A FUZZY DETERMINISTIC DENDRITIC CELL ALGORITHM: A COMPARISON OF DEFUZZIFICATION METHODS.

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Abstract
The Dendritic Cell Algorithm is an inspired algorithm modelled based on the functioning of Biological Dendritic Cells. The concentration values of input signals in the DCA are in crisp form, and this shows that there is no clear boundary between low or high values of concentration level of the input signals. This is part of the reason why the DCA is sensitive to class data order. However, this problem solved with the introduction of FdDCA. Despite the performance of the FdDCA, the choice of the defuzzification method (Centre of Gravity) in the algorithm was based on intuition. We believe that the right choice of defuzzification method will improve the performance of the algorithm. In this paper, we investigate the performance of the FdDCA using different defuzzification methods. The main aim of this paper is to select the best defuzzifiction method for the FdDCA.

Keywords: *Fuzzy, Deterministic, Dendritic, Algorithm, Comparison, Defuzzification.*

Introduction

The Human Immune System (HIS) has mechanisms that can detect and defend the organism's body from foreign substances known as antigens. The main job of HIS is to protect the human body against different types of diseases caused by antigens such as bacteria, parasites, fungi, and viruses. HIS has many interesting properties such as memory, adaptability, pattern recognition, autonomy, and learning. One of the most important characteristics of HIS is its ability to discriminate between an antigen (Non-self) and the body's cell (self).

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The HIS has two interacting subsystems: The innate immune system and the adaptive immune system, the later is responsible for identifying antigens and controls the adaptive immune system while the adaptive immune system learns to adapt and repel antigens very quickly when they attack for the second time. The rich information provided by HIS leads to the development of the immune system- based algorithms.

Artificial Immune System draws its inspiration from HIS. The early AISs draw their inspiration from the adaptive immune system such as the negative selection algorithm and clonal selection algorithm. The negative selection algorithm was the first AIS algorithm to be introduced, and it was developed to handle anomaly detection applications (Gong et al. (2012); Dasgupta and Majumdar (2002); Dasgupta et al. (2004)) such as intrusion detection in computer network and fault tolerance. However, the NSA has issues with detection generation and a high rate of false positives was reported by Stibor (2006).Despite the changes made in the algorithm to improve on the mentioned problems, but the NSA still had almost the same issues. Therefore, Aickelin et al. (2003) proposed a new model that models the danger theory, and this theory is derived from the behaviour of the innate immune system. The danger theory-based model is aimed at developing a model that is more sophisticated than the NSA.

Greensmith et al. (2005) introduces the dendritic cell algorithm (DCA), and the DCA was developed based on the danger theory. DCA has proved to be successful when applied to static datasets for classification, but it faces criticism that it is too stochastic and it has too many parameters which makes it difficult to analyse which brings uncertainty to the algorithm's performance. Greensmith (2007) introduces Deterministic Dendritic Cell Algorithm (dDCA) to address the issue of stochastic nature of DCA. Another issue with DCA is that it is sensitive to data order, and this is due to changes in data order in quick succession. Chelly and Elouedi (2010) and Mukhtar et al. (2016) introduced fuzzy based DCA to handle the issue of data order sensitivity. However, the choice of the defuzzification method (Centre of Gravity) in the FdDCA was based on intuition. There is need to investigate the performance of the FdDCA using different defuzzification methods, and this will help in choosing the right defuzzification method that will improve the performance of the algorithm. The main aim of this paper is to select the best defuzzifiction method for the FdDCA.

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Dendritic cells

In the early days of immunology, it was suggested that it is only antigens and white blood cells that trigger immune defence, (Banchereau and Steinman, 1998; Kapsenberg, 2003). Until the late 80s that COHN and Steinman (1973) found that antigen-presenting cells (APC) are also major players that trigger adaptive immunity by stimulating T and B lymphocytes. Antigens are processed and presented to T cells by APC, and without the APC the T cells cannot be activated. According to Amigorena (2018) and Randolph (2001) DCs are the only APCs that can presents antigens to naive T cells,

DCs are special phagocytic cells that originate from the bone marrow and spread to the blood, olympiads, and potential entry points of pathogens like tissues and skin as suggested by Kapsenberg (2003). DCs have toll-likereceptors (TLRs) on their surface that specialise in recognising exogenous pathogens, through these receptors the DCs receive both endogenous and exogenous signals. When the DCs leave the blood they transformed into three states depending on the type of signals the DCs received: Immature, semi-mature, and mature DCs as presented by Al-Ashmawy (2018); Lutz and Schuler (2002), and Dudek et al. (2013). Figure ?? shows the three state of DC maturation.

Immature DCs

Initially, DCs are in an immature state, and they cannot stimulate naive T cells. As an APC DCs engulf both endogenous and exogenous pathogens, process them for presentation to T cells. They also use receptors to sense various signals in their environment, these signals may be pathogen's structure identified by TLRs called pathogen-associated molecular patterns (PAMP) as suggested by Janeway et al. (1999). Danger signals are sent when a particular tissue is damaged as a result of the activities of pathogens or death of cells called necrosis, this means the cells were killed by pathogens. Safe signals are released as a result of Apoptosis, this means the cells death is natural or programmed. Therefore, the signals received shows the cells are in a healthy condition.

Semi-Mature DCs

When an immature DCs are exposed to safe signals they migrate to the lymph node and transform into semi-mature DCs. These DCs can present antigens but

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are incapable to of activating T cells, instead, they secrete cytokines known as interleukin-10. The cytokines suppress T cells from reacting presented to it since they are collected under apoptotic cells. This prevents T
Cells from attacking self cells and hence, prevent autoimmunity (Tolerance).

Mature DCs

Immature DCs became fully mature when they are exposed to a large quantity of PAMP and danger signals, this makes the DCs migrate to the lymph node and produce cytokines called interleukin-12. This activate T cells and also produce costimulatory molecules (CSM) that help in antigen presentation to cell since the signals receive as a result of necrotic cells.

The Dendritic Cell Algorithm

The Dendritic cell algorithm (DCA) is an immune inspired algorithm proposed by Greensmith (2007). DCA is an abstraction of the biological DC model based on Danger Theory proposed by Matzinger (1994).
The abstraction of DC input and output signals
Signals are responsible for the change in the state of an immature DC. The immature DC process the signals and produces output signals. The abstraction of the signals are highlighted below:

The input signals

- PAMP: According to Ito (2014) PAMPs are a molecular product of a non-host entity, and its recognition by PRS indicates abnormality to the host cell. In the abstract model of DC, a PAMP signal represents a definite indicator of abnormality.
- Danger Signal: Gong et al. (2019) suggests that the DS normally resides within the host cell, but an increase of endogenous activities results in releasing danger signals. This indicates that a cell is damaged or under duress. within the context of DC abstraction, a DS also indicates abnormality but not as a bigger indicator as PAMP.
- Safe Signals: Apoptosis signals released as a result of physiological death of cells tissue as claimed by Strasser et al. (2000). These signals are also referred to as safe signals. In the context of the artificial DC model, safe signals referred to normal behaviour of data.

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The Output Signals

Greensmith et al. (2005) stated that when a DC is exposed to endogenous signals it produces three output signals namely; Co-stimulatory Molecules (CSM), Interleukin-10 (IL-10), and Interleukin-12 (IL-12). The CSM is a subordinate signal that helps the DC to migrate from tissue to the lymph node, and thus stimulates the activation of the immune response as claimed by Lewis (2004); Whitman and Barber (2015). Spellberg and Edwards Jr (2001); Iyer and Cheng (2012) state that IL-10 suppresses antigen from damaging the host cell and also maintaining the healthy tissues, while IL-12 regulates the response of the immune system against antigens. The abstraction of the output signals are presented below:

- CSM: Since the amount of CSM causes the migration of DC to the lymph node, this shows that a DC exhausts its lifespan and a new one will enter the tissue for signal sampling. In the abstraction of DC, the CSM represents the amount of period or time a DC will take to stop sampling signals and antigens, in other words, it is the lifespan of a DC.
- IL-10: it is presented as the semi-mature signal, a large amount of SS produces the semi-mature signal.
- IL-12: it is represented as Mature Signal, a large amount of DS produces the mature signal.

The DCA is composed of four phases; as described below:

- Initialisation / Pre-processing.

The first thing in this phase is to select appropriate attributes to form signals, this is done by feature selection, dimensionality reduction, or statistics. After the selection of the most important attributes, each attribute is mapped to the appropriate signal category i.e PAMP, SS or DS. lastly, initialisation of the algorithm's components such as the population of artificial DCs, migration threshold is carried out.

- Detection Phase.

The second phase is to process the input data, whereby each data instance in the dataset represents an antigen. The attributes represent the signals. Each DC process the inputs by sampling antigens and their corresponding signals to obtain cumulative output values namely: costimulatory molecule signal (CMS), mature- signal (mDC) and semimature signal (smDC).

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Each DC is assigned a migration threshold which determines the time a DC will spend sampling signals and antigens. Therefore, once the cms are computed it is compared with the migration threshold. If the cms value is greater than the migration threshold then the DC is removed from the population and moved to the migrated pool. The migrated DC is replaced by a new one.

- Context Assessment.

In this phase, a comparison is made between the summation values of smDC and mDC. If smDC value is greater than the mDC value then the value 0 is assigned to the context, which means the antigen is collected under the normal context, otherwise the value 1 is assigned to the context, meaning the antigen is collected under a potentially dangerous context.

- Classification Phase.

The Mature Context Antigen Value (MCAV) measures the number of DCs that were collected in the mature context. The MCAV measures the degree of abnormality of the antigen and is calculated by dividing the number of times the antigen is collected under mature context by the total number of antigens presented. The MCAV of each antigen is compared with the anomaly threshold, the anomaly threshold is determined by the total number of anomalous class items divided by the total number of all class items as shown in the equation. once the MCAV of an antigen is greater than the anomaly threshold then that antigen is classified as anomalous otherwise it is classified as normal.

Limitations of DCA

Despite the successes achieved by the DCA, it has its limitations which have made researchers come up with different versions of the DCA to improve the algorithm's performance. One of the major criticism of DCA is that it is sensitive to data order. This means that when the context DC changes several times in quick succession it affect the algorithm's accuracy performance, due to the crisp nature of the separation between normal and abnormal contexts.(Greensmith, 2007; Chelly and Elouedi, 2015)

Based on the mentioned criticism of DCA, Chelly and Elouedi (2010) proposed a hybrid DCA called the fuzzy dendritic cell method (FDCM). The algorithm uses fuzzy logic to qualify the values of normality and abnormality context, and the algorithm outperformed DCA in terms of accuracy. but they also argue that the midpoints of fuzzy membership values are user-defined , this may affect the performance of the system. Therefore, an improved version of FDCM named MFDCM was proposed by Chelly and Elouedi (2011). The algorithm eliminates

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user interference by introducing clustering techniques to automatically define the midpoint values of each variable. The results show much-improved performance compared to other DCA based algorithms. The fuzzy based algorithms developed by Chelly and Elouedi (2010, 2011) did only addressed the issue of imprecision of the output context, and the DCA is known to be stochastic in nature which is not addressed in their algorithm. Therefore, Mukhtar et al. (2016) proposed FdDCA to handle the imprecision of the input signals. The main issue with the FdDCA is that the defuzzification method was intuitively selected , and it is not the only defuzzification method available. Tnere is a need to explore other defuzzification methods so as to have a better method for the FdDCA.

Overview of Defuzifficztion Methods

The FIS produced fuzzy values and these values have to be converted into crisp values, the process of converting fuzzy values into crisp values is called defuzzification. There are several methods of defuzzification, and such methods include the Centre of Gravity method (COG) (Van Broekhoven and De Baets,2006), Maxima method (Lee, 1990), the centre of sum method, and centre of the area.

Algorithm I: Generic DCA, Adopted from Greensmith et al. (2005)

DCA

Input: signals from all categories and antigen Output: antigen plus context values. /* Initialisation Phase*/ initialise DC; /* Detection Phase*/

while CSM output signal < migration threshold do get antigen; store antigen; get signals; calculate interim signals; update cumulative output signals; end if cumulative CSM > migration threshold then; DC migrate remove DC from the population replace with new DC

/* Context Assessment Phase*/ if semi-mature output > mature output then

cell context is assigned as 0 ;

else cell context is assigned as 1 ;

end kill cell; replace cell in population; /* Classification Phase*/ for each antigen do calculate MCAV if MCAV> anomaly threshold antigen is anomalous else antigen is normal

Centre of Gravity

The Centre of Gravity (COG) method is one of the popular choice of defuzzificTion methods, it calculates the centre of gravity of the area membership function as shown in Equation 1. Consistency and linearity are among the characteristics of COG method.

$$cog = \frac{\sum_{i=1}^{n} x_i * \mu c(x_i)}{\sum_{i=1}^{n} \mu c(x_i)} \qquad (1)$$

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Where μc is the area of the membership function, $\mu c(x_i)$ is the centriod of the area, x_i is the sample of elements, and n represents the number of samples in the fuzzy set.

Bisector method

This is another method that divides the region line into two regions of the same area size. Equation 2 shows how the bisector method is calculated.

$$\int_{\alpha}^{z_{BOA}} \mu_A(z)dz = \int_{z_{BOA}}^{\beta} \mu_A(z)dz \quad (2)$$

where α = min {z; z ∈ Z} and β = max {z; z ∈ Z}. The vertical line z = ^{z}BOA partitions the region between z= α, z = β, y = 0 and y = $\mu_A(z)$ into two regions with the same area

Mean of Maxima

In this method, it calculates the mean of points in the fuzzy sets with maximum membership value as shown in Equation 3.

$$Z = \frac{a+b}{2} \quad (3)$$

Minimum of Maxima

Is a method where by the leftmost value with the minimum membership value is selected in the fuzzy set.

Largest of Maxima

Is a method where by the rightmost value with the maximum membership value is selected in the fuzzy set.

Fuzzy Deterministic Dendritic Cell Algorithms

Fuzzy Set Theory

The classical set theory deals with objects in binary form, whereby an element either belongs or does not belong to a set. However, some sets do not present sharp boundaries. In this case, the boundaries are not well defined like warm places, tall men or good students. Fuzzy set theory was introduced by Zadeh (1975) to handle imprecise boundaries of data. It mainly deals with the quantification of ambiguous and vague expressions using natural linguistic terms. In this sense, according to Massad et al. (2009) the fuzzy set became another way to handle uncertainties different from statistical methods.

Zadeh also proposed a membership degree to deal with situations where the belongingness of an element is not well defined, and this allows the element to partially or fully belong to a set. Let X be a set of elements of a universe of discourse, and x be a subset of X. in classical set theory, objects that completely

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belong to x are assigned membership of 1 and 0 is assigned to objects that do not belong to x. Conversely, in fuzzy sets, the membership is the interval between [0 1]. The more the membership value of an element gets closer to 1 the more it belongs to x, and such a varying grade of membership is called a membership function.

Let X be a nonempty set, a fuzzy set A in X is categorised by its membership function

$$A = \{x, \mu A(x) | x \in X\} \quad (4)$$

$$\mu A : X \rightarrow [0,1] \quad (5)$$

$\mu A(x)$ is denoted as the degree of membership of element x in fuzzy set A for each $x \in X$.

There are many different types of membership functions such as triangular, trapezoidal, Gaussian, and sigmoid membership functions. Triangular and trapezoidal are the most commonly used membership functions because they are easy to implement and work well in many problems. In this work, a trapezoidal membership function is used because it is more efficient than other membership functions (Gholamy et al., 2018).

The Fuzzy Deterministic Dendritic Cell Algorithm (FDDCA)

The dDCA has two input signals (danger and safe) as mentioned in Section 3, and these signals combine to generate two intermediate output values csm and K. The csm measures the overall concentration of signals a cell is exposed to during its lifetime, while the K value measures the normality or abnormality of the cell. When the cell exhausts its lifespan it will migrate and be ready to classify the antigens it collected during its lifetime as normal or anomalous. The summation of danger and safe signals form the csm value while the K value is derived by the difference between danger signal and twice of the safe signal as shown in Equations 6 and 7.

$csm_i = DS_i + SS_i$ (6)

$K_i = DS_i - 2SS_i$ (7)

The proposed Fuzzy Deterministic Dendritic Cell (FdDCA) converts the crisp values of the cumulative danger signals (DS) and cumulative safe signals (SS) into fuzzy numbers, and the cumulative signals are the total amount of safe and danger signals that the cells have been exposed to during their lifespan. The signals are used to determine the concentration of both the signals and the K.

The FdDCA consists of the following components:

- Initialisation and signal processing
- Fuzzification.
- Rule Base.
- Fuzzy Inference Engine.
- De-Fuzzification.

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- Context Assessment (Classification).

Initialisation and signal processing

Initialisation

The DC population and its parameters are initialised. The size of the DC population is set up to a maximum of 100 cells as suggested in Greensmith et al. (2005). The lifespan is set uniformly, and the lifespan of each DC is uniformly distributed. The output parameters: K, semi-mature, mature and csm are initialised to be zero for FdDCA.

Signal Processing and Update

• Costimulation (CSM)

The costimulation is the accumulation of signal concentration over a period of DC's lifetime within its environment. When a DC's life span expires, it migrates to the lymph node and presents antigens under a context. Equation 6 shows the calculation of csm.

The lifespan of a DC is the amount of time this DC spend collecting signal concentrations within its environment before it migrates to the lymph node. The lifespan of the DC is subtracted from the accumulated concentration of signals over time until the value of lifespan is less than the sum of the concentration. In this case, lifespan is a fixed value, however, its value is decreasing overtime as shown in Equation 8.

$$\text{lifespan} = \text{lifespan} - (SS_i + DS_i) \quad (8)$$

where i = (1...N).

Fuzzification

Two signals (danger and safe) and one output signal K are defined, and each of the input and output crisp values are fuzzified into linguistic variables. Each of the input and output crisp values also need to be fuzzified into linguistic variables, and a membership function is used to determine the range which each linguistic variable belongs.

• Linguistic Variables

Setting linguistic variables is one of the basic tools in fuzzy logic. SS, DS, semi-mature and mature are classified into three categories: low, medium, and high, as shown in Equations 10 and 11.

Algorithm 2: The Dendritic Cell Algorithm (FdDCA)

Input:Antigen and Signals

Output: Antigen Types and cumulative k values

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```
for i= 0 to nDCs do
| DC creation and Initialisation
end for
for all data input do
| for all DCs in the population do
| | DC kth samples ith antigen and signal matrix
| | DC kth compute its interim output
| | Update DC kth
| | if Cumulative csm > DCs Migration Threshold then
| | | migrate DC kth ;
| | | kill cell;
| | | reset DC;
| | | replace cell in population;
| end for
end for
for each mature and semi-mature value do
| calculate the membership functions of SS values
| calculate the membership functions of DS values
| calculate the membership functions of maturity values
| get the centroid value
| if centriod value > midpiont value of maturity then
| | the context is assign 1
| | else
| | the context is assign 0
| if
end for
for each antigen type do
| calculate MCAV;
end for
```

The output signal is classified into two classes: mature and semi-mature. $K_{Maturity}$ is a variable that interprets the state of the K value as either a mature or semi-mature DC, as shown in Equation 9. Figures 1 and 2 gives an illustrations of safe and danger signals as linguistic variables.

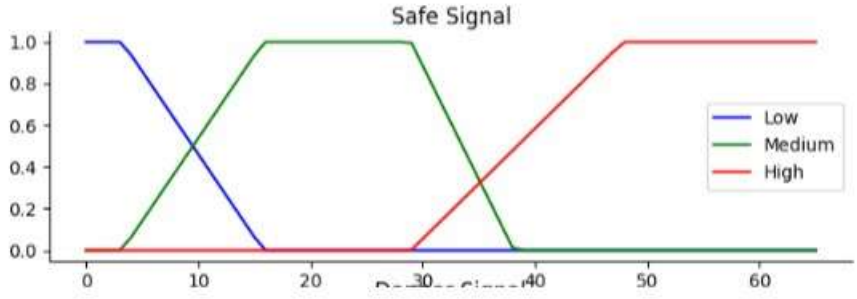

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Figure 1: Membership function for Safe signal

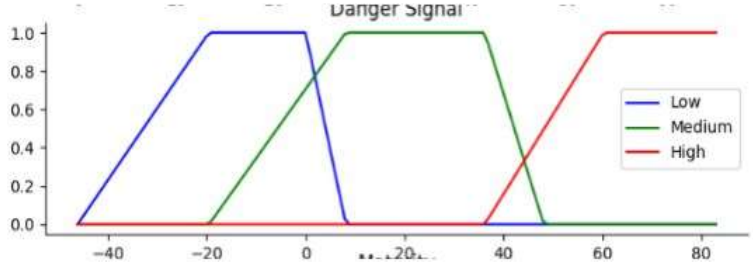

Figure 2: The Membership function for danger signals

$K_{Maturity} = \{Semi - Mature, Mature\}$ (9)

(SS) = {Low,Medium,High} (10)

(DS) = {Low,Medium,High} (11)

• Membership Functions

To construct a membership function, there is a need to specify the range of each linguistic variable. The Deterministic Dendritic cell Algorithm (dDCA) was first run to generate the values of K, DS, SS, semi-mature, mature and maturity. k-means clustering was then used to determine the ranges (as clusters) and core values in the membership function as mid points. The membership functions of input variables were designed to be trapezoidal, and their functions are defined in Equations 12 to 14 . This applies to both signals. The membership functions of output variable K were also designed using trapezoidal function as shown in Equations 15 and 16. x is defined as the actual crisp value, a is the lower limit, b is the lower support limit, d is the upper limit and c is the upper support limit. Parameters a, b, c, and d are all real numbers.

$$\mu S_{Low}(x) = \{0\ , if x > d \frac{d-x}{d-c}, if c \leq x \leq d1, x < c \quad (12)$$

$$\mu S_{Medium}(x) = \{0\ , if x \leq a \frac{x-a}{b-a}, if a \leq x \leq b1, if b \leq x \leq c \frac{d-x}{d-c}, if c \leq x \leq d0, x\ > d \quad (13)$$

$$\mu S_{High}(x) = \{0\ , if x < a \frac{x-a}{b-a}, if a \leq x \leq b1, x > b \quad (14)$$

$$\mu K_{Semi-Mature}(x) = \{0\ , if x > d \frac{d-x}{d-c}, if c \leq x \leq d1, x < c \quad (15)$$

$$\mu K_{Mature}(x) = \{0\ , if x < a \frac{x-a}{b-a}, if a \leq x \leq b1, x > b \quad (16)$$

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The Rule Base

Based on natural DC, the concentration of signals determines the state of a DC. A high value of SS indicates normality, and it reduces the effect of DS on the state of a DC. Likewise, a high value of DS indicates abnormality and thus reduce the influence of the DC which lead the DC to mature. From the information on the effects of signals on the DC, we can generate sets of fuzzy rules based on Chelly and Elouedi (2010) suggestion to support fuzzy inference based on the behaviour of each signal as shown below:

a. if (SS is low) and (DS is low) then (Context is mature)
b. if (SS is low) and (DS is medium) then (Context is mature)
c. if (SS is low) and (DS is high) then (Context is mature)
d. if (SS is medium) and (DS is low) then (Context is semi-mature)
e. if (SS is medium) and (DS is medium) then (Context is semi-mature)
f. if (SS is medium) and (DS is high) then (Context is mature)
g. if (SS is high) and (DS is low) then (Context is semi-mature)
h. if (SS is high) and (DS is medium) then (Context is semi-mature)
i. if (SS is high) and (DS is high) then (Context is mature)

Context Assessment

• Fuzzy Inference System

The next step after the construction of fuzzy rules is to draw a conclusion based on the rules constructed in the fuzzy rules, and fuzzy inference system (FIS) is used to handle that. The FIS interprets the fuzzy input on the sets of IF-Then rules and allots the values to the output. There are two main methods of FIS namely; The MinMax also known as Mamdani method and Sugeno-Type introduced by Mamdani (1974) and Takagi and Sugeno (1985) respectively. Our FdDCA adopts The MinMax method because it is widely used and suited for human input (if x and y, then z) as claimed by Ulloa (2018). Let us say, for example, the values of DS and SS are 41.5 and 100 , respectively. Applying Equations 12 to 14 we get the following membership functions (MF) values DS = (1, 0, 0) and SS = (0.31, 0.87, 0), and the first value represents low, the second medium, and the third high. After applying the MinMax method on the SS and DS values, the following steps are used to determine the context of a DC.

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1. If (DS is Low) and (SS is Low) then (Cell is Mature) min(1 , 0.31) = 0.31 (Mature)
2. If (DS is Low) and (SS is Medium) then (Cell is Semi- Mature) min(1 , 0.87) = 0.87 (Semi-Mature) Now we apply the max operator:

- max(0.31) = 0.31 (Mature)
- max(0.87) = 0.87 (Semi-mature)

Defuzzification

The FIS produced fuzzy values and these values have to be converted into crisp values, the process of converting fuzzy values into crisp values is called defuzzification. There are several methods of defuzzification, and such methods include the Centre of Gravity method (COG) (Van Broekhoven and De Baets, 2006), Maxima method (Lee, 1990), the centre of sum method, and centre of the area. In this work, we test all the defuzzification methods to select the best among them.

Based on the values generated by Mamdani method , the centroid value of 0.48 is generated using Equation 17. The medium value is generated from the range of values of output $K_{maturity}$ is (-1, 1) as shown in Figure 3, and it is calculated as (-1+1)/2 = 0. Once the centroid value is generated, the final context of the cell is determined by comparing the middle value of the output range and the centroid value. The middle value of the output range is greater than the centroid value (0 < 0.48). Hence, the final context of the DC is mature.

$$cog = \frac{\sum_{i=1}^{n} x_i * \mu c(x_i)}{\sum_{i=1}^{n} \mu c(x_i)} \qquad (17)$$

Where µc is the area of the membership function, µc(x_i) is the centriod of the area, x_i is the sample of elements, and n represents the number of samples in the fuzzy set.

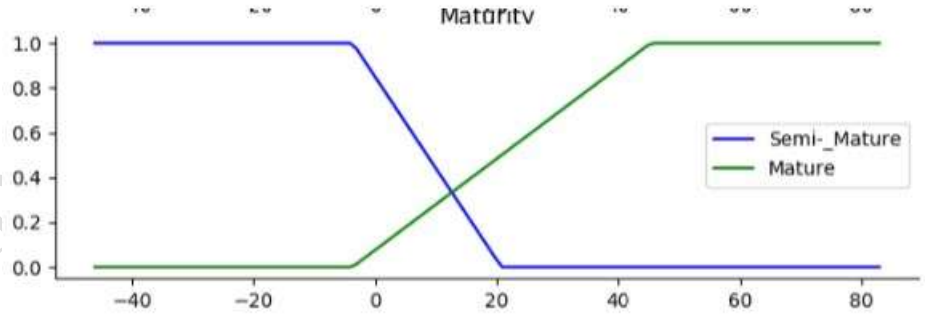

Figure 3: Context Assessment

Implementation of the FdDCA

Experiments and Analysis

The aim of these experiments is to show that our new algorithm can perform classification on a real world data set, and also to compare the competitiveness of different defuzzification methods so as to select the method that best fit to our algorithm.

Data sets

The Wisconsin Breast Cancer (WBS) obtained from UCI database Lichman (2017) is used to test the FdDCA.

Experimental Setup

Three Experiments are conducted using three different data orders of WBS data sets, Experiment 1 (one-step order) uses all class 1 data items followed by all class 2 data items, while Experiment 2 (two-step order) uses part of class 1 items then all class 2 items followed by remaining class 1 item. Experiment 3 (Randomise) randomise the class order several times. Each experiment is performed once, resulting in 700 antigen presentations per run of the used data sets. The final class of each antigen is determined by the anomaly threshold, and it is defined by the total number of malign divide by the sum of both malign and benign classes. The threshold for classification is set to 0.66. Items whose MCAV value is above the threshold are classified as anomalous and below are labelled as normal.

The classification accuracy of our FdDCA is assessed using Accuracy.The accuracy is determined by the summation of the number of items correctly classified (true positive) and the number of items correctly rejected (true negative) divide by the summation of the number of items correctly classified (true positive), the number of items correctly rejected (true negative), items incorrectly classified (false positive), and items incorrectly classified as a negative class while it should be in positive class (false negative). Equations 18 illustrates how accuracy is computed.

$$\text{Accuracy} = TP + TNTP + TN + FN + FP * 100 \quad (18)$$

where TP = true positive, TN = true negative, FP = false positive and FN = false negative.

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Results

Tables 1 - 5 present the positive and negative rates of the three experiments conducted and also the percentage accuracy of FdDCA. The results in Table 3, 2, and 4 show high rates of true positives in experiment 1 and very low rate of false negative with the percentage accuracy of 99.7%. In Tables 1 and 5 show that centroid and LOM have accuracy of 99.4% and 66.9% respectively. In experiment 2, the result is the same as in experiment 1 where by bisector, MOM, and SOM have the highest classification accuracy of 99.1% as shown in Tables ??, 3, and 4. The centriod and LOM methods have 99.0% and 70.8 % respectively.Interestingly, the centroid has the highest rate of true positives and lowest rate of false negative with highest classification accuracy of 97.4 % in experiment 3. The bisector has an accuracy of 97.4% followed by MOM and SOM with 97.0% and LOM with the least accuracy of 67.7 %.

Table 1: Comparing different data orders FdDCA (COG Method) Where E1 = Experiment 1, E2 = Experiment 2 and E3 = Experiment 3.

Experiments	TP	TN	FP	FN	Class 1	class 2	Accuracy
E1	236	459	1	3	239	460	99.4 %
E2	238	454	6	1	239	460	99.0 %
E3	235	447	13	4	239	460	97.5 %

Table 2: Comparing different data orders FdDCA (Bisector).

Experiments	TP	TN	FP	FN	Class 1	class 2	Accuracy
E1	239	458	2	0	239	460	99.7 %
E2	239	454	6	0	239	460	99.1 %
E3	237	444	16	2	239	460	97.4 %

Table 3: Comparing different data orders FdDCA (MOM) .

Experiments	TP	TN	FP	FN	Class 1	class 2	Accuracy
E1	239	458	2	0	239	460	99.7 %
E2	239	454	6	0	239	460	99.1 %
E3	237	441	19	2	239	460	97.0 %

Table 4: Comparing different data orders FdDCA (SOM) .

Experiments	TP	TN	FP	FN	Class 1	class 2	Accuracy
E1	239	458	2	0	239	460	99.7 %
E2	239	454	6	0	239	460	99.1 %
E3	237	441	19	2	239	460	97.0 %

Table 5: Comparing different data orders FdDCA (LOM) .

Experiments	TP	TN	FP	FN	Class 1	class 2	Accuracy
E1	8	460	0	231	239	460	66.9 %
E2	35	460	0	204	239	460	70.8 %
E3	13	460	09	226	239	460	67.7 %

Summary

In this paper, we reviewed the dendritic cell algorithms and fuzzy deterministic algorithm. This led to the introduction of FdDCA with different defuzzification methods. The algorithm aims at finding the right defuzzification method for better classification accuracy. This is done by comparing different defuzzification techniques. The results show that the FdDCA achieved better classification accuracy with bisector method when compared with other defuzzification methods.

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