Fuzzy Exemplification of Hypertension Using Matrix Laboratory (MATLAB)

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Abstract

Fuzzy logic as a concept with its adjoining structure, fuzzy system has indeed been the bedrock of most applications within and outside the domain of computer science. Its versatility has been viewed even within the boundaries of experimental medicine. Though its limitations have been observed in certain fields of application, its usefulness in term of classification has been felt in medicine. This paper has applied fuzzy logic to the classification of hypertension. The fundamental signs and symptoms such as AGE, Systolic and Diastolic was used as fundamental fuzzified input while High Blood Pressure (HBP) and Normal Blood Pressure (NBP) was used as defuzzified output components. The rich mathematical capability of Matric Laboratory: MATLAB as a simulation tool was used in simulating the experimental data obtained from Biostat repository. These simulations have shown the versatility of fuzzy logic for the classification of hypertension.

Keywords: Hypertension, Fuzzy logic, classification, MATLAB

1.0 Introduction

The persistent and continuous pressure mounted against the wall of the blood vessel can be seen as High Blood Pressure (HBP) or Hypertension (Markus, 2016). Usually HBP is an associated condition for other illnesses such as stroke, heart failure, vision loss and chronic kidney disease (Mendis et al., 2011; Lackland, 2015). Acute stress, intense exercise and other factors can briefly elevate blood pressure even in people whose blood pressure is normal; a diagnosis of hypertension requires several readings showing high blood pressure over time (Lifton et al, 2001; Kato et al., 2015).

The categorization of HBP could be viewed from genetic (primary) and non-genetic (secondary) (Carretero et al., 2000 and Poulter et al., 2015).

Generally, genetically induced hypertension is associated usually with human genome and environmental variants, distorting the wall of the blood vessels. These genetic issues perhaps are linked with family history having the propensity of been transmitted from parent to siblings (Ehret et al., 2003; Lifton et al, 2001).

Non-genetic (secondary hypertension) hypertension is caused by non-genetic issues usually not associated with environment or genetic factors as contributing ingredient. Secondary HBP could be associated with disease complication such as kidney failure or un-prescribed consumption of drugs resulting in human body complications. Other cause may be associated with obesity, sleep apnea and even pregnancy (Dluhy and Williams, 1998; O'Brien et al, 2007 Kato et al., 2015).

HBP can be measured in two forms (Lackland, 2015); systolic (maximum) and diastolic (minimum). Normal blood pressure at rest falls within the range of 100 – 140 millimeters mercury (mmHg) systolic and 60 – 90 mmHg diastolic. HBP is present if the resting blood pressure is persistently at or above 140/90 mmHg for most adults (Poulter et al., 2015).

Hypertension; in most cases are diagnosed as a particular illness due to lack of symptoms recognition, although individuals might experience certain symptoms such as headaches, vertigo, tinnitus, altered vision or fainting episodes (Giuseppe et al., 2013). On physical examination, hypertension can be traced along with certain illnesses (Carretero et al., 2000). Lifestyle changes and medications can lower blood pressure and decrease the risk of health complications drastically (Carretero et al., 2000). If lifestyle changes are not sufficient in addressing, managing, monitoring and controlling HBP, the complementary role of medication is introduced.

With a future prediction of 1.56billion persons living with hypertension by 2025 (Markus, 2016), there is indeed a pressing need for a well-coordinated approach in handling, managing and organizing all information relating to the managing of hypertension.

It is the intent of this research paper to apply fully, the components of fuzzy logic with its rich propensity for overlapping and eliminating sharp boundaries for the classification of hypertension. Matrix Laboratory (MATLAB): MATLAB 2007Rb will be explored in eliciting the components of fuzzy logic.

2.0 Applied Method

Fuzzy sets were introduced by Zadeh in 1965 (Zadeh, 1965) to represent and manipulate non statistical data with high propensity for uncertainties. Fuzzy sets provide a means of representing and manipulating data that are not precise, but rather fuzzy. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth - truth values between "completely true" and "completely false (Kasabov 1998; Robert 2000; Christos and Dimitros, 2008).

Fuzzy classification assumes the boundary between two neighbouring classes as a continuous, overlapping area within which an object has partial membership in each class. It not only reflects the reality of many applications in which categories have fuzzy boundaries, but also provides a simple representation of the potentially complex partition of the feature space. Sun and Jang (1993) propose an adaptive-network-based fuzzy classifier to solve fuzzy classification problems. Conventional approaches of pattern classification involve clustering training samples and associating clusters to given categories. The complexity and limitations of previous mechanisms are largely due to the lacking of an effective way of defining the boundaries among clusters. This problem becomes more intractable when the number of features used for classification increases (Kasabov 1998; Robert, 2000; Rudolf, 2008; Christos and Dimitros, 2008). Fuzzy classifier a subset of fuzzy logic can assign classes or boundaries (Robert, 2000 Rudolf, 2008; Christos and Dimitros, 2008).

A Fuzzy classifier is an algorithm that assigns a class label to an object, based on the object description. It is also said that the classifier predicts the class label (Angelov and Zhou, 2008). The object description comes in the form of a vector containing values of the features (attributes) deemed to be relevant for the classification task (Ishibuchi et al., 1995, Takagi and Sugeno, 1985, Yager and Kacprzyk, 1997). Typically, the classifier learns to predict class labels using a training algorithm and a training data set. When a training data set is not available, a classifier can be designed from prior knowledge and expertise. Once trained, the classifier is ready for operation on unseen objects (Cordon et al., 1999, Roubos et al., 2005).

Classification belongs to the general area of pattern recognition and machine learning (Babuska, 1998). Soft labeling fails within these categories which assume that the classes are mutually exclusive. A standard classifier will assign a single crisp label. A fuzzy classifier can assign degrees of membership (soft labels). A fuzzy classifier, D, producing soft labels can be perceived as a function approximator D: F→ [0, 1] c, where F is the feature space where the object descriptions live, and c is the number of classes. These Classes C must exist within a fuzzy set which takes boundary between 0 and 1 (0 – 1). While tuning such a function approximator outside the classification scenario would be very difficult, fuzzy classifiers may provide a solution that is both intuitive and useful (Mamdani 1977, Nauck et al., 1997 and Kuncheva, 2000).

Interpretability another form of pattern matching, automatically classify in most challenging applications such as medical diagnosis has been sidelined due to ethical, political or legal reasons, and mostly due to the black box philosophy underpinning classical pattern recognition. Fuzzy classifiers are often designed to be transparent, i.e., steps and logic statements leading to the class prediction are traceable and comprehensible (Kuncheva, 2003).

3.0 MATLAB Hypertension Fuzzification

Matrix Laboratory (MATLAB) is a high level technical computing language and interactive environment for mathematical function, algorithms development, data visualisation, data analysis and numerical computation (Mathworks, 2012). MATLAB possess tools and inbuilt mathematical function which provides a platform in solving computing problems possibly faster with traditional programming tool (C, C++ or JAVA). Matrix Laboratory (MATLAB); specifically MATLAB 7.5 (R2007b) was used in this study for model simulation.

The experimental dataset for hypertension comprising of three main attributes (AGE, SBP: Systolic Blood Pressure and DSP: Diastolic Blood Pressure) shown on Table 1, with 20 samples (fourteen male and six females) was obtained from *http://biostat.mc.vanderbilt.edu/wiki/Main/DataSet.* These experimental data was used for Matlab simulation.

Table1: Experimental Date from Hypertension

SN	Gender	AGE	SBP	DBP	SN	Gender	AGE	SBP	DBP
1	Male	56	150	100	11	Male	51	190	110
2	Male	42	120	90	12	Male	56	90	50
3	Male	69	120	90	13	Male	60	130	80
4	Male	70	180	80	14	Male	36	120	76
5	Male	62	138	78	15	Female	43	200	120
6	Male	63	115	80	16	Female	50	140	70
7	Male	31	130	80	17	Female	34	110	80
8	Male	35	150	90	18	Female	59	134	90
9	Male	40	200	100	19	Female	52	160	105
10	Male	38	120	80	20	Female	56	150	100

The conventional diagnostic rule for hypertension given as: **If systolic ≥ 140mmhg and diastolic = 90 then HBP** was obtained based on a constructive interview with physicians. Figure 1 - 7 portrays the MATLAB simulations.

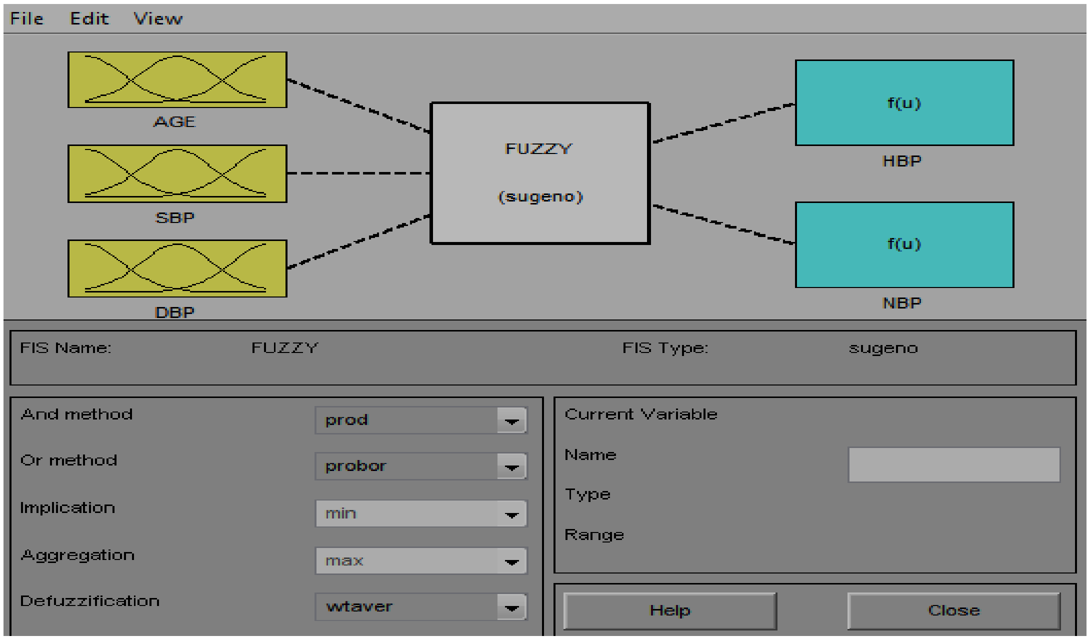

Figure 1: Hypertension Fuzzy Inference System

Figure 1 shows the Fuzzy Inference System (FIS) for hypertension showing the relationship between AGE, Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) as fuzzified input variables and High Blood Pressure (HBP) and Normal Blood Pressure (NBP) as defuzzified output. These input variables are enhanced using the Fuzzy Sugeno system which produces a weighted average defuuzzifed output. The sugeno implication process utilises AND operator in returning the minimum antecedent and truncated consequent value. With the aggregation process in play, the middle of middle of maximum defuzzified is produced.

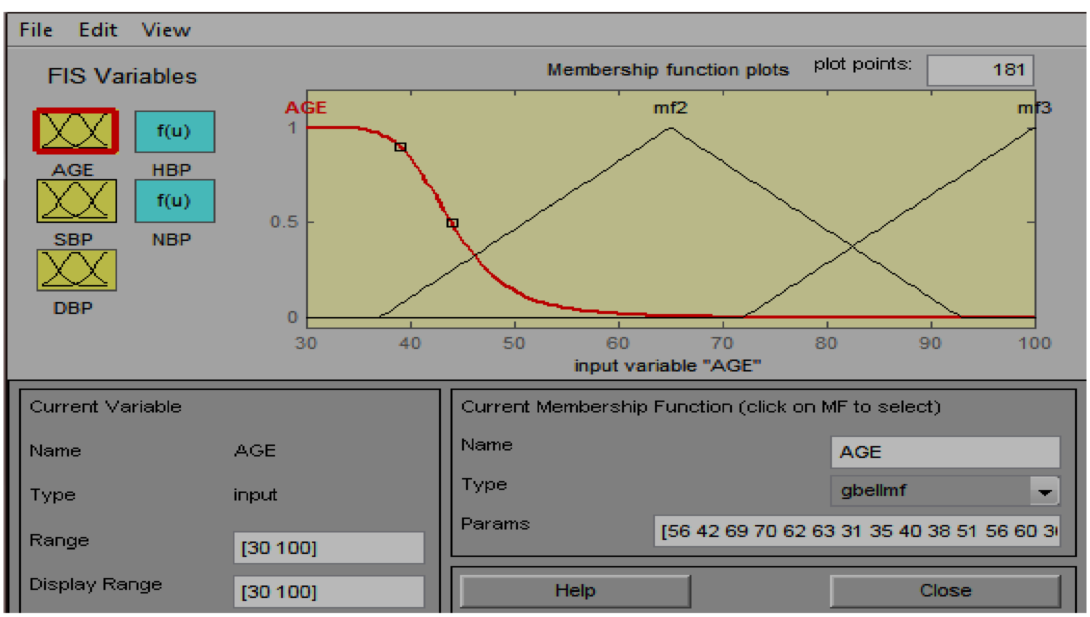

Figure 2: Fuzzy Hypertension AGE Membership Function

Figure 2 shows the fuzzy Generalized Bell Membership Function (GBMF) viewer portraying AGE as an input contributing to High Blood Pressure (HBP) and Normal Blood Pressure (NBP). The X-axis shows the varied input variables while the Y-axis shows the degree of membership functions. The membership function was tagged from dilation or contraction using the small square drag points on the membership function lines.

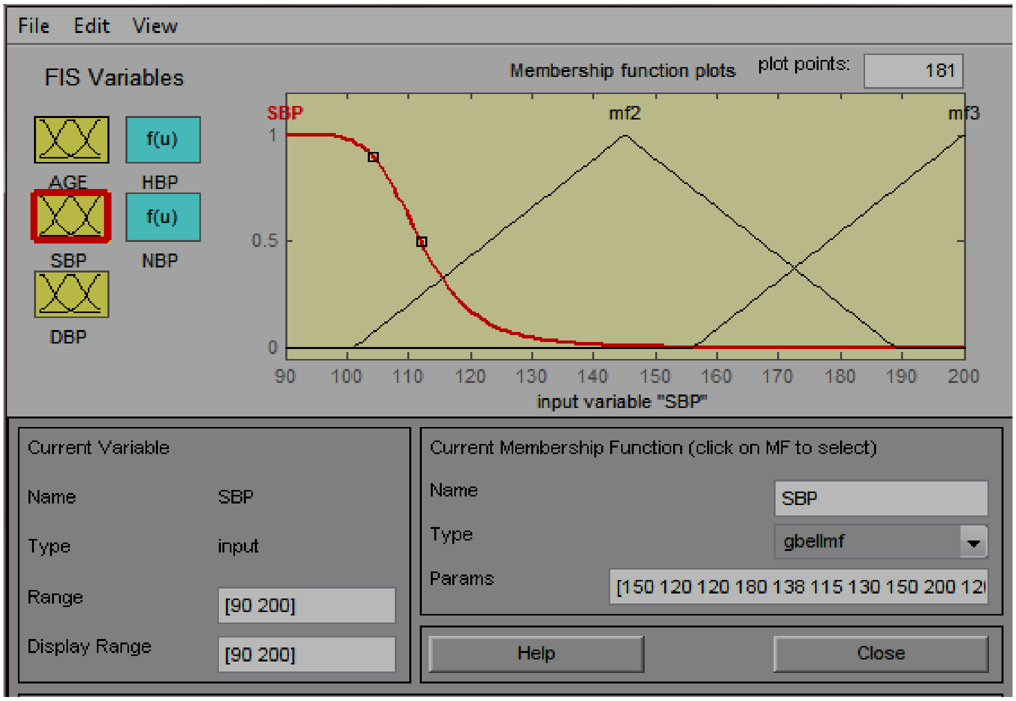

Figure 3: Fuzzy Hypertension SBP Membership Function

Figure 3 shows the fuzzy generalized membership function viewer portraying input (SBP) with associated membership function and output variables (HBP and NBP) generated with the Generalized Bell Membership Function (GBMF). The X-axis shows the range of input as (90 – 200) while the Y-axis shows the degree of membership function (0 - 1).

Figure 4 shows the fuzzy generalized membership function viewer portraying input (DBP) with associated membership function and output variables (HBP and NBP) generated with the Generalized Bell Membership Function (GBMF). The X-axis shows the range of input as (70 – 120) while the Y-axis shows the degree of membership function (0 - 1).

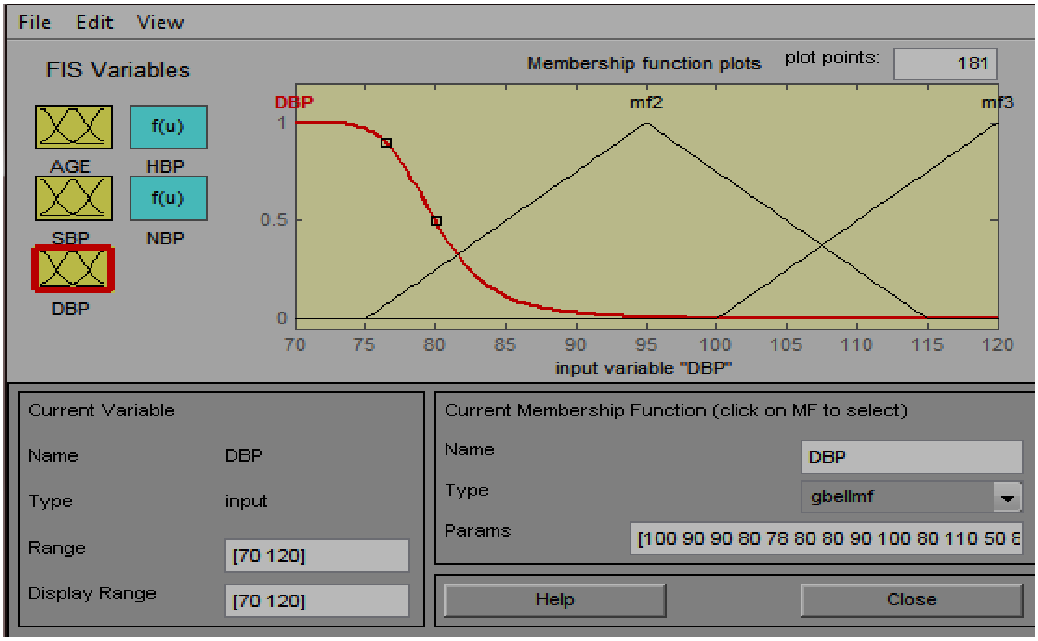

Figure 4: Fuzzy Hypertension DBP Membership Function

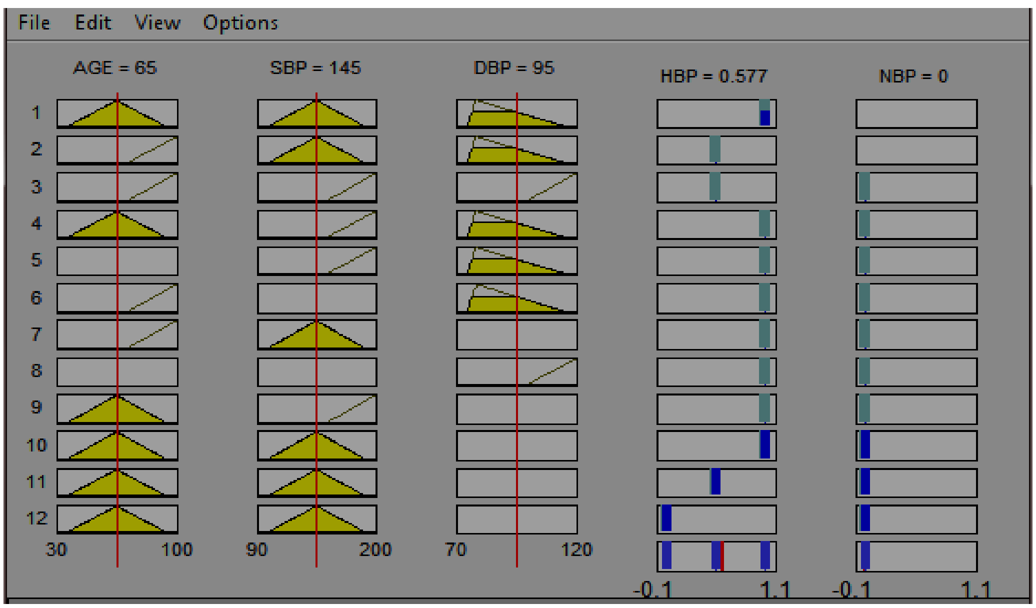

Figure 5: Fuzzy-Hypertension Rule Viewer

Figure 5 depicts the rule viewer with each hypertension rule shown as a row number. The first three column plots; AGE, SBP and DBP shows varied membership functions referenced by its antecedent, or the if-then-part of each rule. The last two column plot represents the aggregate weighted prediction output values for High Blood Pressure (HBP) or Normal Blood Pressure (NBP) with the deffuzzified value captured as the marker within these column.

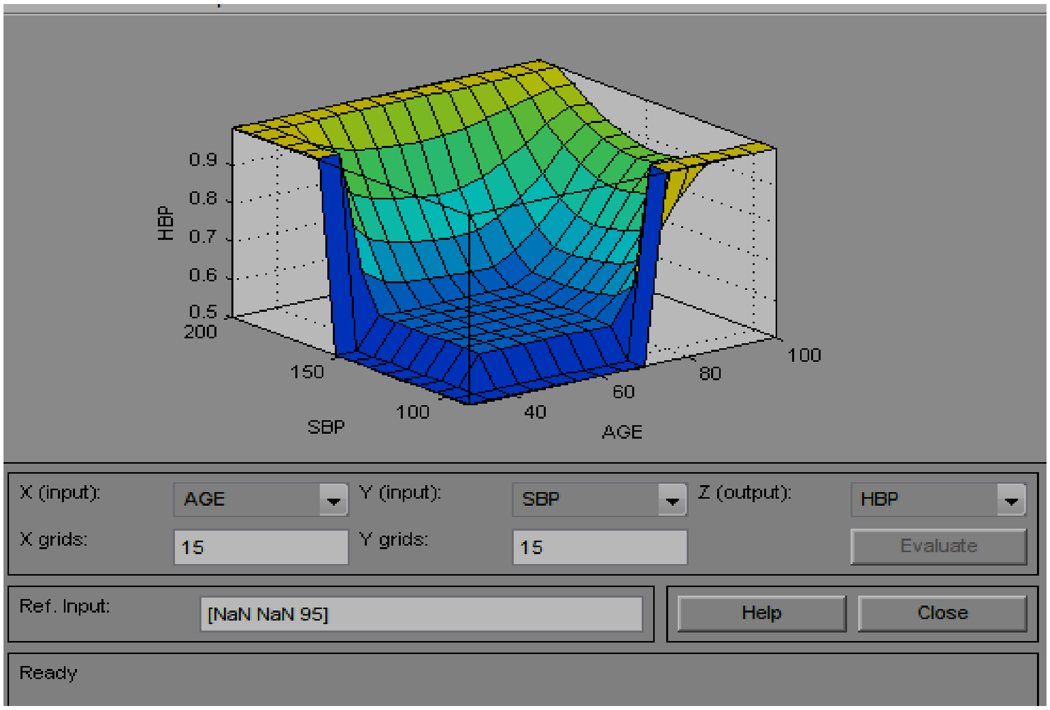

Figure 6: Fuzzy Hypertension Surface Viewer

Figure 6 depict a three-dimensional view of the Fuzzy hypertension variables: AGE (40 - 100), Systolic (100 – 150) and HBP (0.5 – 0.9). Each variable, X, Y or Z is given a grid plot line of 15 to enhance clarity. In this viewer AGE and Systolic are taken as input and the output is High Blood pressure (HBP).

4.0 Result: Simulation Analysis

The following finding and result were captured from the simulation Figures.

a. Figure 1: the input variables (AGE, SBP and DBP) accommodate overlapping membership function portrayed by the curve within each variable which perhaps could be impossible with the conventional classification.
b. Figure 2-4: The input variables (AGE, SBP and DBP) are fuzzified with the range of values streaming between 0 -1 as opposed to conventional classification with crisp values (x > 0)
c. Figure 5: The prediction values accommodated with the fourth and fifth columns are adjusted based on fuzzy set values (0 - 1) and produces a defuzzifed output (0-1) which could be impossible with conventional approaches
d. Figure 6: This figure produces a three-dimensional view with the capability of identifying the contributing input of two values to the final output, possibly difficult with conventional approaches.

5.0 Conclusion

Hypertension has been identified as a complicated condition bearing largely on several illnesses. This complication has been tenacious base on the traditional meaning of classifying hypertension with it bivariate boundaries not accommodating overlapping boundaries. This research paper has applied fuzzy logic as a mean for classifying hypertension utilising it rich components: membership function, fuzzy inference system, fuzzy rule with the aim of lowering this sharpness in classification boundaries while accommodating multivariate classification. MATLAB was used in portraying integral components simulation. This paper has addressed uncertainty and preciseness in hypertension classicisation.

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