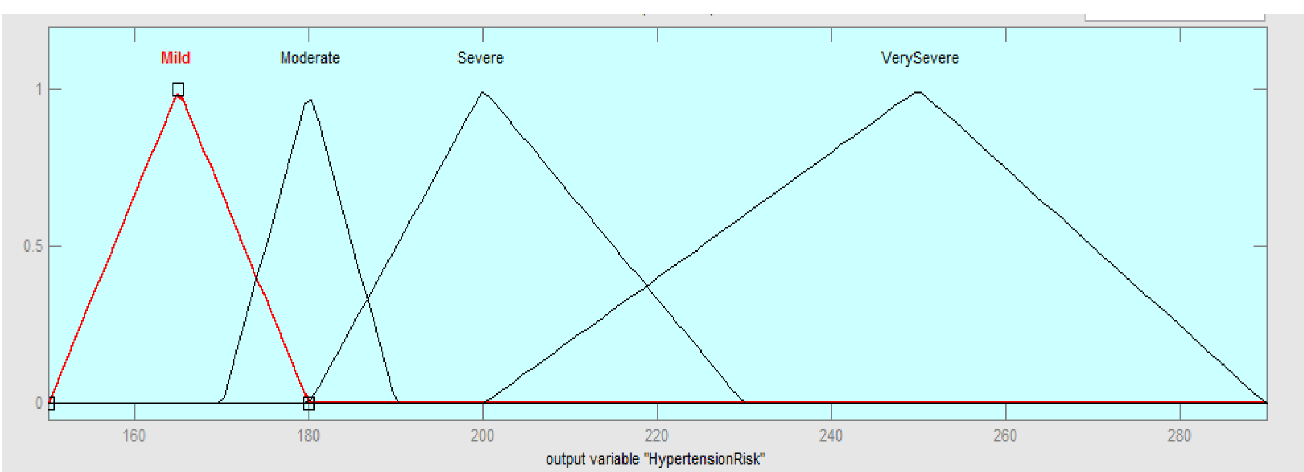

Figure 6: Membership Function for Hypertension Risk

MEDDIAD knowledge-base

The knowledge base for MEDDIAG contains both static and dynamic information. Knowledge is a key factor in the performance of intelligent systems. The knowledge-base of MEDDIAG is composed of structured and concise representation of the knowledge of domain experts of tropical medicine. The structure knowledge is concerned with facts, rules and events of hypertension, which were commonly agreed upon by experts in the field of medicine. The fuzzy rules for this research were developed with the assistance of domain experts (five medical doctors) who are experts in the field of internal medicine. The knowledge-base of MEDDIAG has 256 fuzzy rules. Sample fuzzy rule base for hypertension diagnosis is shown in table 1 below:

Table 1: Sample Rules for MEDDIAG

	IF				THEN
Rule No	**SBP**	**DBP**	**BMI**	**AGE**	**Hypertension Risk**
1	Mild	Severe	Very High	Very Old	Mild
2	Moderate	Moderate	Low	Young	Moderate
3	Severe	Mild	Normal	Middle Age	Severe
4	Severe	Mild	Normal	Old	Severe
50	Mild	Mild	Normal	Very Old	Mild
69	Moderate	Moderate	Very High	Old	Moderate
70	Mild	Severe	High	Middle Age	Severe
86	Moderate	Mild	Low	Young	Severe
99	Severe	Mild	Low	Middle Age	Mild
150	Moderate	Moderate	Normal	Young	Moderate
158	Mild	Severe	High	Old	Moderate
190	Moderate	Moderate	Low	Very Old	Mild
225	Mild	Severe	Normal	Old	Mild
238	Mild	moderate	High	Young	Severe
246	Severe	mild	Very High	Middle Age	Severe
160	Moderate	Moderate	Normal	Very Old	Mild
167	Mild	Severe	Low	Young	Mild
170	Moderate	Moderate	Normal	Middle Age	Mild
205	Severe	Mild	High	Old	Moderate
256	Severe	Mild	Very High	Very Old	Moderate

Some of the rules (Rules 1, Rules 167, Rule 205 and Rules 256) can be interpreted as follows:

Rule 1: IF SBP = Mild and DBP = Severe and BMI = Very High and Age = Very Old THEN hypertension risk = Mild

Rule 167: IF SBP = Mild and DBP = Severe and BMI = Low and Age = Young THEN hypertension risk = Mild

Rule 205: IF SBP = Severe and DBP = Mild and BMI = High and Age = Old THEN hypertension risk = Mild

Rule 256: IF SBP = Severe and DBP = Mild and BMI = Very High and Age = Very Old THEN hypertension risk = Moderate

MEDDIAD Fuzzification

Fuzzification is a process that determines the degree of membership to the fuzzy set based on fuzzy membership function. Analytical representation of membership function for the four input parameters to the fuzzy expert system is shown below:

$$SBP(i) = \begin{cases} i; & 80 \le i \le 300 \\ 0; & i < 80 \\ 1; & i > 300 \end{cases} \tag{1}$$

i represents several measurements of SBP

$$DBP(j) = \begin{cases} j; & 30 \le j \le 160 \\ 0; & j < 30 \\ 1; & i > 160 \end{cases} \tag{2}$$

j represents several measurements of DBP

$$BMI(l) = \begin{cases} l; & 20 \le l \le 40 \\ 0; & l < 20 \\ 1; & l > 40 \end{cases} \tag{3}$$

where l represents patient's BMI

$$Age(h) = \begin{cases} h; & 20 \le h \le 85 \\ 0; & h < 20 \\ 1; & h > 85 \end{cases} \quad (4)$$

$where\ \ h\ \ represents\ patient's\, age$

On the basis of domain experts' knowledge, both input and output parameters selected for this research were described with four linguistic variables (mild, moderate, severe and very severe). The degree of membership for a fuzzy system is of the range [0 1]. The range of fuzzy value for each linguistic is shown in table 2 below:

Table 2: Range of Fuzzy Values for Hypertension Risk

Linguistic Variables	Fuzzy Values
Mild	$0.1 \le x \le 0.3$
Moderate	$0.3 \le x \le 0.6$
Severe	$0.6 \le x \le 0.8$
Very Severe	$0.8 \le x \le 1.0$

MEDDIAD Inference Engine

The process of drawing conclusion from existing data is called inference. Fuzzy inference is the process of mapping from a given input to an output using the theory of fuzzy sets [21]. The core of decision making output is process by the inference engine using the rules contained in the rule base. The fuzzy inference mechanism employed in this research is the Mamdani Inference type. The fuzzy inference engine uses the rules in the knowledge-base and derives conclusion base on the rules. MEDDIAG inference engine uses a forward chaining mechanism to search the knowledge for the symptoms of a hypertension. The inference engine technique employed in this research is the Root Sum Square (RSS). RSS is given by the formula in equation (5):

$$\sqrt{\sum R^2} \quad = \sqrt{\left(R_1^2 + R_2^2 + R_3^2 + \ldots R_n^2\right)} \quad (5)$$

Where $R_1^2 + R_2^2 + R_3^2 + \ldots R_n^2$ are strength values (truth values) of different rules which share the same conclusion.

Using triangular fuzzifier and calculating the RSS for each of the linguistics variables mild, moderate, severe and very severe, (for patient number 030) we obtained:

Mild = 0.3
Moderate = 0.4
Severe = 0.7
Very Severe = 0.9

MEDDIAD Defuzzification

The defuzzifier translates the output from the inference engine into crisp output. The input to the defuzzification process is a fuzzy set while the output of the defuzzification process is a single number (crisp output). This is due to the fact that the output from the inference engine is usually a fuzzy set, while for most real life applications, crisp values are often required. The three common defuzzification techniques are: max criterion, center-ofgravity and the mean of maxima. Though the max criterion is the simplest to implement because it produces the point at which the possibility distribution of the action reaches a maximum value [1]. The defuzzification technique employed in this research work the Centroid approach. The centroid formula is defined by:

$$\mathrm{CoG}\left(\mathrm{Y}'\right) = \frac{\sum \mu_Y(x_i)x_i}{\sum \mu_Y(x_i)} \qquad (6)$$

Where $\mu_Y(x_i)$ = Membership value in the membership function and

x_i = center of membership function.

The approach is adopted in this research because it is computationally simple and intuitively plausible.

The above output (fuzzy set: Mild = 0.3, Moderate = 0.4, Severe = 0.7 and Very Severe = 0.9) from RSS is then defuzzified to obtain the crisp output. Defuzzifying (for patient number 030) using the Centroid approach we obtained 0.68. This means that patient number 030 has severe hypertension with 68% intensity. The other patients' data were similarly computed and the results for 30 patients are presented in table 4 below:

RESULTS AND DISCUSSION

A medical diagnostic support system for the management of Hypertension (MEDDIAG) has been developed using fuzzy logic approach. Fuzzy diagnosis resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution. In the fuzzy logic implementation, the selection of fuzzifier, rule base and inference engine determined the output of MEDDIAG. We choose triangular fuzzifier, the rule base was designed based on knowledge of domain experts (five medical doctors), and the inference technique we employed was RSS. The study evaluated the diagnosis of thirty (30) patients with hypertension using fuzzy methodology. Table 4 below presents the summary of the diagnosis from MEDDIAG. The severity of hypertension was rated as Mild ($0.1 \le x \le 0.3$), Moderate ($0.3 \le x \le 0.6$), Severe ($0.6 \le x \le 0.8$) and Very Severe ($0.8 \le x \le 1.0$). Patient number 030 was diagnosed for severe hypertension with 68% possibility Table 3 shows that the fuzzy diagnosis had 85% exact diagnosis. One advantage fuzzy diagnosis has over other soft computing methodologies is that it resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution.

Table 3: Fuzzy Results

Patient Number	% Possibility	Diagnosis
001	55	Moderate
002	30	Mild
003	41	Moderate
004	88	Very Severe
005	67	Severe
006	56	Moderate
007	43	Moderate
008	54	Moderate
009	56	Moderate
010	51	Moderate
011	81	Very Severe
012	48	Moderate
013	57	Moderate
014	34	Mild
015	56	Moderate
016	66	Severe
017	86	Very Severe
018	71	Severe
019	52	Moderate
020	53	Moderate
021	85	Very Severe
022	67	Severe
023	45	Moderate
024	39	Moderate
025	83	Very Severe
026	84	Very Severe
027	59	Moderate
028	77	Severe
029	58	Moderate
030	68	Severe

Figure 7 shows the stimulated rule view for the system (MEDDIAG). The rule base constructed was simulated using Fuzzy Logic Toolbox in Matlab 7.10.0 to identify the input parameters used for the system.

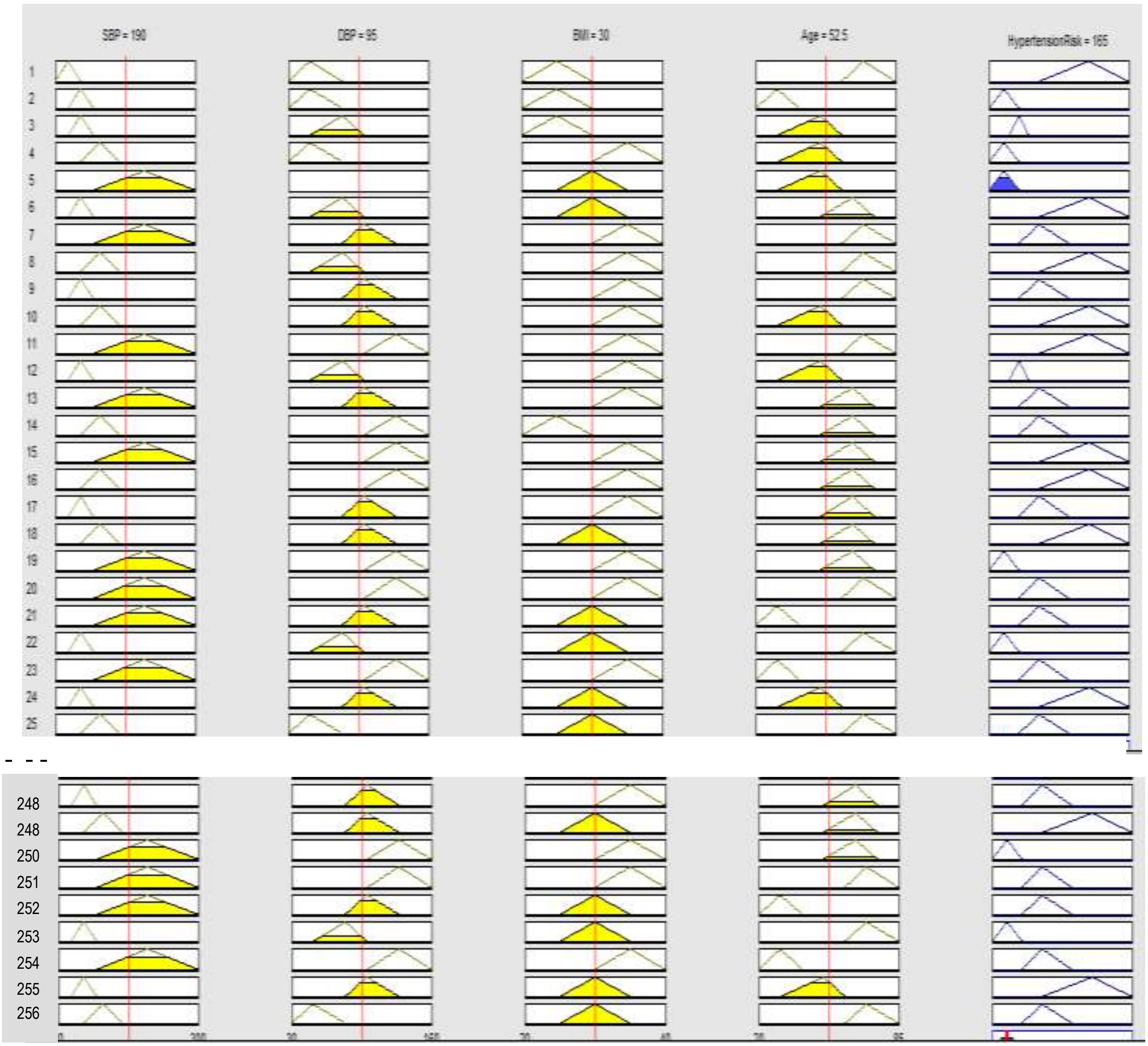

Figure 7: Simulated Rule Viewer of the Rule-base of Hypertension Risk

Figure 8 below is the surface viewer of the system. The Surface viewer was constructed using Fuzzy Logic Toolbox in Matlab 7.10.0. The surface viewer presents a three-dimensional view cure that represents the mapping from input parameters to the output parameter.

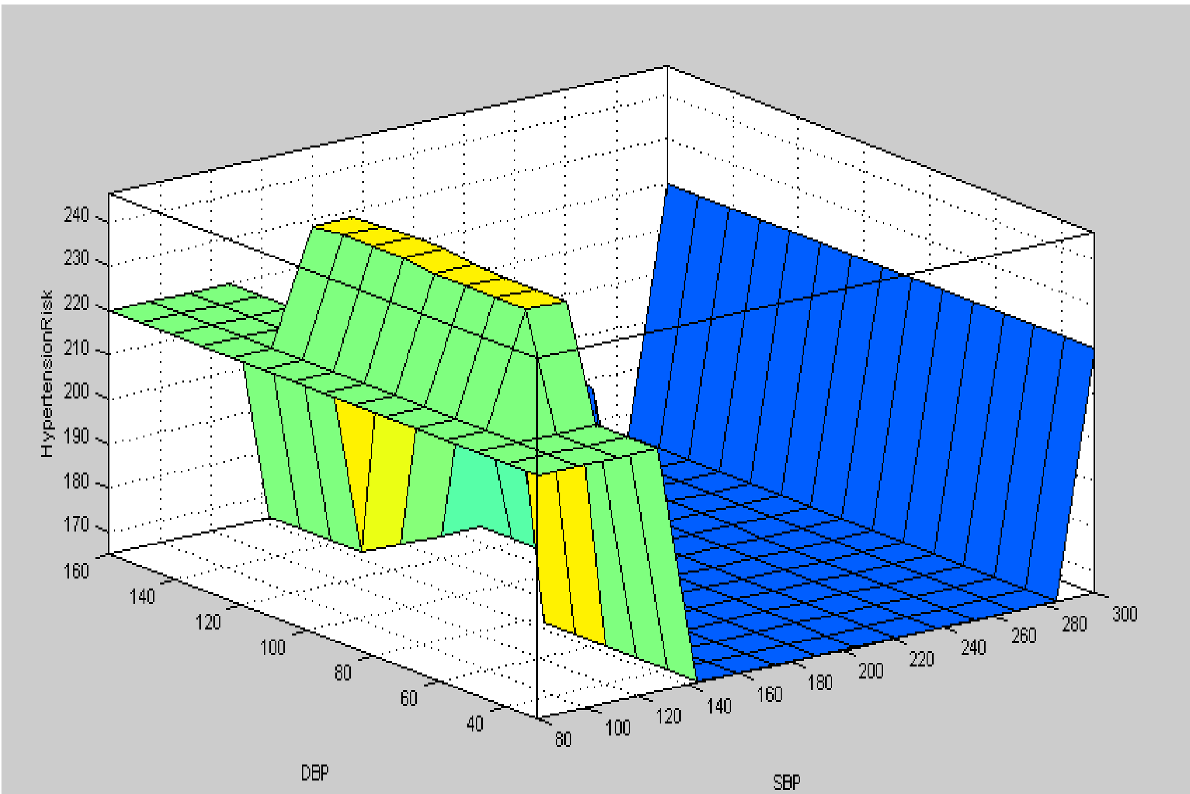

Figure 8: Surface Viewer of SBP and DBP Generated in MEDDIAG Fuzzy Inference

Fuzzy logic has been shown to relate to probability theory, but with fuzzy logic being able to represent common sense knowledge and addressing the issue of uncertainty and ambiguity of data by determining the exact degree of severity of hypertension.

CONCLUSION

This study has clearly shown the use of fuzzy logic in medical diagnosis. The complexity of medical practices makes traditional approaches of diagnosis inappropriate [5]. Fuzzy logic approach for diagnosis provides an efficient way to assist doctors in the diagnosis of hypertension. Fuzzy logic technology provides a simple way to arrive at a definite conclusion from vague, ambiguous and imprecise data (as found in medical data). Artificial Intelligence, as a branch of Computer Science, has offered itself as a useful device for man survival. Using MEDDIAG can assist medical experts in the tedious and complicated task of diagnosing hypertension.

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