

Support of elderly people with cognitive impairment by trustworthy companion robots

George Siavalas, Vassilis Kaburlasos*

Department of Informatics, Computer and Telecommunications Engineering
School of Engineering, International Hellenic University (IHU)

GR-62124 Terma Magnisias, Serres, Greece

* Corresponding author email: vgkabs@ihu.gr

Abstract

The demographic problem of Greece is characterized by both a slow decrease of the general population and, at the same time, a rapid increase of the percentage of the (overly-)elderly. A likewise trend is also experienced in other countries. In conclusion, substantial issues are raised such as supporting the elderly because there are not enough young people to take full care of all the elderly. A solution might be to import human labor from abroad. However, such a solution is not affordable to many. Furthermore, due to the limited material resources available to sustain a population combined with an increasing human life expectancy, likewise trends are ultimately expected everywhere even in sub-Saharan countries whose population is currently increasing exponentially. As a viable solution, Companion Robots (COROs) are proposed here as assistants to human-caregivers. Two critical problems emerge including, first, a seamless interaction of COROs with humans and, second, the trustworthiness of COROs. This work proposes overcoming the aforementioned problems by rigorously "computing with semantics" in a mathematical lattice data domain, where semantics is represented by a partial order relation. Preliminary computational experiments demonstrate the application of an Intelligent Agent Model, or IAM for short, to be mounted on a CORO, for abductive reasoning. The proposed IAM algorithm enables a conversational intervention involving a CORO and an elderly. In particular, the CORO displays non-annotated images on a tablet and, when an elderly provides a false positive /negative response then the CORO both returns the right answer and, furthermore, it substantiates it. Potential extensions of the proposed methods are discussed.

Keywords: Companion Robot (CORO); Demographic Problem; Economic Opportunities.

JEL Classifications: I10, I31

1 Introduction

Certain demographics of interest are reviewed next. The world population is currently increasing exponentially (Kaburlasos et al., 2023). Specifically, the population of 1) Western /Far Eastern countries increases marginally if at all; 2) Middle Eastern countries increases linearly; 3) African countries increases exponentially as it doubles nearly every 25 years. However, common sense suggests that the future world population size is upper bound due to the limited material resources available to sustain it.

An additional demographic trend of interest regards the increase of the percentage of the elderly, i.e. over 65 years old, in the general population. In particular, since the end of the 20th century, especially rapidly does increase the percentage of overly-elderly, i.e. over 85 years old (Bar-Tur, 2021), who often lose their daily functionality due to cellular aging; the latter implies cognitive impairment and renders those elderly bedridden and/or dementia patients with significant socio-economic impact not only for themselves, but also for their caregivers (Liao et al., 2023). As cognitive decline worsens, people increasingly need assistance with (a) household chores, (b) personal care, (c) more psychological support, and (d) regular supervision (Gale et al., 2018). The support of the elderly is a healthcare issue which, often, engages family members. There is a significant "economic impact" in the treatment of the elderly, including Alzheimer Disease (AD) patients. For instance, it has been reported that the total 2020 spending on AD in the USA was comparable to the USA military and defense spending; moreover, the effectiveness of treating dementia conventionally with drugs is questionable (Diamant, 2024).

Instead of treating dementia with drugs exclusively, an alternative is to also provide the elderly with companion support, around the clock, so as to keep their brain operating constructively. A variety of non-pharmacological interventions have already been presented with relatively positive results. However, these interventions come at a cost of involving ever more caregivers in ever more tasks. Moreover, it turns out that daily care is an exhaustive task for the caregivers and it may also require special skills, a typical family member does not have. It is noteworthy that public/private health services around the world are not yet ready to provide effective care to overly-elderly. Under the aforementioned circumstances, there is a need for developing instruments to deliver personalized healthcare for the (overly-)elderly (Becker et al., 2016).

The aforementioned needs as well as the demographics reveal a looming labor shortage for supporting the elderly. A solution might be to import human labor from abroad. However, such a solution is not affordable to many; moreover, this is not a long-term viable solution because human labor shortages are reasonably expected everywhere due to the limited material resources available to sustain the population combined with an increasing human life expectancy everywhere even in sub-Saharan African countries whose population is currently increasing exponentially. A tentative solution to the aforementioned labor shortage problem may be an engagement of Companion Robots (COROs) as assistive tools of human caregivers; that is, instead of engaging exclusively human caregivers, engage COROs as well toward keeping the brain of the elderly operating constructively e.g. by engaging the elderly in a constructive conversation. Two practical problems regard 1) interactivity and 2) trustworthiness of COROs.

Taking into account the shortage of socio-economic resources available to secure caregivers for every elderly person with cognitive impairment (Culberson et al. 2023), other authors have proposed the use of socially assistive robots (SARs) or social robots as a possible solution to the problem, since robots can tirelessly (a) provide companionship, (b) entertain, (c) exercise the individual

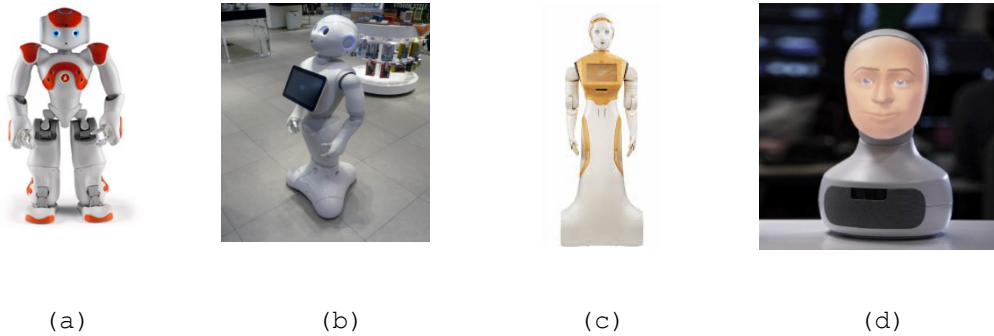
multisensory and cognitively, (d) exercise the individual physically, (e) perform basic caregiver tasks, while regulating the elderly person's emotions (Liao et al., 2023). Anthropomorphic social robots, in contrast to animal-shaped social robots or robots with an unfamiliar appearance, seem to increase the chances of interaction with elderly users (Strutz et al., 2024). In fact, they have been tested relatively successfully in long-term care structures for the elderly, replacing the professional (or typical) caregiver in specific tasks and helping maintain and/or enhance the daily functionality and cognitive functions of individual users (Zuschnegg et al., 2021). It should be noted that social robots with a physical body are more effective than "software agents" (Belpaeme et al., 2018) because they can potentially exchange useful physical objects with a user as well.

In this work, the interest is in anthropomorphic SARs with physical body, namely COROs. For example, Picture 1 (a), (b) and (c) display the popular COROs NAO, Pepper and ARI, respectively, which can move their limbs; whereas, CORO Furhat in Picture 1(d) cannot; however, Furhat can represent emotions by colors.

A CORO is driven by software. The latter implements a mathematical model. Even though a CORO, by construction, may have the physical capacity to carry out a task, many times it does not. Assuming a reliable implementation of a mathematical model in software, the only reasonable explanation for such a shortage is in the model itself.

Typical Artificial Intelligence (AI), e.g. deep-learning, is pursued by "numerical" models defined on the Euclidean space R^N following suit after the practices introduced by Isaac Newton toward modeling aspects of the physical world. However, when humans are involved, non-numerical percepts emerge, e.g. symbols /words and other, representing semantics. Any percept becomes "datum" as soon as it is recorded. In response, this work proposes a paradigm shift in AI from deep-learning (statistical) models in R^N to computing with semantics represented by partial order in a mathematical lattice data domain as detailed in the following section.

The layout of this paper is as follows. Section 2 delineates a paradigm shift in AI toward computing with semantics. Section 3 describes a method for Explainable AI (XAI). Section 4 presents preliminary experimental results. Finally, section 5 concludes by discussing both the results and potential future work extensions.



Picture 1. Various types of Companion Robots (COROs): (a) NAO, (b) Pepper, (c) ARI, (d) Furhat.

2. Computing with Semantics

The most popular AI models currently are real-functions defined on the Euclidean space $\mathbb{R}^N$ for an integer N , where $\mathbb{R}$ is the set of real numbers. The achievements of AI can be attributed to capacities of digital computer hardware (Okeke, 2024) including: 1) fast data processing and 2) the consideration of vast data. At “machine level”, data processing occurs by handling strings of 0s and 1s, which are interpreted as real numbers. In particular, AI is pursued by implementing statistical models, i.e. deep-learning models (LeCun, Bengio, Hinton, 2015), that carry out “number crunching” without involving any semantics during data processing. The latter is a major reason that current AI models a) do not demonstrate a reasonable capacity for generalization and may produce blatantly wrong answers during testing especially when they are fed with few and/or spurious data during training and b) they operate as “black boxes” whose answers are neither transparent nor explainable.

Important as they are, real numbers emerge from the conventional measurement process of successive comparisons in the physical world. The Pythagorean doctrine that “(rational) numbers is the ultimate reality” has been dominant in physical sciences, e.g. Physics, since the time of Isaac Newton. The deep-learning models follow suit by considering multi-parameter models defined on a Cartesian product $\mathbb{R}^N$, whose parameters tune both learning and generalization. Nevertheless, when humans are involved, non-numerical percepts emerge, e.g. words /sentences, concepts, symbols, rules, structures, intentions, emotions and other representing semantics. Historically, perhaps the first non-numerical percepts studied are the truth values of propositions whose study has ushered in Boolean algebra by George Boole in 1854 (Boole, 2003) – It is noteworthy that Boolean algebra is the *par excellence* tool for designing digital computer hardware. In turn, Lattice Theory (LT) or, alternatively, Order Theory, has emerged as a spin-off of work on formalizing propositional logic including Boolean algebras (Kaburlasos, 2006). A preeminent feature of LT is its unifying capacity (Birkhoff, 1967). Popular lattice-ordered data in applications include tree data structures (Kaburlasos et al., 2021), ontologies (Lytridis et al., 2023), possibility /probability distributions (Kaburlasos, Kehagias, 2007; Kaburlasos, Papakostas, 2015) and other. Furthermore, the set of real numbers constitutes a (totally-ordered) mathematical lattice. Hence, mathematical lattices emerge as a unifying data domain including both numerical data and non-numerical data toward computing with semantics (Kaburlasos, 2011). In

particular, rigorous mathematical instruments can be introduced in a mathematical lattice including: a) order measures – previously called inclusion measures, and b) metric distance functions. In conclusion, the “Lattice Computing (LC) (information processing) paradigm”, or LCparadigm for short, has emerged for modeling on a mathematical lattice data domain (Kaburlasos, 2022).

It is remarkable that lattices have emerged in Physics as well. In particular, the 1954 Nobel prize laureate Max Born has instrumentally employed probability theory in quantum mechanics – Note that Andrey Kolmogorov had already formalized probability theory in 1933 by introducing the notion of Probability Space. The latter was shown to be a mathematical lattice whose elements are events (sets), moreover a probability measure is a positive valuation (Birkhoff, 1967).

Popular practices can be included and further be enhanced within the LCparadigm. For instance, the activation of a fuzzy rule in a conventional fuzzy inference system (FIS) is effected by an order measure (Kaburlasos, Kehagias, 2014); the Rule of Bayes is yet another order measure in a Probability Space (Kaburlasos, 2006); furthermore, a positive valuation function can introduce non-linearities in a Cartesian product lattice $L = L_1 \times \dots \times L_N$ thus enhancing the scope of Riemannian geometry (Bazinas et al., 2023).

2.1 The Lattice Computing paradigm

A *fuzzy lattice* is defined as a triplet $(L, \sqsubseteq, \mu)$, where $(L, \sqsubseteq)$ is a conventional (crisp) mathematical lattice and $(L \times L, \mu)$ is a fuzzy set such that $\mu(x, y) = 1$ if and only if $x \sqsubseteq y$. A fuzzy lattice $(L, \sqsubseteq, \mu)$ fuzzifies the binary (crisp) order relation “ $\sqsubseteq$ ” of lattice $(L, \sqsubseteq)$.

Definition 1: A *fuzzy order* or, equivalently, *order measure* or *inclusion measure*, is defined on a crisp lattice $(L, \sqsubseteq)$ as a function $\sigma: L \times L \rightarrow [0, 1]$ which satisfies the following two conditions

C1: $u \sqsubseteq w \Leftrightarrow \sigma(u, w) = 1$.

C2: $u \sqsubseteq w \Rightarrow \sigma(x, u) \leq \sigma(x, w)$.

Any use of an “order measure” is called *fuzzy lattice reasoning*, or FLR for short (Kaburlasos, 2006). It turns out that an order measure can implement four types of reasoning, namely 1) *Inductive Reasoning*, 2) *Deductive Reasoning*, 3) *Reasoning by Analogy* (Kaburlasos et al., 2007) and 4) *Abductive Reasoning*, as explained below.

A *valuation function* on a lattice $(L, \sqsubseteq)$ is defined as a real function $v: L \rightarrow \mathbb{R}$ that satisfies $v(x) + v(y) = v(x \sqcap y) + v(x \sqcup y)$. A valuation function is called *monotone* if and only if $x \sqsubseteq y \Rightarrow v(x) \leq v(y)$, and *positive* if and only if $x \sqsubset y \Rightarrow v(x) < v(y)$.

If $v: L \rightarrow [0, +\infty)$ is a positive valuation function on a lattice $(L, \sqsubseteq)$ there follows the metric distance function

$$d(x, y) = v(x \sqcup y) - v(x \sqcap y). \quad (1)$$

Furthermore, both functions

$$\text{sigma-meet: } \sigma_n(x, u) = \sigma_n(x \sqsubseteq u) = \frac{v(x \sqcap u)}{v(x)}, \text{ and} \quad (2)$$

$$\text{sigma-join: } \sigma_u(x, u) = \sigma_u(x \sqsubseteq u) = \frac{v(u)}{v(x \sqcup u)} \quad (3)$$

are order measures. A parametric valuation function $v(\cdot)$ introduces tunable nonlinearities.

Given a lattice $(L, \sqsubseteq)$, the corresponding *lattice of generalized intervals* is defined as $(L \times L, \sqsubseteq \times \sqsubseteq)$ with meet $(\sqcap)$ and join $(\sqcup)$ defined as $[a, b] \sqcap [c, d] = [a \sqcup c, b \sqcap d]$ and $[a, b] \sqcup [c, d] = [a \sqcap c, b \sqcup d]$.

A function $\phi: P \rightarrow Q$, where both $(P, \sqsubseteq)$ and $(Q, \sqsubseteq)$ are lattices, is called *order preserving* or, equivalently, *monotone*, if $x \sqsubseteq y \Rightarrow \phi(x) \sqsubseteq \phi(y)$. If, in addition, ϕ satisfies $x \sqsubseteq y \Leftarrow \phi(x) \sqsubseteq \phi(y)$ then ϕ is called *order embedded*; a bijective order embedded function is called *isomorphism*. When there is an isomorphism between two lattices $(P, \sqsubseteq)$ and $(Q, \sqsubseteq)$ then $(P, \sqsubseteq)$ and $(Q, \sqsubseteq)$ are called *isomorphic*, symbolically $(P, \sqsubseteq) \approx (Q, \sqsubseteq)$. The *dual* of a lattice $(L, \sqsubseteq)$ is another lattice $(L, \sqsubseteq)^\delta = (L, \sqsubseteq^\delta) = (L, \sqsupseteq)$ whose order relation is the inverse one. If for two lattices $(P, \sqsubseteq)$ and $(Q, \sqsubseteq)$ it holds $(P, \sqsubseteq) \approx (Q, \sqsubseteq)^\delta$ then lattices $(P, \sqsubseteq)$ and $(Q, \sqsubseteq)$ are called *dually isomorphic*.

Given a positive valuation function on a lattice $(L, \sqsubseteq)$ as well as a (bijective) dual isomorphic function $\theta: (L, \sqsubseteq)^\delta \rightarrow (L, \sqsubseteq)$ it turns out that the composite function " $\text{vo}\theta$ " is a positive valuation function on lattice $(L, \sqsupseteq)$; furthermore, the function $v_1([x, y]) = v(\theta(x)) + v(y)$ is a positive valuation on the lattice $(L \times L, \sqsubseteq \times \sqsubseteq)$ of generalized intervals. There follows the metric distance

$$d_1([a, b], [c, e]) = [v(\theta(a \sqcap c)) - v(\theta(a \sqcup c))] - [v(b \sqcup e) - v(b \sqcap e)] \quad (4)$$

as well as the order measures

$$\text{sigma-meet: } \sigma_n([a, b], [c, e]) = \frac{v(\theta(a \sqcap c)) - v(\theta(a \sqcup c))}{v(b \sqcup e) - v(b \sqcap e)}, \text{ and} \quad (5)$$

$$\text{sigma-join: } \sigma_u([a, b], [c, e]) = \frac{v(b \sqcup e) - v(b \sqcap e)}{v(\theta(a \sqcap c)) - v(\theta(a \sqcup c))} \quad (6)$$

in the partially ordered lattice of conventional intervals.

Learning, from the training data, and generalization, on the testing data, in a lattice data domain is pursued as follows. Training /testing data pairs (a_i, c_i) , $i \in \{1, \dots, I\}$, which may be thought of as samples of an unknown function $f: L \rightarrow M$, where both $(L, \sqsubseteq)$ and $(M, \sqsubseteq)$ are crisp lattices are given. Here a data pair (a_i, c_i) is interpreted as a rule " R_i : if a_i then c_i ", symbolically $a_i \rightarrow c_i$, $i \in \{1, \dots, I\}$. An estimate $\hat{f}$ of function f is computed during training by Inductive Reasoning, namely *Type I Generalization*; whereas, the Deductive Reasoning has been called *Generalized Modus Ponens* (Kaburlasos et al., 2007). A positive valuation function is an instrument for computing a tunable Riemann space resulting in a *tunable Reasoning by Analogy* or, equivalently, *Type II Generalization* (Kaburlasos et al., 2007). Testing is carried out by Deductive Reasoning as well as by Reasoning by Analogy. Finally, transparency as well as explainability are attained by Abductive Reasoning as described below.

A lattice $(L, \sqsubseteq)$ may be the Cartesian product of N - possibly different - constituent lattices $(L_i, \sqsubseteq_i)$, $i=1, \dots, N$ i.e. it may be $(L, \sqsubseteq) = (L_1, \sqsubseteq_1) \times \dots \times (L_N, \sqsubseteq_N)$, where every constituent lattice $(L_i, \sqsubseteq_i)$, $i=1, \dots, N$ is characterized by its own order relation $\sqsubseteq_i$.

Learning occurs by computing intervals $[a_i, b_i]$, $i \in \{1, \dots, N\}$ in a mathematical lattice. A lattice interval $[a_i, b_i]$ is mapped to a class c_0 . Explainability by Abductive Reasoning, based on a rule R_i (conjunction over the constituent lattices) "if $[a_i, b_i]$ then c_0 ", is pursued as follows: Given " c_0 " then return $[a_i, b_i]$ as an explanation.

Features of the LCparadigm include (a) Hierarchical data fusion of numerical and non-numerical data *per se*. (b) Computing with data semantics represented by partial order. (c) Rigorous mathematical analysis and design, i.e. rigorous modeling. (d) Decision support based on logic.

Of specific interest, both theoretical- and practical-interest, have been extensions in the lattice $(F_1, \preceq)$ of Intervals' Numbers (INs), where an IN may be interpreted either as a fuzzy number (Kaburlasos, Kehagias, 2007) or as a probability distribution (Kaburlasos, Papakostas, 2015).

The metric distance $d_1(.,.)$ as well as order measures $\sigma_u(.,.)$ and $\sigma_n(.,.)$ can be extended to the lattice $(F_1, \preceq)$ of INs by function $D_1: F_1 \times F_1 \rightarrow \mathbb{R}_{+0}$, $\sigma_\lambda: F_1 \times F_1 \rightarrow [0, 1]$ and $\sigma_v: F_1 \times F_1 \rightarrow [0, 1]$, respectively, as

$$D_1(E, F) = \int_0^1 d_1(E_h, F_h) dh \quad (7)$$

$$\sigma_\lambda(E, F) = \int_0^1 \sigma_\cap(E_h, F_h) dh \quad (8)$$

$$\sigma_v(E, F) = \int_0^1 \sigma_\sqcup(E_h, F_h) dh \quad (9)$$

Finally, functions (7), (8) and (9) can be extended to a Cartesian product $F = F_1 \times \dots \times F_N$ by a convex combination as follows

$$D(\mathbf{E} = (E_1, \dots, E_N), \mathbf{F} = (F_1, \dots, F_N)) = \lambda_1 D_1(E_1, F_1) + \dots + \lambda_N D_1(E_N, F_N) \quad (10)$$

$$\sigma_{c\lambda}(\mathbf{E} = (E_1, \dots, E_N), \mathbf{F} = (F_1, \dots, F_N)) = \lambda_1 \sigma_{c\lambda}(E_1, F_1) + \dots + \lambda_N \sigma_{c\lambda}(E_N, F_N) \quad (11)$$

$$\sigma_{c\gamma}(\mathbf{E} = (E_1, \dots, E_N), \mathbf{F} = (F_1, \dots, F_N)) = \lambda_1 \sigma_{c\gamma}(E_1, F_1) + \dots + \lambda_N \sigma_{c\gamma}(E_N, F_N) \quad (12)$$

where $\lambda_1 + \dots + \lambda_N = 1$.

3. A Method for Explainable Artificial Intelligence

The long-term objective of this work is the development of a CORO that keeps an elderly person busy by showing him/her pictures from a vineyard and asking whether there is a grape in the picture. If the answer of the elderly is true positive /negative then the CORO confirms; otherwise, the CORO substantiates the correct answer to the elderly. The implementation details follow.

Using a YOLO deep learning model (Anish et al, 2023; Lu et al, 2024), a Convolutional Neural Network (CNN) is trained to recognize grapes on a digital image by putting a bounding box (BB) on a grape bunch. Given a trained YOLO, a series of rules is induced from images with and without grape bunches by implementing the "antecedentInduction" algorithm next.

For each digital image, run the following algorithm.

The "antecedentInduction" algorithm

1. Run the YOLO model to place a grape bunch, if any, within a BB. If there are no grapes in an image then define a BB randomly.
2. Compute one IN per RGB channel from the corresponding pixel intensities distribution.
3. Compute individual grapes (circles) in each BB by algorithm HoughCircles.
4. Represent the number of individual grapes (circles) in the BB by a trivial IN.
5. Compute one IN from the distribution of all circles' radii.
6. Compute one IN from the distribution of the distances between all circle centres.

In conclusion, a user defines a rule per BB with antecedent the aforementioned 6-tuple IN and consequent a label "grape"/"no grape".

The above rules are induced "off line", in a batch processing mode. The following model runs "on line".

The "Intelligent Agent Model" (IAM) Algorithm

- A. A digital image is shown to both a CORO and an elderly person.
- B. The elderly needs to say whether he/she sees a grape bunch or not. In particular, if the answer is "yes" then he/she is required to specify the corresponding BB. If there are no grapes in an image then a BB is defined randomly.

- C. If the answer of the elderly is true positive/negative then the CORO confirms.
- D. Otherwise, the CORO runs the "antecedentInduction" algorithm.
- E. Classification by a "nearest neighbour technique" i.e. by computing the "nearest" of a 6-tuple IN of unknown class to a 6-tuple IN antecedents of all rules.
- F. If the answer of the elderly is false positive/negative then the CORO substantiates the correct answer to the elderly by abductive reasoning on the rule with the "nearest" 6-tuple IN antecedent. A corresponding degree of certainty is also given computed by either an order measure or a metric distance.

4. Preliminary Computational Experiments and Results

In a preprocessing step all IN domains were normalized on the unit interval $[0,1]$. Furthermore, the convex combination coefficients $\lambda_1 = \dots = \lambda_6 = 1/6$ were used as well as the functions $v(x) = x$ and $\theta(x) = 1-x$ per constituent lattice $[0,1]$.

The computational experiments were designed as follows. The CORO displays an image for testing and asks an elderly person to recognize an object; in particular, it asks to recognize a grape bunch. The CORO itself uses the IAM algorithm to compute the right answer. Explainable Artificial Intelligence (XAI) (Cabitza et al., 2023; Minh et al., 2022; Yang et al., 2023) by abductive reasoning in the context of the LC paradigm is carried out by applying user-defined *a posteriori* knowledge on top of the results of deep-learning (YOLO) in order to either accept or reject them toward explaining "why there is a grape in the picture, if any" as outlined next.

The image in Picture 2(a) was shown to the IAM algorithm. Seven BBs were computed labeled by $0,1,\dots,6$. Six BBs corresponded to "true positive", whereas one BB, namely BB3, corresponded to "true negative" grape bunch. Picture 2(b) displays BB3, whereas Picture 2(c) displays BB6. In conclusion, six rules " R_i : if BB_i then grape", where $i \in \{0,1,2,4,5,6\}$ and one rule " R_3 : if BB_3 then no-grape" were computed. In particular, Picture 3 shows three INs computed from RGB histograms, respectively, in BB6. Furthermore, Picture 4 displays the 6-tuple IN antecedent of rule R_6 .

According to the Resolution Identity Theorem (Zadeh, 1975), a fuzzy set can be represented (equivalently) either by its membership function or by its α -cuts. The aforementioned theorem was used to represent an IN. For example, each figure in Picture 4 displays an IN F both in its "membership function representation" as $F(x)$, $x \in R$ and its "interval representation" as $\cup[a_h, b_h] = \cup F_h$, $h \in [0,1]$. In particular, the IN T in Picture 4(d) is *trivial* in the sense that $T = \cup[22,22]_h$ for $h \in [0,1]$. An advantage of INs is that an IN can represent all-order statistics (Kaburlasos, Kehagias, 2014).

Tables 1, 2 and 3 are Confusion Matrices for $\sigma_A(.,.)$, $\sigma_V(.,.)$ and $D_1(.,.)$, respectively, for a "leave-one-out" mode of training /testing meaning that one

of the seven rules was left out for testing by a kNN scheme with $k=1$. All of Tables 1, 2 and 3 show that the two classes, namely "grape" and "no grape", are clearly separable in the following sense. The maximum of any of Table 1 lines 0,1,2,4,5 and 6 is above 0.68; whereas, the maximum of Table 1 line 3 equals 0.53; hence, the two classes "grape" and "no grape" are separable. Likewise for Table 2 and Table 3.



(a)



(b)

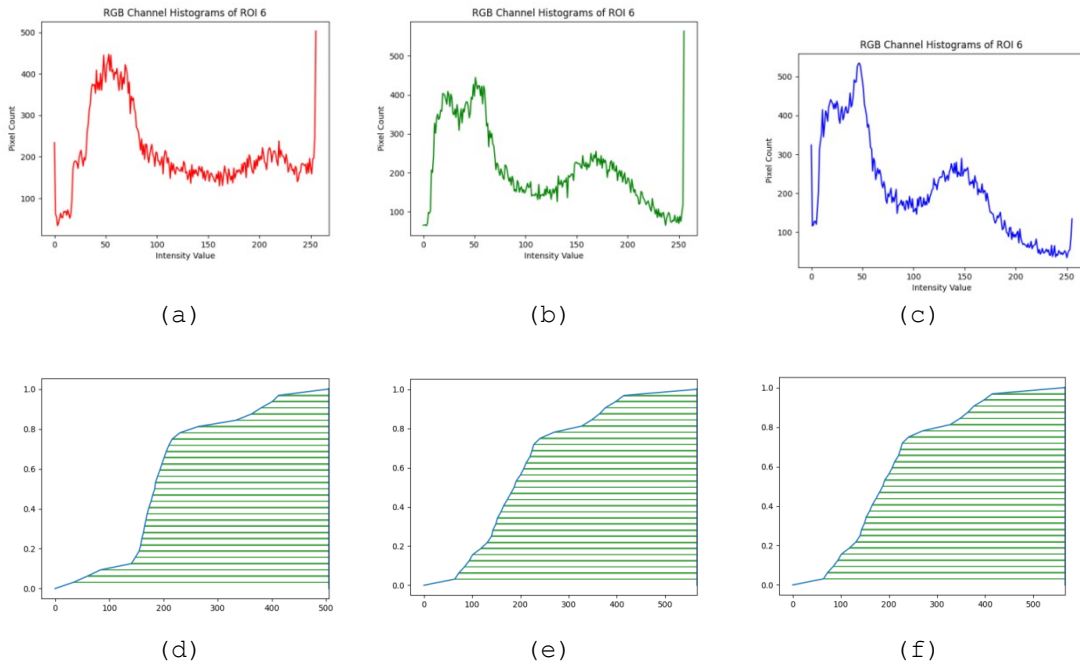


(c)

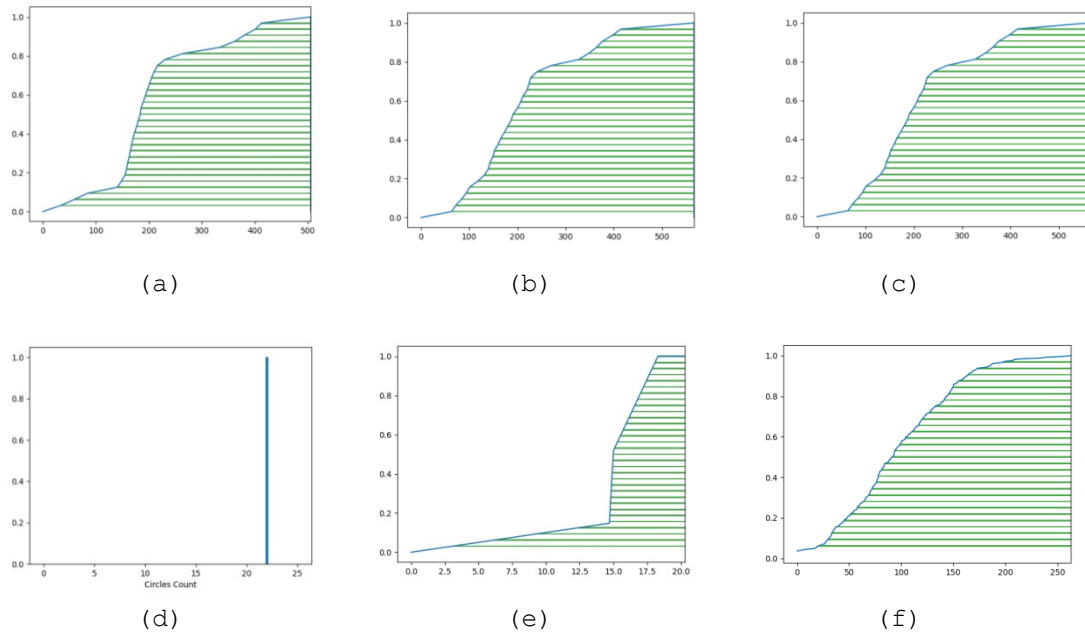


(d)

Picture 2. Images and ROIs indicated by BBs in green color. (a) An image with grapes. (b) The image in (a) with BB3. (c) The image in (a) with BB6. (d) Circles (grapes), indicated in red color, in BB6 computed by algorithm HoughCircles.



Picture 3. IN induction from RGB histograms for BB6. (a) R(ed) histogram and the corresponding IN in (d). (b) G(reen) histogram and the corresponding IN in (e). (c) B(lue) histogram and the corresponding IN in (f).



Picture 4. The 6-tuple IN antecedent of a Rule R6. (a), (b) and (c) are copied from Picture 3 (d), (e) and (f), respectively. (d) Trivial IN representing the number 22 of circles (i.e. grapes) in BB6. (e) IN representing the distribution of the radii of circles (i.e. grapes) in BB6. (f) IN representing the distribution of the distances of the centers of circles (i.e. grapes) in BB6.

Table 1. Non-symmetric Confusion Matrix for $\sigma_A(E,F)$ involving a convex combination of 6-tuple IN E and F each one of the latter represents a Bounding Box BB_i , $i \in \{1,2,3,4,5,6\}$.

	BB0	BB1	BB2	BB3	BB4	BB5	BB6
BB0	1	0.72	0.64	0.53	0.78	0.70	0.68
BB1	0.74	1	0.72	0.33	0.77	0.73	0.75
BB2	0.67	0.73	1	0.23	0.65	0.78	0.77
BB3	0.39	0.26	0.20	1	0.37	0.53	0.23
BB4	0.77	0.73	0.61	0.50	1	0.69	0.64
BB5	0.62	0.63	0.68	0.63	0.62	1	0.65
BB6	0.69	0.74	0.75	0.28	0.68	0.74	1

Table 2. Non-symmetric Confusion Matrix for $\sigma_Y(E,F)$ involving a convex combination of 6-tuple IN E and F each one of the latter represents a Bounding Box BB_i , $i \in \{1,2,3,4,5,6\}$.

	BB0	BB1	BB2	BB3	BB4	BB5	BB6
BB0	1	0.92	0.92	0.89	0.98	0.89	0.92
BB1	0.95	1	0.95	0.87	0.94	0.94	0.98
BB2	0.95	0.96	1	0.87	0.95	0.94	0.97
BB3	0.66	0.63	0.62	1	0.66	0.69	0.63
BB4	0.96	0.90	0.90	0.88	1	0.88	0.90
BB5	0.82	0.85	0.84	0.85	0.82	1	0.85
BB6	0.94	0.97	0.95	0.86	0.94	0.93	1

Table 3. Non-symmetric Confusion Matrix for $D_1(E,F)$ involving a convex combination of 6-tuple IN E and F each one of the latter represents a Bounding Box BB_i , $i \in \{1,2,3,4,5,6\}$.

	BB0	BB1	BB2	BB3	BB4	BB5	BB6
BB0	0	0.16	0.15	0.87	0.05	0.38	0.16
BB1	0.16	0	0.09	1.03	0.19	0.25	0.04
BB2	0.15	0.09	0	1.03	0.18	0.26	0.08
BB3	0.87	1.03	1.03	0	0.88	1.00	1.03
BB4	0.05	0.19	0.18	0.88	0	0.40	0.19
BB5	0.38	0.25	0.26	1.00	0.40	0	0.26
BB6	0.16	0.04	0.08	1.03	0.19	0.26	0

5. Discussion and Conclusion

It has been reported that “promising drugs” for the treatment of AD have failed e.g. drug Aduhelm (Diamant, 2024). It appears that the aforementioned drugs are developed ignoring the capacity of the brain to process information including semantics. In response, this work has proposed Companion Robots (COROs), supported by models for computing with semantics, toward keeping the brain of elderly operating constructively as an alternative treatment of Mild Cognitive Impairment (MCI).

The preliminary results reported in this work have been encouraging. In particular, algorithm IAM has demonstrated a capacity to explain, by abductive reasoning, its answers regarding the existence of a grape bunch on any image presented. Future work extensions will consider additional objects beyond grapes to be recognized. Optimization techniques will also be used toward computing optimal $\lambda_1, \dots, \lambda_6$ values, optimal positive valuation parameters and other.

This work has applied computing with semantics on top of machine learning. More specifically, user-defined *a posteriori* rules have been defined on top of BB computed by deep-learning (YOLO) techniques. Future work will consider multilayer neural network architectures toward computing with semantics by processing INs all along. Real world applications of the IAM algorithm with elderly having MCI will also be considered.

The application of the XAI models developed in this paper toward supporting elderly, could be extended elsewhere, e.g. to typical education /entertainment /business of services via other robots and/or software agents. Furthermore, conventional Computing With Words (CWW) techniques in the context of fuzzy sets (Gupta and Andreu-Perez, 2022) can also be tuned by parametric positive valuation functions in the context of the LC-paradigm. Hence, the proposed methods can entail economic opportunities in applications.

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