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Original Article

The Relevance of Fuzzy Logic in the Prediction of Clinical Progression from HIV to AIDS

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Abstract *- The development of methods to forecast an individual's clinical course after the acute phase of infection is over is crucial to effective treatment and management of the infection. However, there are still a number of questions that need to be answered about the connection between possible markers and clinical course. In this piece of work, we provide a model that makes use of fuzzy logic in order to establish a connection between the amount of HIV in a person's system, the number of T cells, and the clinical progression to AIDS in HIV-positive individuals.*

Keywords *- Viral load, T cells, Fuzzy logic, Centoid defuzzification.*

1. Prologue

Researchers have shown that untreated AIDS patients take an average of 10 years from infection to symptom presentation. However, a sizable percentage of infected people develop full-blown AIDS within a few years. However, over 12% of those who contract HIV do not develop AIDS for at least 20 years after initial infection. Variation in outcomes has been linked to viral load at an early stage of infection. According to Gupta et al. (2011), data mining techniques have been studied in several healthcare datasets, with potential applications in disease diagnosis, prognosis, and treatment all being possible. In 2013, Igodan et al. described the architecture of a web-based system for knowledge storage and mining regarding HIV/AIDS diagnosis and treatment via a Fuzzy Logic and data mining strategy. It was proposed that a Fuzzy Control and Cholera treatment system be developed by Umoh et al. (2013). To monitor the potential spread of highly pathogenic avian influenza H5N1, Maseleno et al. (2015) introduced a method that uses fuzzy logic and mathematical theory of evidence. Weighted fuzzy standards were developed, and a decision-supporting network based on fuzzy recommendations was developed, by Kora et al. (2019). In order to provide a decision support platform for HIV/AIDS researchers, physicians, and other healthcare practitioners in HIV endemic locations, Oye and Isah (2019) introduced a fuzzy model for the treatment of HIV/AIDS. Protein, red blood cells, lymphocytes, neutrophils, and eosinophils are all examples of inputs that Avanzo et al. (2020) propose expanding the system designed for. They base their suggestions on the types of tumours, haemorrhages, and brain tumours that are most common. The knowledge-based FIS for Sepsis diagnosis was created by Shehu et al. (2020). To better analyze Malaria and typhoid, Orozco-del-Castillo et al. (2020) revised the FIS. The input is the symptom, and the output is the disease. In 2020, Naseer et al. proposed a fuzzy logic-based decision support system for heart disease detection, which can foresee the likelihood of heart illness for the next decade. Prediction of diabetic disease with FIS was described by Thakkar et al. (2020) to facilitate the early action against diagnosis and speedy treatment by users of this application. Fuzzy logic-based Diabetes decision making was defined by Al-Behadili and Ku-Mahamud (2021). With the Internet of Things (IoT) and the fuzzy inference system (FIS), Alam et al. (2022) showed how to implement smart disease detection for a variety of illnesses.

2. Steps of Fuzzy Based Model for Clinical progression of HIV to AIDS

2.1. Definition of input and output variables

Input variable				Output variable	
Virus Load (V)		T Cells Count (T)		Clinical Progression to Aids (CPA)	
ELV	Extremely Low	ELT	Extremely Low	EFCPA	Extremely Fast
LV	Low	LT	Low	FCPA	Fast
MV	Moderate	MT	Moderate	MCPA	Moderate
HV	High	HT	High	SCPA	Slow
		EHT	Extremely High	ESCPA	Extremely Slow

Membership Plot Function

2.2. Definition of Membership Functions of Input and Output Variables

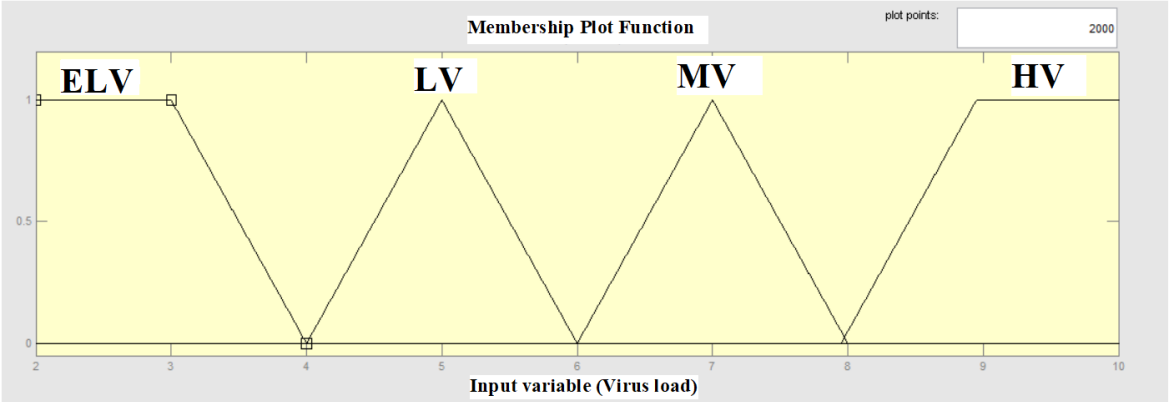

Fig. 1 Membership plot function of viral load

$$\mu_{ELV} = \begin{Bmatrix} 1 & x \leq 3 \\ 4 - x & 3 < x \leq 4 \end{Bmatrix}$$

$$\mu_{LV} = \begin{Bmatrix} x - 4 & 4 < x \leq 5 \\ 6 - x & 5 < x \leq 6 \end{Bmatrix}$$

$$\mu_{MV} = \begin{Bmatrix} x - 6 & 6 < x \leq 7 \\ 8 - x & 7 < x \leq 8 \end{Bmatrix}$$

$$\mu_{HV} = \begin{Bmatrix} x - 8 & 8 < x \leq 9 \\ 1 & 9 < x < 10 \end{Bmatrix}$$

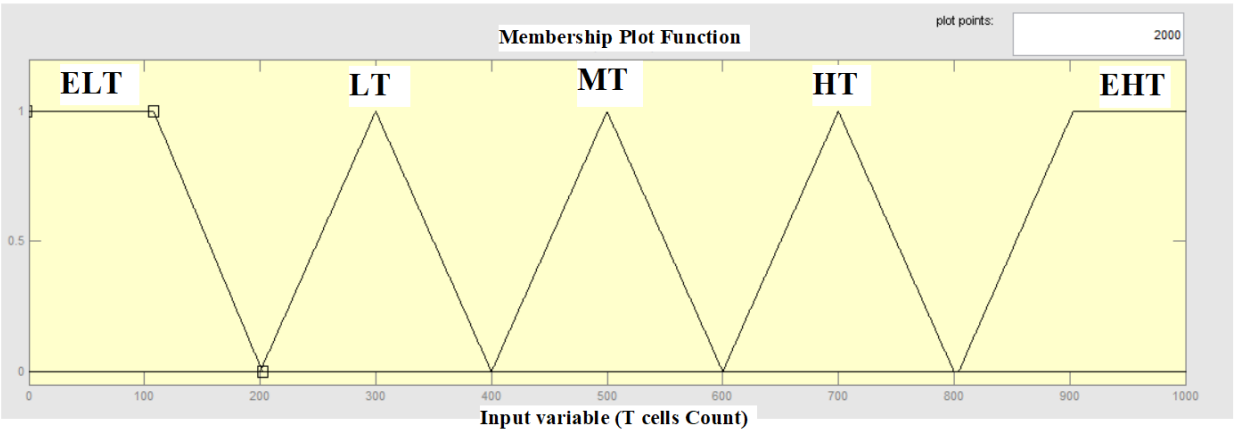

Fig. 2 Membership plot function of T cells count

$$\mu_{ELT} = \begin{Bmatrix} 1 & x \leq 100 \\ 2 - 0.01x & 100 < x \leq 200 \end{Bmatrix}$$

$$\mu_{LT} = \begin{Bmatrix} 0.01x - 2 & 200 < x \leq 300 \\ 4 - 0.01x & 300 < x \leq 400 \end{Bmatrix}$$

$$\mu_{MT} = \begin{Bmatrix} x - 6 & 400 < x \leq 500 \\ 8 - x & 500 < x \leq 600 \end{Bmatrix}$$

$$\mu_{HT} = \begin{Bmatrix} x - 8 & 600 < x \leq 700 \\ 1 & 700 < x \leq 800 \end{Bmatrix}$$

$$\mu_{EHT} = \begin{Bmatrix} x - 8 & 800 < x \leq 900 \\ 1 & 900 < x \leq 1000 \end{Bmatrix}$$

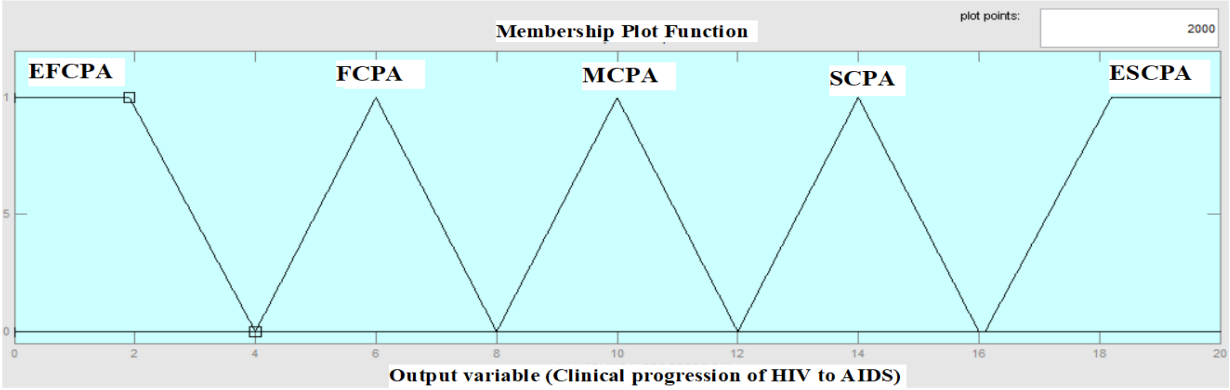

Fig. 3 Membership plot function of clinical progression to AIDS

$$\mu_{EFCPA} = \begin{Bmatrix} 1 & x \leq 2 \\ -0.5x + 2 & 2 < x \leq 4 \end{Bmatrix}$$

$$\mu_{FCPA} = \begin{Bmatrix} 0.5x - 2 & 4 < x \leq 6 \\ -0.5x + 4 & 6 < x \leq 8 \end{Bmatrix}$$

$$\mu_{MCPA} = \begin{Bmatrix} 0.5x - 4 & 8 < x \leq 10 \\ -0.5x + 6 & 10 < x \leq 12 \end{Bmatrix}$$

$$\mu_{SCPA} = \begin{Bmatrix} 0.5x - 6 & 12 < x \leq 14 \\ -0.5x + 8 & 14 < x \leq 16 \end{Bmatrix}$$

$$\mu_{ESCPA} = \begin{Bmatrix} 0.5x - 8 & 16 < x \leq 18 \\ 1 & 18 < x \leq 20 \end{Bmatrix}$$

2.3. Set up Rule Base

Rules are fundamental to the forecasting process in the Fuzzy Rule Base System. In this way, the rules offer context for language variables and MF (membership function). We have so used these fuzzy inputs in the preceding portion of the rules. Twenty guidelines have been used to the treatment of HIV in this study. In our method, the antecedent of a rule consists of a single piece that specifies the expected outcome of antecedent development as an opinion. The level of danger will be determined using fuzzy logic, and our rules will be instrumental in making this forecast. The model is made up of 20 independent fuzzy rules that were developed with the help of an expert.

Rule 1: If virus load is extremely low and number of T cells is extremely high then clinical progression of AIDS is extremely slow.
Rule 2: If virus load is extremely low and number of T cells is high then clinical progression of AIDS is extremely slow.
Rule 3: If virus load is extremely low and number of T cells is moderate then clinical progression of AIDS is slow.
Rule 4: If virus load is extremely low and number of T cells is low then clinical progression of AIDS is slow.
Rule 5: If virus load is extremely low and number of T cells is extremely high then clinical progression of AIDS is moderate.
Rule 6: If virus load is low and number of T cells is extremely high then clinical progression of AIDS is extremely slow.
Rule 7: If virus load is low and number of T cells is high then clinical progression of AIDS is slow.
Rule 8: If virus load is low and number of T cells is moderate then clinical progression of AIDS is moderate.
Rule 9: If virus load is low and number of T cells is low then clinical progression of AIDS is moderate.
Rule 10: If virus load is low and number of T cells is extremely low then clinical progression of AIDS is fast.
Rule 11: If virus load is moderate and number of T cells is extremely high then clinical progression of AIDS is moderate.
Rule 12: If virus load is moderate and number of T cells is high then clinical progression of AIDS is moderate.
Rule 13: If virus load is moderate and number of T cells is moderate then clinical progression of AIDS is moderate.
Rule 14: If virus load is moderate and number of T cells is low then clinical progression of AIDS is fast.
Rule 15: If virus load is moderate and number of T cells is extremely low then clinical progression of AIDS is extremely fast.
Rule 16: If virus load is high and number of T cells is extremely high then clinical progression of AIDS is fast.
Rule 17: If virus load is high and number of T cells is high then clinical progression of AIDS is fast.
Rule 18: If virus load is high and number of T cells is moderate then clinical progression of AIDS is fast.
Rule 19: If virus load is high and number of T cells is low then clinical progression of AIDS is extremely fast.
Rule 20: If virus load is high and number of T cells is extremely low then clinical progression of AIDS is extremely fast.

2.4. An Analysis of the Clinical Development of AIDS-Related

Fuzzy models use a rules-based framework and a centroid defuzzification technique to estimate a person's clinical progression to AIDS in years, based on their Viral load (V) and T cells values. Figure 4 shows the mapped surface that was found by the model. Clinical progression estimates for various combinations of viral load and T cell count are provided in Table (1).

Table 1. Random data for purpose of Analysis

Viral Load	T cell count	Clinical Progression to AIDS
3.5	100	10
3.5	300	14
3.5	900	18.3
7	100	1.49
7	200	1.9
7	900	10
10	1000	6
9	500	6
8	500	6
2	1000	18.6
5	500	10
2	400	10
6	300	10
2	500	14
4.224	500	10
5.93	617	14

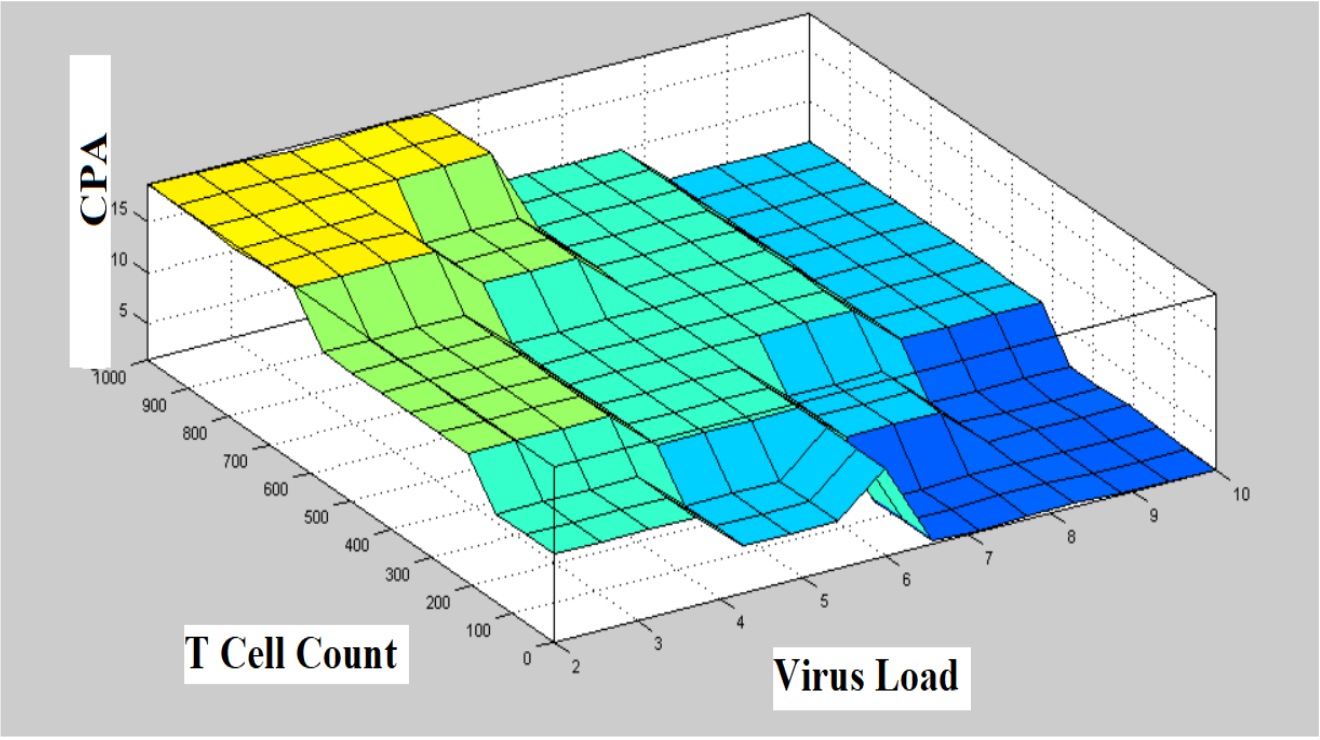

Fig. 4 A HIV model mapping study reveals a flat surface

MATLAB is used to perform the simulation, and the programme accepts two input parameters in exchange for a single simulated result. The proposed technology generates several different sorts of results. The following figure depicts a lookup rules diagram for the proposed system.

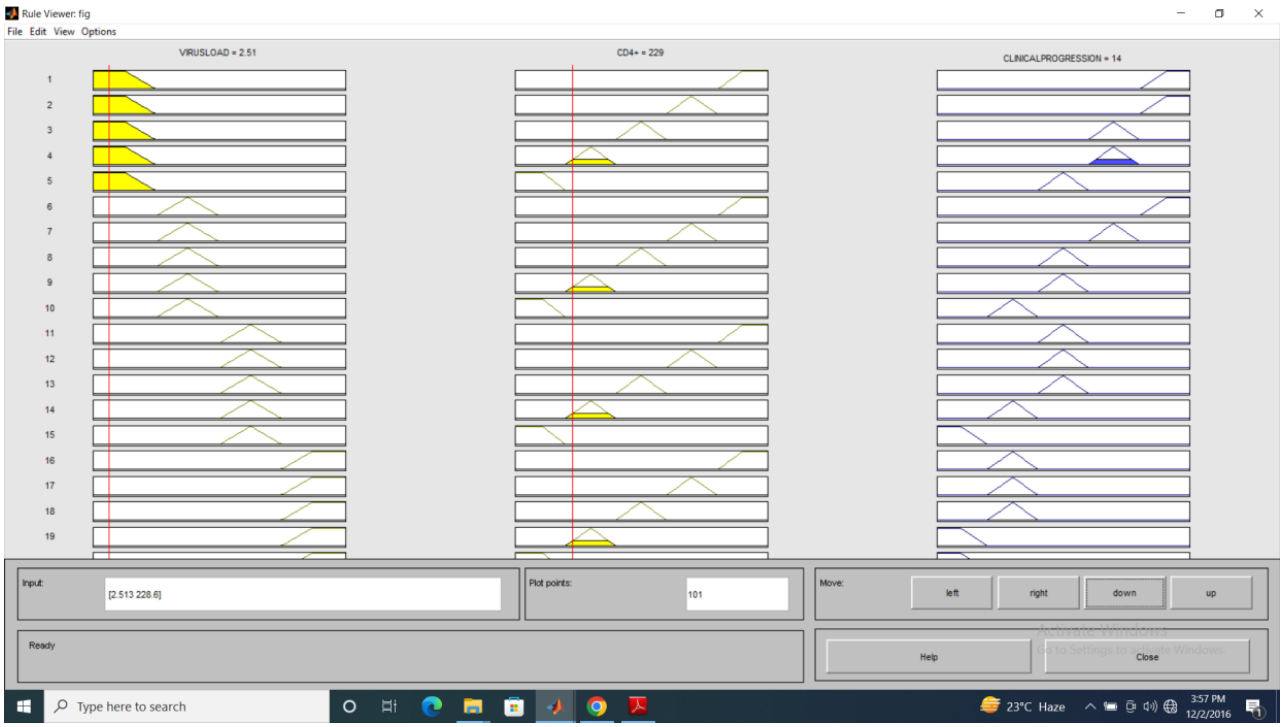

Fig. 5

3. Conclusion

It must be emphasized that the model does not account for any interventions in the natural course of the disease, such as the use of medication. To rephrase, the expected value to clinical advancement would be useful merely to direct some first clinical activities, hence facilitating physicians' positioning of patients. However, once treatment has commenced, the model is unable to offer any further insight into the clinical condition of the patient. In fact, thanks to the development of medicine combinations, AIDS may be regarded to be reasonably under control from an individual's perspective. The lives of HIV-positive people are being significantly (and favorably) prolonged by these treatment combinations. This is so despite the fact that the offered model was not verifiable. The principal advantage is its simplicity, but another advantage is that it may be used to include the subjective view of HIV/AIDS professionals into an analytical model. As far as we're aware, this is one of the attempts to use fuzzy logic and approximate reasoning to solve a specific problem in HIV/AIDS epidemiology.

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