INTUITIONISTIC TYPE-II FUZZY LOGIC-BASED INFERENCE SYSTEM AND ITS IMPLEMENTATION IN MEDICAL DIAGNOSIS

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Abstract: Accurate medical diagnosis is a critical challenge due to uncertainty in symptoms, variability in patient responses, and overlapping disease characteristics. This paper explores the application of an Intuitionistic Type-II Fuzzy Logic-Based Inference System (IT2FL-BIS) to enhance the accuracy and reliability of medical diagnosis. Traditional fuzzy logic systems often struggle with the inherent uncertainties and vagueness present in medical data. By incorporating both intuitionistic fuzzy sets, which account for degrees of membership and non-membership, and type-II fuzzy sets, which handle higher-order uncertainties, the proposed IT2FL-BIS offers a more robust framework for medical decision-making. The architecture of the system is detailed, and its inference mechanism is explained. Furthermore, the paper presents a case study demonstrating the implementation of the IT2FL-BIS in diagnosing a specific medical condition, highlighting its potential to improve diagnostic accuracy and provide more informative assessments for medical practitioners.

Keywords: Intuitionistic Fuzzy Logic, Type-II Fuzzy Logic, Fuzzy Inference System, Medical Diagnosis.

1.Introduction

Medical diagnosis involves complex decision-making were patient symptoms and test results often present ambiguities. Traditional methods, including statistical and machine learning approaches, sometimes struggle with imprecise or incomplete data. Intuitionistic Type-II Fuzzy Logic (IT2FL) offers a robust framework for reasoning under such conditions by incorporating both membership, non-membership, and hesitation degrees in diagnostic inference. As a generalization of the classical notion of a bi-valued set and a premise to accommodate degree of truth, as demonstrated in human language gave extension of fuzzy set. Despite the extensive utilize of type- I fuzzy set, previous works established that type-I fuzzy logic models' uncertainty to a certain degree in real-life many applications gave a generalization of his previously given type-I fuzzy set theory, to incorporate type-II fuzzy set theory accomplish of handling uncertainties where type-I fuzzy set grapples due to membership functions of type-II fuzzy sets are themselves fuzzy sets. In the type-I fuzzy logic-based system the knowledge used to build certain rules, with uncertain antecedents and consequents, and these uncertainty present in this system translate into membership functions Some other theories exist in which the uncertainty of the antecedent or consequent membership functions are in type-II fuzzy sets form. Type-II fuzzy sets is the set in which the membership function themselves is type-I fuzzy sets. Type-II fuzzy sets are more applicable in such circumstances in which, it is difficult to find exact membership values for a given fuzzy set. generalised the concept of intuitionistic fuzzy logic over interval valued intuitionistic fuzzy logic. used type-II fuzzy logic systems whose degree of membership are the intervals which gives better performance in real-life applications in comparison to the type-I fuzzy logic system. In the study of fuzzy set theory, type-II fuzzy logic is a generalization of conventional fuzzy logic i.e., type-1 fuzzy logic. In type-II fuzzy logic, the uncertainty is not limited to the linguistic variables, but also is present in the form of the membership grades. On the other hand, intuitionistic fuzzy sets can also be considered as generalization of type-1 fuzzy sets. To represent the uncertainty of belongingness of element of a universal set, the intuitionistic fuzzy sets are not limited over membership function, but also a non-membership function. introduced interval valued type-II fuzzy sets in the context of intuitionistic fuzzy sets during the process means clustering s being used

2. Literature Review

Previous studies have explored fuzzy logic in medical diagnosis, but standard fuzzy systems (Type-I) lack the capacity to address deep uncertainty and subjective hesitation. Type-II fuzzy systems extend this capability, but their effectiveness improves significantly when combined with intuitionistic logic. Recent research highlights the superiority of IT2FL in scenarios requiring human-like reasoning under vague conditions. Due to economic growth, technological advances, and increasing demand, planning for energy is now a complex multi-variable, multi-objective problem. Accordingly, a variety of models are developed to solve the problem based on a different point of view worldwide [1]. While they have pros and cons, many of them cannot be considered as decision-making assistance tools. Also, some of them do not adequately reflect energy policies. For instance, they do not take into account the policies which the World Energy Council has proposed: e.g., by 2050, new technologies should generate about 37% of the total energy in the world [2]. Pollution and environmental problems caused by overuse of fossil fuels, especially for transportation, have exacerbated the need for alternative fuels. Romm [3] thoroughly investigated alternative fuels for transportation systems in the future. Arslan et al. [4] reviewed possible scenarios of supplying energy for cars rather than fossil fuels in Turkey. Also, Babtista et al. [5] studied short-term and long-term resources and road consumption scenarios in Portugal and found alternative fuels necessary for longer horizons. Sehatpour et al. [6] made comprehensive research on fossil-fuel alternatives for light-duty vehicles and, based on a multi-criteria evaluation, concluded NG and biogas are superior options for the mid-term in Iran. Santisirisomboon et al. [7] studied policies of carbon taxation to study the competitiveness of biomass energy with fossil fuels in Thailand. Due to the importance of the problem, there are many decision support tools and simulation models available, such as the Vienna Automated System Planning Package, MESSAGE (Model for Energy Supply Strategy Alternatives and their General Environmental Impact) [8], the Long-range Energy Alternatives Planning system (LEAP), the MARKAL-EFOM Integrated System (TIMES), and the Energy PLAN [9]. These models allocate energy based on minimizing costs and priorities of demands. Environmental concerns, planning policies, and availability of energy resources can be defined as constraints [10]. A different application of these models is recorded in the literature. Strachan & Kannan [11] employed MARKAL-Macro (M-M) to study the long-term reduction of CO2 emissions in the UK energy sector. Liu et al. [12] applied the energy model of MESSAGE-China to study the trend of novel energy technologies and their contributions to GHG reduction in China. Ball et al. [13] employed the energy system model MOREHyS to plan spatially and temporally a set-up of a hydrogen-based transport infrastructure system in Germany for the horizon of 2030. Chiodi et al. [14] analyzed the competing demands for land-use, import dependency, availability of sustainable bioenergy, and economics under the framework of an Irish energy systems model of TIMES. Tavakoli et al. [15] and Valinejad et al. [16] found the energy model system as a convenient and user-friendly approach to analyze energy policies. Goal programming (GP) is a current multi-objective optimization method, which can address multi-criteria decision analysis (MCDA) problems. Jayaraman et al. [17] used a GP model for efficient allocation of labor resources considering the criteria of economic, energy, and environment in the United Arab Emirates using the approach of prioritizing areas for strategic planning and resource allocation for the sustainability of the strategies. They presented mathematical and economic indicators in order to digitize criteria. Kumar et al. [18] developed an insight into the application of various multiple criteria decision-making (MCDM) methods in the renewable energy sector. Zografidou et al. [19] programmed a GP model with all possible weight combinations to analyze energy allocation and budgeting in Greece and provided a multi-dimensional decision-makers' framework to determine the optimal budgeting mix to attract investors and guarantee the success of the venture. Kumar et al. [20] optimized priorities among suppliers considering the three dimensions of economic, social, and environmental sustainability in India. They integrated fuzzy AHP and fuzzy multi-objective linear programming approaches. Other extensions to GP are also applied to energy suitability problems.

Type-II to type -I intuitionistic fuzzy reducer and DE fuzzifier. The block diagram for representation of the proposed system is given in fig

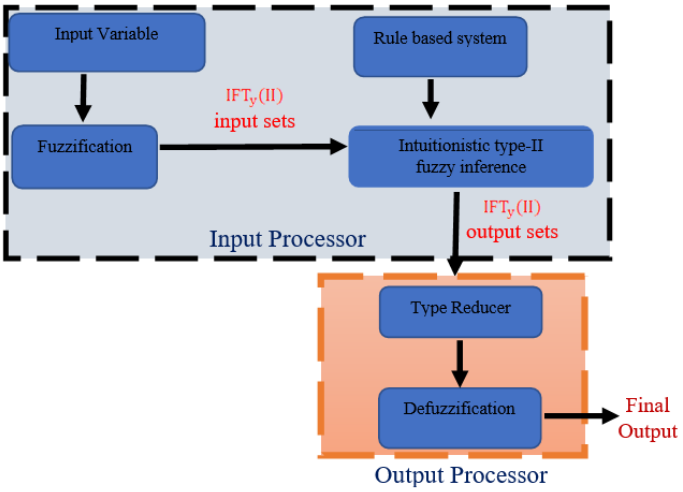


Figure:1 Intuitionistic type-II fuzzy inference system

Intuitionistic Type-II Fuzzy Logic Based Inference System

The architecture of the proposed intuitionistic type-II fuzzy logic-based inference system is given by fig

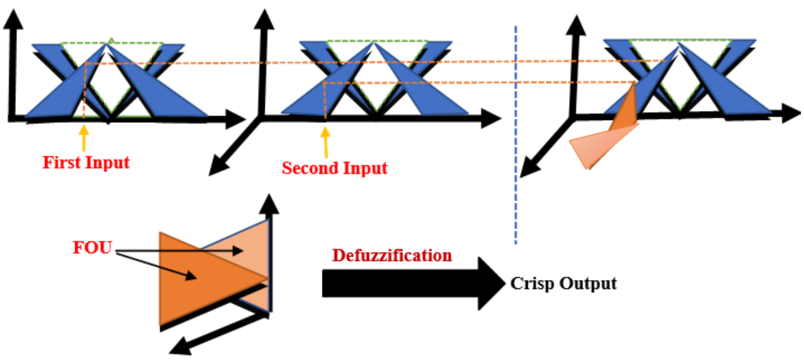


Figure:2 Proposed Intuitionistic Type-II Fuzzy Inference

3.Architecture of the Intuitionistic Type-II Fuzzy Logic-Based Inference System (IT2FL-BIS):

Block Diagram: Present a clear block diagram illustrating the main components of the IT2FL-BIS. These typically include:

Fuzzification Module: Maps crisp input values (e.g., patient symptoms, lab results) to IT2FSs. Explain the choice of primary and secondary membership functions for the IT2FSs.

Rule Base: A collection of IF-THEN rules where the antecedents and consequents involve IT2FSs. Provide examples of such rules in the context of medical diagnosis (e.g., IF temperature is high AND cough is severe THEN diagnosis is likely pneumonia).

Inference Engine: Performs fuzzy reasoning based on the input IT2FSs and the rule base. Explain the operations involved in evaluating the antecedents of the rules (using operations on IT2FSs like intersection or T-norms).

Aggregation Module: Combines the outputs of the fired rules, which are IT2FSs. Describe the aggregation method used (e.g., union or S-norms for IT2FSs).

Type-Reduction Module: Since the output of the inference process is an IT2FS, it needs to be reduced to a Type-I fuzzy set or a crisp value for practical interpretation. Explain the type-reduction method employed (e.g., extending the Karnik-Mendel algorithms or other suitable techniques for IT2FSs).

Defuzzification Module (if needed): If the type-reduction results in a Type-I fuzzy set, a defuzzification method (e.g., centroid, mean of maxima) is used to obtain a crisp diagnostic output or a level of likelihood for a specific disease.

4.ALGORITHM For the Intuitionistic Type-II Fuzzy Logic Based Model

Step 1: First take the set of input factors involved in the problem and these input factors are defined as;

Step 2: Applying fuzzification process to make triangular intuitionistic fuzzy number for each input factors is stated as;

$$I = \{I_1, I_2, \dots\dots\dots I_n\}$$

$$IF = \{(x, \mu(x), \nu(x)) : x \in I;\ \mu, \nu : I \to [0,1]\}$$

Step 3: Generate secondary membership and non-membership values denoted by $\mu_{IFT_y(II)}(x, \varrho)$ and $\nu_{IFT_y(II)}(x, \sigma)$ by giving a membership and non-membership grade to each input variable with set of primal membership value and primal non- membership value.

Step 4: After the step 3, the generalization of type-II intuitionistic fuzzy set, as three-dimensional space is defined as

$$IFT_y(II) = \{((x, \varrho, \sigma), \mu_{IFT_y(II)}(x, \varrho), \nu_{IFT_y(II)}(x, \sigma)) : x \in I \ \&\ \varrho \in I_x, \sigma \in J_y \ \subseteq [0,1]\}$$

Also, consider the output factors $\_{IFT_y}^{Out}(II)'$ (categories into m linguistic categories) in the form of intuitionistic type-II fuzzy sets, that denotes the final crisp output of the system.

Step 5: Now, for the inference system process, the use of some rules based on knowledge-based system is needed. For this process, consider the conditional and unqualified intuitionistic fuzzy proposition to obtain the input factors in the

$$\text{IF}\left\{\text{ If } I_i \text{ is } \mathrm{IFT_y}^{i}(\mathrm{II})\right\} \text{ THEN } \left\{\text{ Output is } \mathrm{IFT_y}^{out}(\mathrm{II})\right\}$$

Step 6: The consequent part obtained from the intuitionistic fuzzy rule-based system in the form of intuitionistic type-II fuzzy set. This reduces the intuitionistic type-II fuzzy set and convert it in to the form of intuitionistic type-I fuzzy set by fuzzifying the area obtained in the third direction of the intuitionistic type-II fuzzy set.

Step 7: Now, the output is obtained in the form of intuitionistic type-I fuzzy set by using the defuzzification process and finally the crips output of the proposed system is obtained.

5.Results and discussions

In this chapter the extension of type-II fuzzy logic, in order to obtain the intuitionistic fuzzy logic, and further, develop an intuitionistic type-II fuzzy logic based fuzzy inference system is performed. The generalization of the concept of intuitionistic type-I fuzzy logic with the help of intuitionistic type-I fuzzy logic in novel way is initiated. Due to this generalization intuitionistic type-II fuzzy logic, one can get a third additional dimensional for the conducted study. The objective behind the concept of intuitionistic type-II fuzzy logic is to handle the uncertainty into linguistic variables form that can easily be handled by using the membership functions as well as the non-membership functions. This concept is applied over secondary data of lung cancer patients. In this work, the novel concept of underlying type-II intuitionistic fuzzy logic is presented and also discussed some detail in intuitionistic type-II fuzzy set theory, fuzzy reasoning and develop an intuitionistic type-II fuzzy inference system with the Mamdani approach. In this study, an intuitionistic type-II fuzzy approach to the lung cancer patient‘s prediction is presented. The intuitionistic type-II fuzzy logic can accommodate more imprecision thereby imprecise knowledge and modelling better than the type-I fuzzy or intuitionistic fuzzy approaches. The key point in this design of intuitionistic type-II fuzzy logic-based inference system is to model the level of each lung cancer infected patient.

Table:2 Collected data of lung cancer infected patients

P-114	**P-113**	**P-112**	**P-111**	**P-110**	**P-11**	**P-109**	**P-108**	**P-107**	**P-106**	**P105**	**P-104**	**P-103**	**P-102**	**P-101**	**P-1000**	**P-100**	**P-10**	**P-1**	**Patient Id**
36	34	17	73	27	34	39	64	44	46	35	28	52	35	46	37	35	17	33	**Age**
6	6	3	5	3	6	4	6	6	2	4	3	2	4	6	7	4	3	2	**Air Pollution**
7	7	1	6	1	7	5	8	7	3	5	1	4	5	8	7	5	1	4	**Alcohol use**
7	7	5	6	4	7	6	7	7	4	6	4	5	6	7	7	6	5	5	**Dust Allergy**
7	6	4	6	3	6	5	7	7	4	6	2	3	5	7	6	5	4	3	**Genetic Risk**
6	7	2	6	3	7	6	7	7	3	5	4	2	6	7	7	6	2	2	**Balanced Diet**

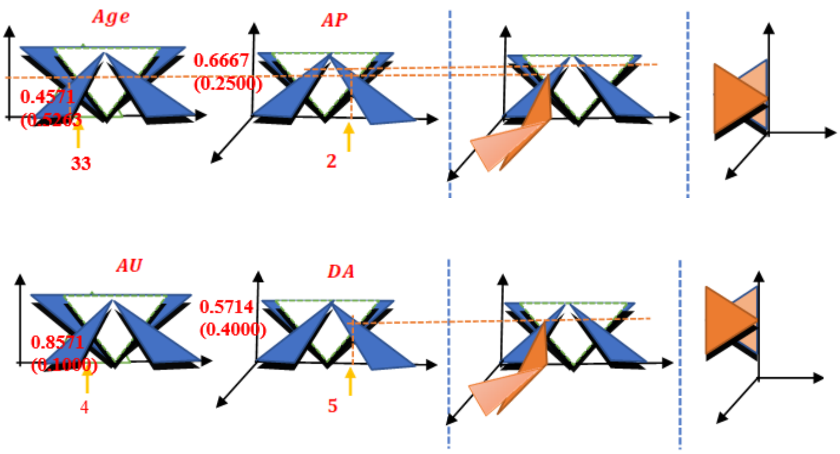
7	7	2	5	3	7	6	7	7	3	5	3	4	7	7	7	7	2	4	**Obesity**
7	7	2	8	2	7	6	7	7	2	6	1	3	2	8	7	2	2	3	**Smoking**
7	7	2	5	4	7	6	7	7	4	6	3	2	4	7	7	4	2	2	**Chest Pain**
7	8	3	5	2	8	6	7	7	4	5	1	4	8	9	8	8	3	4	**Coughi ngof Blood**
8	4	1	4	2	4	5	9	5	1	1	3	3	8	3	4	8	1	3	**Fatigue**
5	2	3	3	2	2	3	6	3	2	4	2	4	7	2	2	7	3	4	**Weight Loss**
7	3	7	6	3	3	2	5	2	4	3	2	2	9	4	3	9	7	2	**Shortn essof Breath**
7	4	6	1	1	4	3	2	8	5	4	2	3	1	4	4	1	6	3	**Swallow ing Difficult y**
6	7	7	6	6	7	5	1	5	1	4	4	3	7	2	7	7	7	3	**Dry Cough**
7	7	2	5	2	7	4	6	6	3	5	3	2	4	6	7	4	2	2	**Chronic Lung Disease**
H	H	M	M	L	H	M	H	H	M	M	L	L	H	H	H	H	M	L	**Level**

For the future prospective, one will show that how intuitionistic type-II fuzzy logic can be applicable to identify and the solution process of many real-world complex problems including engineering and agriculture fields etc. In future the intention to learn the parameters of the intuitionistic type-II fuzzy sets using Gaussian membership function and some hybrid approach to evaluate the real-world datasets will also be implemented. This concept will be applied over the Sugeno's type fuzzy inference system out of 1000 lung cancer infected patient, we have taken 20 patients data set, to apply our approach to the conducted data set. The patients with the values of their various symptoms are given in tab.

Numerical Computations

Consider the patient one with patient ID P1, with age 33, air pollution 2, alcohol use 4, dust allergy 5, genetic risk 3, balance diet 2, obesity 4, smoking level 3,

chest pain 2, coughing of blood 4, fatigue 3, weight loss 4, shortness of breath 2, swallowing difficulty 2, dry cough 3, and coughing up



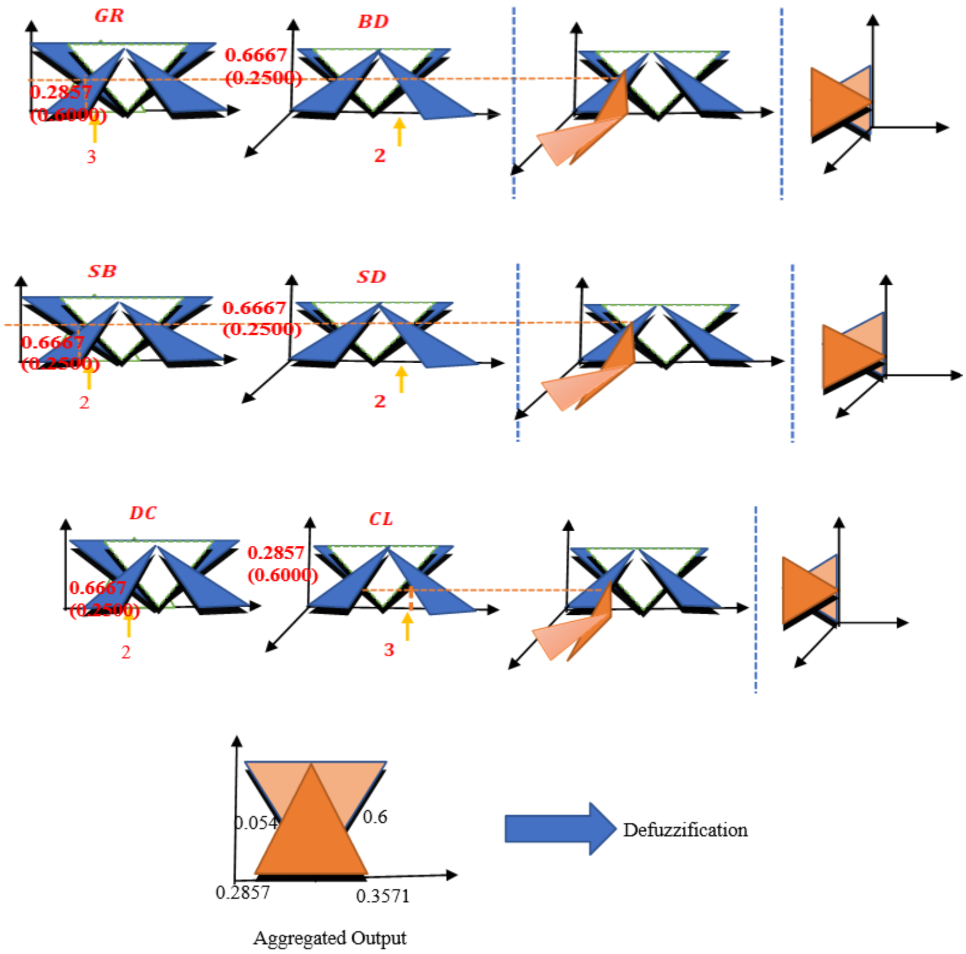


Fig.3 Computation

Let I= {33, 2, 4, 5, 3, 2, 4, 3, 2, 4, 3, 4, 2, 2, 2, 3} be set of inputs with membership values {0.4571, 0.6667, 0.8571, 0.5714, 0.2857, 0.6667, 0.8571, 0.2857, 0.6667, 0.8571, 0.2857, 0.8471, 0.6667, 0.6667, 0.666, 0.2857} and non-membership values {0.5263, 0.2500, 0.1000, 0.4, 0.6, 0.2500, 0.1000, 0.6000 0.2500, 0.100, 0.2500, 0.2500, 0.2500, 0.600} with respect to these input the output of the inference system is {0.4571/0.5263, 0.5714/0.4000, 0.2857/0.6000, 0.2857/0.6000, 0.6667/0.2500, 0.2857/0.6000, 0.2857/0.6000, 0.6667/0.2500}. Take minimum set of value, we get {0.2857, 0.6000}. Corresponds to this output the set of membership and non-membership values assigned for the third dimension is {0.3571/0.054} and corresponding value of FOU is given in the form of triangular membership function [0.2857,0.3214, 0.3571] and triangular non-membership function [0.054, 0.327, 0.6] after the defuzzification process, we reduce the intuitionistic type-II fuzzy set in the form of intuitionistic type-I fuzzy set with membership and non-membership values of the output 0.3214 and 0.327. Now, taking the average of membership and non- membership values, we get the final output of the system i.e., 0.3242. The value is slightly large to the range of none category of the output factor; hence the patient is suffering by the stage-I of the lung cancer category.

Discussions:

- Interpretation of Results: Discuss the findings of your case study, interpreting the diagnostic outcomes and the role of uncertainty modeling in the results.
- Advantages of the IT2FL-BIS in Medical Diagnosis: Highlight the benefits of using an IT2FL-BIS, such as:
- Improved handling of various types of uncertainties.
- More robust and reliable diagnostic decisions.
- Potential for better representation of medical knowledge and expert opinions.
- Providing a degree of confidence or likelihood in the diagnosis.

5.Conclusion

The integration of Intuitionistic Type-II Fuzzy Logic into medical diagnosis provides an advanced approach to dealing with uncertainty. Future research should focus on hybrid models integrating deep learning techniques with fuzzy inference for further improvement in diagnostic accuracy and real-time adaptability. a concept of generalization of fuzzy set theory into type-II fuzzy logic and type-II intuitionistic fuzzy is discussed. A new way to represent the intuitionistic type-II fuzzy sets is given. Type-II fuzzy logic consists IF-Then rules, and the uncertainty is handled with type-II fuzzy sets. An introduction of type-II intuitionistic fuzzy inference system is also discussed. Finally, A brief address to the features and problems of intuitionistic fuzzy modelling type-II fuzzy logic is given in this work.

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