Implementation of Fuzzy Classifier System Ability to Improve Performance for Real Time Environment

Varsha S.Chaudhari[1]
[1]Department of Master in Computer Application
[1]A. C. Patil College of Engineering University of Mumbai, India

Abstract— An Implementation of Fuzzy Classifier Systems is described in this paper. The classifier system is based on ability to improve performance for real time environment Open environment is full of pollution in the presence of the air. One can find the physical parameters of the pollution using fuzzy logic membership functions & fuzzy cardinality and relative fuzzy cardinality. We propose also an interface that makes easier to the user the task of writing, compiling and administering the rules stored in theKnowledgeBase. Fuzzy logic is a natural basis for modelling and solving problems involving imprecise knowledge and contin-uous systems. Unfortunately, fuzzy logic systems are invariably static (once created they do not change) and subjective (the creator imparts their beliefs on the system). In this paper we address the question of whether systems based on fuzzy logic can e ectively adapt themselves to dynamic situations.

Key words: Fuzzy Classifier Systems, Fuzzy Logic, Expert Systems, Fuzzy Real Time Environment

I. INTRODUCTION

Fuzzy Logic provides a simple method to empower computer systems with knowledge and reasoning abil-ity that can handle imprecision, complexity and con-tinuity. However, Fuzzy Logic systems, while easy to create, have subjective knowledge inherent in their construction process. The representation of this sub-jective knowledge is static; once it is created it does not adjust to suit the domain. Adaptation of this knowledge to provide a more optimal representation is one method of improving the output and allowing the system to respond to changes apparent in the do-main.

Adaptive systems are typically implemented in the the form of learning systems based on neural net-works (Kruse & Nrnberger 1998). These systems, while producing good results in the application areas researched, have the burden of poor computational complexity relative to the number of inputs to the sys-tem, as well as being slow to adapt to new situations (Langholz 1992). This causes these approaches to be unsuited to an environment that requires real time adaptation with limited sample data and communi-cation of discovered optimisations in the presense of real world communication restraints.

A novel approach to on-line adaptation and op-timisation using linguistic modi ers and a fuzzy logic based adaptive function;

An implementation of cooperative adaptation that allows two or more agents to e ectively com-municate and cooperatively adapt via this online fuzzy logic adaptation system;

A statistical veri cation of the performance and e cacy of the proposal.

In our life we find several complex situations commanded by rules: control systems, safety systems, bank transactions, etc. Rule-based systems are an efficient tool to deal with these specific problems. The Knowledge Base contains the variables and the rules defining the problem, ant the inference engine obtains the conclusions through the application of classic logic to these rules. A rule is defined – in our field of work- as a "If premise, then conclusion" structure, where premise and conclusion are expressions which can be based on fuzzy logic, with one or more affirmative statements, connected via logic operators like "AND", "OR" or "NOT".

Since its appearance in the sixties, Fuzzy Logic applications have earned consolidation [3, 4]. They are found in solutions for industrial control problems, time series prediction, Operative Research, maintenance strategies, search methods in databases, and so on. Probably, the main reasons to such vast array of applications are the conceptual simplicity of the fuzzy systems, their ability to combine in a unified manner the linguistic expressions with numeric data, and their implementation without sophisticated algorithms. Particularly, it is possible to use Fuzzy Classifier Systems (FCS) in situations that imply uncertainty and incomplete or complex information management [2]. The FCS are a type of learning machine that uses rules based on Fuzzy Logic for modeling a problem.

The main objective of this paper is to develop a rule compiler that can be used by Expert Systems and FCS. This is achieved through the utilization of the ANTLR language (Another Tool for Language Recognition) [2], which generates compilers from a grammar specification of the language to be recognized. Hence, one of the main contributions of this paper is the proposal of a grammatical structure that defines how the rules should be. Our system is developed using Java [9], and defines an interactive interface, which allows the user, in a comfortable and practical way, to use the system. This paper is a part of the project named "Computational Platform for the development of Expert Systems and Fuzzy Systems" [8].

This paper presents only the rule compiler's design for the FCS. In order to study the Expert System please refer to [7]. This article is organized as follows: section 2 introduces the Theoretical Framework, section 3 describes the System Design, section 4 presents a Study Case, and finally in section 5, we present the Conclusions and Limitations found, as well as the possible eventual further works.

However, most of the techniques proposed suffer from a common failing: they attempt to classify each text in a single most likely class, in a winner-takes-all fashion. Real-world texts, however, often belong to several classes at once, with different degrees. For example, a news article can cover both politics and business, while a novel can be both romance and mystery. A single-class classification system is clearly inappropriate in such cases. In addition, systems that rely on fuzzy logic require accurate fuzzy rules, the creation of which is an arduous and time-consuming task. In this paper, we propose a new multi-class fuzzy-logic-based classifier. This classifier differs from traditional crisp and fuzzy classifiers in that it does not assume that the text belongs to one single class, but rather computes the degree to which the text belongs to each known class, and that it learns its fuzzy rules automatically from a training data set.

The rest of this paper is organized as follows. The next section gives the reader a review on some key notions of fuzzy set theory, which are necessary to understand this work. Section III provides a description of the fuzzy system we have built, including its rule-learning algorithm. We present two types of experimental results in section IV. We finally draw some conclusions of this work in section V, and propose possible directions for future research.

Fuzzy logic has rapidly become one of the most successful of today's technologies for developing sophisticated control systems. The reason for whichis very simple. Fuzzy logic addresses such perfectly as it resembles human decision making with an ability to generate precise solutions from certain or approximate information. While other approaches require accurate equations to model real-world behaviors, fuzzy design can accommodate the ambiguities of real-world in human language and logic. Although genetic algorithms and neural networks can perform just as well as fuzzy logic in many cases, fuzzy logic has the advantage that the solution to the problem can be cast in terms that human operators can understand, so that their experience can be used in the design of the controller. This makes it easier to mechanize tasks that are already successfully performed by humans.[1]

In a broad sense, fuzzy logic refers to fuzzy sets - a set with unclear boundaries. Examples of fuzzy sets are “hot,” “tall,” “medium,” etc. In a narrow sense, fuzzy logic is a logical system that aims to formalize approximate reasoning .In fuzzy logic a fuzzy symbol can take any truth values from the closed set [0, 1] of real numbers thus generalizing the Boolean truth values. As the technology was further embraced, fuzzy logic was used in more useful applications.

II. Background

A. Fuzzy Set Theory:

The need to extract knowledge from domain experts or from training data obtained in the real world, known as knowledge acquisition, is a task central to applications of knowledge engineering. However, the vagueness intrinsic to human knowledge and to the real world makes this task quite difficult to accomplish using a conventional mathematical model, as such a model attempts to precisely represent all the characteristics of the expert system we are building and lacks flexibility. Fuzzy set theory, introduced by Zadeh [1], should provide the needed tools needed to deal with the vagueness of our knowledge, and allows us to represent the parameters of a system using vague linguistic terms rather than exact mathematical values. However, we are left with the task of building the membership functions of these parameters and the fuzzy rules of the system. This is an important bottleneck in the construction of fuzzy expert systems, and if done manually, would require expensive resources from domain experts and knowledge engineers [3].

Fortunately, for most real-world applications, numerical data can be easily obtained from instruments or from the environment. Several researchers have come up with ways to use this data to allow the system to construct its own fuzzy rules, using various types of learning algorithms. For example, Wang and Mendel [4] used a table-lookup technique to generate their rules. A more popular approach is to use neural networks [6][8], modular neural networks [7] or hybrid systems [5] to extract knowledge from the training examples and build the rules. Hoang and Lee [9] proposed a simpler learning system, based only on fuzzy clustering and decision tables, that is capable of defining the membership functions and the fuzzy rules without relying on complex computational schemes like neural networks. However, the size of their decision table grows with the number of input variables, and the system becomes overly complicated in accurate real-world applications, which may involve a very high number of variables. Wu and Chen [2] proposed another simple learning algorithm. Their technique divides the training data into clusters the using the a -cuts of fuzzy equivalence relations and of fuzzy sets, and then derives the membership function of each of these clusters. This learning algorithm generates on average half the number of rules the one by Hoang and Lee generates, but despite that simplicity it yields slightly more accurate results that Hoang and Lee’s system.

We will study Wu and Chen’s learning algorithm in more details in section III. In the rest of this section, we give a brief overview of the basic mathematical notions behind fuzzy set theory.

To design a fuzzy controller, linguistic rules and mem-bership functions to represent linguistic values must be determined. The speci cation of good linguistic rules typically depends on the knowledge of the do-main expert. The translation of these linguistic rules into fuzzy set theory is not formalized and arbitrary choices have to be made. This includes choice of a membership function representing a linguistic term and the degree of overlap with other linguistic terms in the same fuzzy variable.

As an example, consider a temperature variable and the linguistic terms hot, medium and cold. If the linguistic term hot is considered, obviously the cor-responding fuzzy set de nitions should consist of a function reaching its maximum at the value the oper-ator assigns as depicting hot. Neither the shape, the support of the membership function or the degree of overlap with the linguistic term medium is uniquely determined by the linguistic term hot. In general, the domain expert has some idea about the range and the shape of the membership function, however there is some imprecision in the boundaries and shape of the function (Pearson 2001).

B. Fuzzy Explanation:

A fuzzy expert system consists of three different types of entities: fuzzy sets, fuzzy variables and fuzzy rules. The membership of a fuzzy variable in a fuzzy set is determined by a function that produces values within the interval [0, 1]. These functions are called membership functions. Fuzzy variables are divided into two groups: antecedent variables, that are assigned with the input data of the fuzzy expert system and consequent variables, that are assigned with the results computed by the system.

The fuzzy rules determine the link between the antecedent and the consequent fuzzy variables, and are often defined using natural language linguistic terms. For instance, a fuzzy rule can be ”if the temperature is cold and the wind is strong then wear warm clothes”, where temperature and wind are antecedent fuzzy variables, wear is a consequent fuzzy variable and cold, strong and warm clothes are fuzzy sets.

The process of a fuzzy system has three steps. These steps are Fuzzification, Rule Evaluation, and Defuzzification. In the fuzzification step, the input crisp values are transformed into degrees of membership in the fuzzy sets. The degree of membership of each crisp value in each fuzzy set is determined by plugging the value into the membership function associated with the fuzzy set. In the rule evaluation step, each fuzzy rule is assigned with a strength value. The strength is determined by the degrees of memberships of the crisp input values in the fuzzy sets of antecedent part of the fuzzy rule. The defuzzification stage transposes the fuzzy outputs into crisp values.

C. Fuzzification and Membership Functions:

The fuzzy set is a powerful tool and allows us to represent objects or members in a vague or ambiguous way. The fuzzy set also provides a way that is similar to a human being’s concepts and thought process. However, just the fuzzy set itself cannot lead to any useful and practical products until the fuzzy inference process is applied. To implement fuzzy inference to a real product or to solve an actual Fundamentals of Fuzzy Logic Control 25 problem, as we discussed before, three consecutive steps are needed, which are: Fuzzification, fuzzy inference and defuzzification. Fuzzification is the first step to apply a fuzzy inference system. Most variables existing in the real world are crisp or classical variables. One needs to convert those crisp variables (both input and output) to fuzzy variables, and then apply fuzzy inference to process those data to obtain the desired output.

Finally, in most cases, those fuzzy outputs need to be converted back to crisp variables to complete the desired control objectives. Generally, fuzzification involves two processes: derive the membership functions for input and output variables and represent them with linguistic variables. This process is equivalent to converting or mapping classical set to fuzzy set to varying degrees. In practice, membership functions can have multiple different types, such as the triangular waveform, trapezoidal waveform, Gaussian waveform, bell-shaped waveform, sigmoidal waveform and S-curve waveform. The exact type depends on the actual applications. For those systems that need significant dynamic variation in a short period of time, a triangular or trapezoidal waveform should be utilized. For those system that need very high control accuracy, a Gaussian or S-curve waveform should be selected.

To illustrate the process of fuzzification, we still use the air conditioner example developed in the previous section. Assume that we have an air conditioner control system that is under the control of only a heater. If the temperature is high, the heater control motor should be turned off, and if the temperature is low, that heater motor should be turned on, which are common sense.

D. Fuzzy Decision-Making:

Fuzzy decision-making is a specialized, language oriented fuzzy system used to make personal and business management decisions, such as purchasing cars and appliances. It’s even been used to help resolve the ambiguities in spouse selection! On a more practical level, fuzzy decision-makers have been used to optimize the purchase of cars and VCRs. The Fuji Bank has developed a fuzzy decision-support system for securities trading.

III. FUZZY INFERENCE SYSTEM

A. Fuzzification:

Converting crisp facts into fuzzy sets described by linguistic expressions. Membership functions can be flat on the top, piece-wise linear and triangle shaped, rectangular, or ramps with horizontal shoulders. These three choices can be explained by the ease with which a parametric functional description of a membership function can be obtained, stored with minimum use of memory and employed efficiently, in terms of real time requirements by the inference engine.

B. Defuzzification:

Defuzzification is the process of producing a quantifiable result in fuzzy logic The fuzzy inference will output a fuzzy result, described in terms of degrees of membership of the fuzzy sets Defuzzification interprets the membership degrees in the fuzzy sets into a specific action or real-value.

IV. METHODS OF DEFUZZIFICATION

There are many methods for defuzzification One of the more common types of defuzzification technique is the maximum defuzzification techniques. These select the output with the highest membership function They include:

1) First of maximum
2) Middle of maximum
3) Last of maximum
4) Mean of maxima
5) Random choice of maximum

A. Inference:

The fuzzy IF-THEN rule expresses a fuzzy implication relation between the fuzzy sets of the premise and the fuzzy sets of the conclusion.

B. Fuzzy Inference System:

Fuzzy Inference System (FIS) is the procedure of formulating the deduction from the set input variables to the output variables by using fuzzy logic. The procedure allows the making of decisions or recognising of a certain pattern. For the needs of this paper the mamdani type of FIS was used. The Mamdami type of inference mechanism assumes that the functions of belonging of the output variables are fuzzy sets. The fuzzy deduction procedure includes: • Taking the values of input variables; • Defining of If-Then rules. It is necessary to define a number of deduction rules which contain the knowledge about the device assessment, referred to by the system in making the final decision (judgement) – in this example FINAL GRADE. The rules consist of If-Then statements which are used for the formulation of the conditional statements (premises and consequences), e.g.: IF (housing IS “good”) AND (keyboard IS “very good”) THEN (final grade IS “good”). • A knowledge base is created from the mentioned rules. It is changed depending on the input rules. • The application of logic operators (AND, OR, NOT). • The application of the implication method. • Aggregation (sum) of solutions (values) obtained by applying the rules.

C. Fuzzy Logic Adaptive Techniques:

To design a fuzzy controller, linguistic rules and mem-bership functions to represent linguistic values must be determined. The speci cation of good linguistic rules typically depends on the knowledge of the do-main expert. The translation of these linguistic rules into fuzzy set theory is not formalized and arbitrary choices have to be made. This includes choice of a membership function representing a linguistic term and the degree of overlap with other linguistic terms in the same fuzzy variable.

As an example, consider a temperature variable and the linguistic terms hot, medium and cold. If the linguistic term hot is considered, obviously the corresponding fuzzy set de nitions should consist of a function reaching its maximum at the value the operator assigns as depicting hot. Neither the shape, the support of the membership function or the degree of overlap with the linguistic term medium is uniquely determined by the linguistic term hot. In general, the domain expert has some idea about the range and the shape of the membership function, however there is some imprecision in the boundaries and shape of the function.

D. Neural Networks:

Neural Networks have been suggested as a method of o ine adapting and optimising fuzzy controllers to increase their performance. A straightforward ap-proach is to assume a certain shape for the member-ship functions which depend on di erent parameters that can be learned by a Neural Network. This idea was carried out in (Nauck, Flawonn & Kruse 1992) where the membership functions are assumed to be symmetrical triangular functions depending on two parameters one of them determining where the func-tion reaches its maximum the other giving the length of the support. Another approach is summarised in (Kruse & Nrnberger 1998). The literature is exten-sive regarding this topic, with many well regarded and successful implementations documented, a summary and bibliography of these can be found in (Nauck & Kruse 2002).

V. FUZZY SET BASED APPROACH FOR TEX CLASSIFICATION

Current approaches for text classification have been subject to two major limitations. First, they attempt to classify each text into a single category. This is not always appropriate, as authors often cover several topics in a single text. In such cases, a single-category classification might be inaccurate and insufficient. The second limitation of current text classification algorithms pertains to the fact that the approaches make crisp classifications according to text features. An example of such a crisp rule is: “if the word government is present more than 10 times per thousand words, classify the text as political.” Natural language texts are too diverse and varied for such strict rules to apply in more than a few cases.

The classifier we propose helps avoiding those two limitations. As we will show in the next section, our classifier works like several independent classifiers, each one computing how much a given text belongs to one category. It is therefore possible for a text to belong to several categories at once, or none at all if it is not part of any of the categories we have trained our system for. And our classifier uses fuzzy rules rather than crisp rules, which makes it better suited to handle the fuzzy and uncertain nature of natural discourse.

A. Input Data:

The input data we chose to use are news articles. These articles are freely available through Internet news services [12]. They can be easily classified into categories based on their respective topics, which can be deduced from their content. But before these news articles can be fed to the classifier, they must go through a few pre-processing stages.

It has been shown in [11] that all news reports are written following a certain stylistic convention. That convention dictates that the crucial information of the event is stated right away at the beginning of the text. The rest of the article can contain supplementary details, historical information, legal precedents, comments from the parties concerned or reactions from the public. This observation allows us to infer that, for classifications purposes, the classifier can limit its scope to the first paragraph of the text and still reach good conclusions – even better conclusions than it would by considering the whole article, as it won’t be burdened by extraneous information.

Next, the selected text goes through word stemming. This step removes stop words from the text (common words that carry no meaning, such as “and”, “or”, “for”, “not”) and cuts prefixes and suffixes from words, keeping only their root (for example, the words “governing”, “government”, “governor” would all be reduced to “govern”).

Finally, we construct the semantic vector of the article. Several techniques have been proposed to accomplish this task [10]. In the current system, we use the word frequency weighting, or the number of time each keyword has been encountered in the news article. We have also experimented using the tf idf weighting [10] instead of the word frequency weighting, but this did not provide improvement. The keywords in question are the words that were present in the training articles that were used to construct the fuzzy rules of the system. They are the only words the system has been trained to recognise. For the present work, we assume that we have no prior knowledge about which words are more important for the classification. Therefore, we keep all the words found in the articles.

B. Output Data:

The output of the classifier is the membership degree of the article being analysed in each of the classes for which fuzzy rules are available. This membership is represented by a number between 0 (not at all a member of the class) and 100 (fits perfectly in the class). In the context of the present article, we will train our classifier to recognise three classes, politics, business and sports. Internally, those classes allow different degrees of membership: for example, an article about a visiting political dignitary can be said to be "more political" than an article about industry representatives asking the government for tax breaks. There is also a lot of overlap between those two classes: for example, an article about the impact of the government's fiscal policy on the unemployment rates is very relevant in the business and politics classes, one about the NHL lockdown is relevant in business and sports, while one about government sponsorship of the Olympic team is relevant in politics and sports. These scenarios illustrate even further the need for a fuzzy classifier.

C. The Learning Algorithm:

The learning algorithm devised by Wu and Chen and presented in detail in [2] is used to build the n-input-single-output fuzzy system. To accomplish this task, it is given a numerical training data set P, which is composed of m input-output pairs and is defined as:

$$P = \{ (x_{1,j},\dots, x_{n,j}, y_j) \mid j = 1,\dots, m \}$$

In our case, the number *m* is the number of training articles, and the *n* input variables represent the *n* different words encountered in these articles. More precisely, the input variables $x_{1,j},\dots, x_{n,j}$ represent the frequency with which each one of the *n* words was encountered in the j^{th} training article, and the output variable y_j is the degree to which that article belongs to the class we are training the system for. To take a simple example, suppose the j^{th} training article contains 3 occurrences of the word "parliament" (x_1), 5 occurrences of the word "elected" (x_2), and that it has a membership degree of 92 to the "political" class. Its input-output pair in *P* will be:

$$P = \{ (3, 5, 0,\dots, 0, 92) \}$$

The learning algorithm devised by Wu and Chen begins by sorting the training set *P* in ascending order according to the values of the output variables, and computes the fuzzy equivalence between each pair of training articles. It then partitions the training set using the α-cut of the fuzzy equivalence relation, and constructs a fuzzy set representing the output values of each of the partitions. The algorithm uses triangular sets, which are simply represented as a triplet (*a*, *b*, *c*), composed of an average value, *b*, and the left and right vertexes, *a* and *c* respectively.

The algorithm then proceeds to repeat those steps for each of the *n* input variables of each of the partitions already made. Therefore, it sorts each input variable of each partition in ascending order, computes their fuzzy equivalence as described previously, partitions the set according to the α-cut of that relation, and constructs a fuzzy triangular set representing each partition.

After the algorithm has constructed fuzzy sets covering all possible values the input and output variables can take, it can assemble them to build fuzzy if-then rules of the form:

IF x1 is (a_1, b_1, c_1) AND … AND x_n is (a_n, b_n, c_n)
THEN y is (a, b, c)

This should be read as "if the frequency count of word 1 belongs to the triangular fuzzy set defined by the triplet (a_1, b_1, c_1) and … and the frequency count of word *n* belongs to the triangular fuzzy set defined by the triplet (a_n, b_n, c_n), then the article's membership to the modelled class belongs to the fuzzy set defined by the triplet (*a*, *b*, *c*)". Of course, since all the sets are generated independently from each other, it is possible, even likely, that some of them will cover similar values of the variables. Those sets are merged together in the final step of the algorithm. This simplifies the fuzzy rules by reducing the number of fuzzy sets generated, without affecting the accuracy of the rules, since the sets merged are equivalent.

VI. FUZZY LOGIC

Fuzzy Logic is, essentially, the incorporation of the concept of multivalued logic 2, 3, 4. Human reasoning uses truth values that are not necessarily determining (statements with just true or false values). For instance, when it is said that "The sky is blue", it could be possible to think how blue the sky is indeed. Likewise, it would be possible to think "if a vehicle moves fast", it would be possible to think how fast it moves, since this last observation does not imply necessarily the quantification of speed with the accuracy required.

The adjective "fuzzy" is due to the fact that the non-determining truth values used in them have, generally, an uncertainty meaning. A half-full glass, notwithstanding the fact that it is also half-empty, is not totally full nor totally empty. This is the type of indeterminate properties that we can manage with fuzzy theory.

A Fuzzy System can be developed based on a set of heuristic rules, in which the inputs and outputs linguistic variables are represented by fuzzy sets. The following figure shows the main components [3:

A Fuzzy System is composed of a mechanism that transforms discreet data into Fuzzy data (fuzzification mechanism), another mechanism that makes the inverse process based on one of the classic techniques of defuzzification, such as the centroid method, a knowledge base that stores the Fuzzy rules, and the mechanism of Fuzzy reasoning.

VII. FUZZY CLASSIFIER SYSTEM

One of the most important challenges in the Intelligent Computing area consists of modelling intelligent behavior through the use of Intelligent Techniques (Artificial Neural Networks, Genetic Algorithms, etc.). The systems that attempt to model intelligent behaviors similar to the humans' belong to the area known as Learning Machines [2, 8. The FCSs are a type of Learning Machine based on Fuzzy Logic.

The FCSs try to imitate the way in which human beings make decisions. These systems are generally robust and tolerant to imprecision and noises in the input data. The FCSs apply the Fuzzy Logic with the aim of imitating human reasoning in computers. In order to achieve this goal, mathematic theory based on fuzzy set is used to map subjective notions, such as hot, warm, cold, to concrete values that can be manipulated by computers. A FCS is composed of the following elements.

A message detector system is the responsible of the information fuzzification. An actuator system generates the commands derived from the reasoning process of the system. It also performs defuzzification tasks, in case of being required. The Fuzzy Rules System has a Fuzzy reasoning mechanism that takes such rules and the messages provenient from the exterior to perform the inference process. The Adaptative System allows the generation or removal of rules in the rules system, in accordance with their quality. Those rules that are not suitable for the environment where the FCS is operating must be discarded and the combination of the best rules generates new rules. In order to determine the non-suitable rules and the best ones, the Credit Assignment System is used. This system gives points to each rule, taking into account if it is activated or activates others rules when a requirement (message) arrives to the FCS.

The Inference Engine starts the Fuzzy reasoning process taking the system input variables and verifying the rules that are activated (Knowledge Base). The Fuzzy reasoning mechanism used is the classic “Modus Ponens” [8]. The Adaptative System updates automatically the set of rules, in accordance with the usage they have during the functioning of the system.

A. Blood Pressure

Blood pressure is typically recorded as two numbers, written as a ratio like this:
Diastolic. The bottom number, which is also the lower of the two numbers, measures the pressure in the arteries between heartbeats (when the heart muscle is resting between beats and refilling with blood).

B. Causes of Blood Pressure

Blood pressure is the measure of the force of blood pushing against blood vessel walls. The heart pumps blood into the arteries (blood vessels), which carry the blood throughout the body. High blood pressure, also called hypertension, is dangerous because it makes the heart work harder to pump blood to the body and contributes to hardening of the arteries, or atherosclerosis, and to the development of heart failure.

C. Normal Blood Pressure

A blood pressure reading has a top number (systolic) and bottom number (diastolic). The ranges are:
Normal: Less than 120 over 80 (120/80) Pre hypertension: 120-139 over 80-89

1) Stage 1 high blood pressure: 140-159 over 90-99
2) Stage 2 high blood pressure: 160 and above over 100 and above. People whose blood pressure is above the normal range should consult their doctor about steps to take to lower it.

D. Causes for high Blood Pressure

The exact causes of high blood pressure are not known, but several factors and conditions may play a role in its development, including: smoking, being overweight or obese Lack of physical activity, Too much salt in the diet, Too much alcohol consumption (more than 1 to 2 drinks per day), Stress, Older age, Genetics, Family history of high blood pressure, Chronic kidney disease, Adrenal and thyroid disorders.

E. Essential Hypertension

In as many as 95% of reported high blood pressure cases in the U.S., the underlying cause cannot be determined. This type of high blood pressure is called essential hypertension. Though essential hypertension remains somewhat mysterious, it has been linked to certain risk factors. High blood pressure tends to run in families and is more likely to affect men than women. Age and race also play a role. In the United States, blacks are twice as likely as whites to have high blood pressure, although the gap begins to narrow around age 44. After age 65, black women have the highest incidence of high blood pressure. Essential hypertension is also greatly influenced by diet and lifestyle. The link between salt and high blood pressure is especially compelling. People living on the northern islands of Japan eat more salt per capita than anyone else in the world and have the highest incidence of essential hypertension. By contrast, people who add no salt to their food show virtually no traces of essential hypertension. The majority of all people with high blood pressure are "salt sensitive," meaning that anything more than the minimal bodily need for salt is too much for them and increases their blood pressure. Other factors that can raise the risk of having essential hypertension include obesity; diabetes; stress; insufficient intake of potassium, calcium, and magnesium; lack of physical activity; and chronic alcohol consumption.

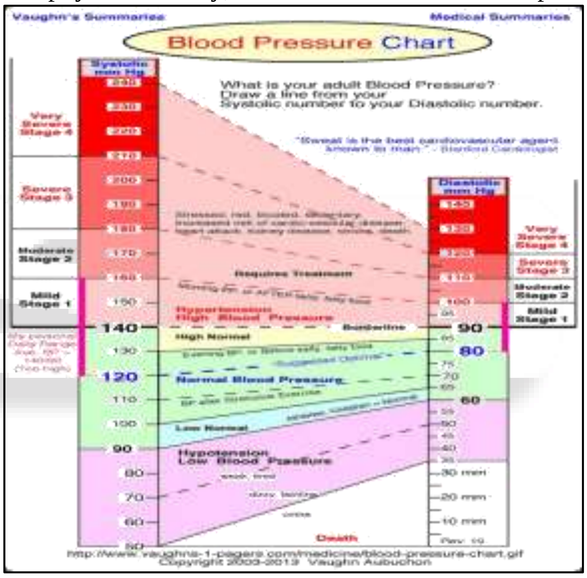

Fig. 1: A Sample Medical Blood Pressure Chart

What is Normal Blood Pressure? Buy and use an automatic blood pressure monitor. Compare your BP reading with the numbers on the chart above. Draw a line from your systolic pressure to your diastolic pressure. Is the slope of the line about the same as shown on the chart? Where do YOU fit in? What are your risk factors? Are your blood pressure readings within the normal blood pressure range? Should you take anti-hypertension medication to lower your blood pressure? Normal human daily Blood Pressure Range can vary widely, so any single blood pressure monitor reading is not reliable. BP monitor readings must be taken at different times of day, to determine AVERAGE blood pressure levels over time.

F. Blood Pressure Measures The Force Pushing Outwards On Your Arterial Walls:

The organs in your body need oxygen to survive. Oxygen is carried through the body by the blood. When the heart beats, it creates pressure that pushes blood through a network of tube-shaped arteries and veins, also known as blood vessels and capillaries. The pressure --- blood pressure --- is the result of two forces. The first force occurs as blood pumps out of the heart and into the arteries that are part of the circulatory system. The second force is created as the heart rests between heart beats. (These two forces are each represented by numbers in a blood pressure reading.) .

1) HBP Damages Arteries:

There are two root causes of erectile dysfunction (ED): psychological and medical. High blood pressure is a contributing medical factor that leads to ED. HBP damages the entire vascular system[2].

2) Adequate Blood Flow Is Necessary For Erection:

Because effective blood flow through the arteries and veins is essential to achieve and sustain an erection, any problem that impairs blood flow can cause ED. A number of medical causes associated with erectile dysfunction are problems with the arterial system.

VIII. DATASET

This chart reflects blood pressure categories defined by the American Heart Association.

A single high reading does not necessarily mean that you have high blood pressure. However, if readings stay at 140/90 mm Hg or above (systolic 140 or above OR diastolic 90 or above) over time, your doctor will likely want you to begin a treatment program. Such a program almost always includes lifestyle changes and often prescription medication for those with readings of 140/90 or higher. If, while monitoring your blood pressure, you get a systolic reading of 180 mm Hg or higher OR a diastolic reading of 110 mm HG or higher, wait a couple of minutes and take it again. If the reading is still at or above that level, you should seek immediate emergency medical treatment for a hypertensive crisis. If you can't access the emergency medical services (EMS), have someone drive you to the hospital right away. Even if your blood pressure is normal, you should consider making lifestyle modifications to prevent the development of HBP and improve your heart health[2].

High blood pressure, also known as HBP or hypertension, is a widely misunderstood medical condition. Some people think that those with hypertension are tense, nervous or hyperactive, but hypertension has nothing to do with personality traits. The truth is, you can be a calm, relaxed person and still have HBP. Let's look at the facts about blood pressure so you can better understand how your body works and why it is smart to start protecting yourself now, no matter what your blood pressure numbers are.

By keeping your blood pressure in the healthy range, you are: Reducing your risk of the walls of your blood vessels walls becoming overstretched and injured. Reducing your risk of having a heart attack or stroke; and developing heart failure, kidney failure and peripheral vascular disease. Protecting your entire body so that your tissue receives regular supplies of blood that is rich in the oxygen it needs.

Damaged arteries cannot deliver adequate blood flow to the body's organs. The organs suffer because they do not receive a full supply of blood, which they depend on for oxygen and nutrients. So over time, not only are the arteries unable to function properly, but the organs can't perform as they should either.

When arteries are narrowed by fatty deposits, you have a greater risk for developing blood clots. Your blood can carry these clots until they become lodged in narrow spaces. When this happens, the clot can significantly or completely block the blood supply to parts of the body.

A. HBP Damages Arteries:

Blood Pressure Category	Systolic mm Hg (upper #)		Diastolic mm Hg (lower #)
Normal	less than 120	and	less than 80
Prehypertension	120 – 139	or	80 – 89
High Blood Pressure (Hypertension) Stage 1	140 – 159	or	90 – 99
High Blood Pressure (Hypertension) Stage 2	160 or higher	or	100 or higher
Hypertensive Crisis (Emergency care needed)	Higher than 180	or	Higher than 110

Table 1: A Sample Chart Refers BP Categories Defined By American Hert Association

Blood vessel to the brain is either blocked by a clot (ischemic stroke) or bursts (hemorrhagic stroke). When that happens, part of the brain is no longer getting the blood and oxygen it needs, so it starts to die. Your brain controls your movement and thoughts, so a stroke doesn't only hurt your brain. It also hurts the brain's ability to think and control body functions. Strokes can affect language, memory and vision as well as cause paralysis and other health issues.

IX. CONCLUSION

In this Research Paper, we have built a fuzzy classifier that is capable of generating its own fuzzy rules as well as the number of rules it will need, based only on the training data provided to it. This classifier is an n-input-single-output system, which can easily be expanded to an n-input-o-output system to recognise o classes. And although our classifier is used for news articles, it can just as easily handle any input that can be represented as a numerical data set. The experimental results presented in section IV have shown that the system constructed by the learning algorithm is simple, as it only has three or four fuzzy rules per class, yet reliable enough to correctly cluster test articles it had never seen before.

REFERENCES

[1] L. A. Zadeh, "Fuzzy sets", Information and Control, Vol. 8, 1965, pp. 338-353.
[2] T-P Wu, S-M Chen, "A new method for constructing membership functions and fuzzy rules from training examples", IEEE Transactions on Systems, Man and Cybernetics, Part B, Volume 29, Issue 1, February 1999, pp. 25-40.
[3] J. C. Cano, P. A. Nava, "A fuzzy method for automatic generation of membership function using fuzzy relations from training examples", Proceedings of the Annual Meeting of the North American Fuzzy Information Processing Society, 27-29 June 2002, pp. 158-162.
[4] L. X. Wang, J. M. Mendel, "Generating fuzzy rules by learning from examples", IEEE Transactions on Systems, Man and Cybernetics, Vol. 22, Issue 6, 1992, pp. 1414-1427.
[5] N. K. Kasabov, "Learning fuzzy rules and approximate reasoning in fuzzy neural networks and hybrid systems", Fuzzy Sets and Systems, Vol. 82, no. 2, 1996, pp. 135-149.
[6] J. J. Shann, H. C. Fu, "A fuzzy neural network for rule acquiring on fuzzy control systems", Fuzzy Sets and Systems, Vol. 71, No. 3, 1995, pp. 345-357.
[7] R. Langari, L. Wang, "Fuzzy models, modular networks, and hybrid learning", Fuzzy Sets and Systems, Vol. 79, No. 2, pp. 141-150, 1996.
[8] C. T. Lin, C. S. G. Lee, "Neural-network-based fuzzy logic control and decision system", IEEE Transactions on Computers, Vol. 40, Issue 12, 1991, pp. 1320-1336.
[9] T. P. Hong, C. Y. Lee, "Induction of fuzzy rules and membership functions from training examples", Fuzzy Sets and Systems, Vol. 84, No. 1, 1996, pp. 33-47.
[10] K. Aas, L. Eikvil, "Text categorisation: a survey", Report No. 941, June 1999, ISBN 82-539-0425-8.
[11] E. Riloff, "Automatically constructing a dictionary for information extraction tasks", Proceedings of the Eleventh National Conference on Artificial Intelligence, 1993, pp. 811–816.
[12] "Google News Canada", http://news.google.ca/
[13] A. Lotfi, A. C. Tsoi, "Importance of membership functions: a comparative study on different learning methods for fuzzy inference systems", Proceedings of the Third IEEE Conference on Fuzzy Systems, vol. 3, 26-29 June 1994, pp. 1791-1796.
[14] S. Zhou, T. W. Ling, J. Guan, J. Hu, A. Zhou, "Fast text classification: a training-corpus pruning based approach", Proceedings of the Eight International Conference on Database Systems for Advanced Applications, 26-28 March 2003, pp. 127-136.
[15] M. Lu, L. Diao, Y. Lu, L. Zhou, "The design and implementation of an excellent text categorization system", Proceedings of the 4th World Congress on Intelligent Control and Automation, vol. 1, 10-14 June 2002,

