Cognitive Development Optimization Algorithm Based Support Vector Machines for Determining Diabetes

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Abstract

The definition, diagnosis and classification of Diabetes Mellitus and its complications are very important. First of all, the World Health Organization (WHO) and other societies, as well as scientists have done lots of studies regarding this subject. One of the most important research interests of this subject is the computer supported decision systems for diagnosing diabetes. In such systems, Artificial Intelligence techniques are often used for several disease diagnostics to streamline the diagnostic process in daily routine and avoid misdiagnosis. In this study, a diabetes diagnosis system, which is formed via both Support Vector Machines (SVM) and Cognitive Development Optimization Algorithm (CoDOA) has been proposed. Along the training of SVM, CoDOA was used for determining the sigma parameter of the Gauss (RBF) kernel function, and eventually, a classification process was made over the diabetes data set, which is related to Pima Indians. The proposed approach offers an alternative solution to the field of Artificial Intelligence-based diabetes diagnosis, and contributes to the related literature on diagnosis processes.

Keywords: diagnosis diabetes, support vector machines, cognitive development optimization algorithm, classification, pimaindians diabetes.

1. Introduction

Since 1965 the World Health Organization (WHO) has been publishing guidelines for the diagnosis and classification of diabetes. These were last reviewed in 1998 and were published as the guidelines for the definition, diagnosis and classification of Diabetes Mellitus and its complications. Since then, more information relevant to the diagnosis of diabetes has become available. In November 2005, a joint WHO and International Diabetes Federation (IDF) technical advisory Group met in Geneva in order to review and update the current WHO guidelines[1]. In 2013, the International Diabetes Federation (IDF) published a report of an estimated 385 million people with diabetes worldwide, the majority being diagnosed with type-2 diabetes. The epidemiologic projections for the year 2035 now estimate an increase to 592 millions[2].

The social, economic and medical burden of diabetes represents an enormous public health problem, raising diabetes to the 4th cause of death worldwide[3]. Moreover, the devastating micro- and macro vascular complications associated with diabetes significantly reduce the Quality of Life (QoL) and life expectancy (Veresiu et al., 2015). Therefore, the definition, diagnosis and

[1] World Health Organization & International Diabetes Federation (2005). Definition and diagnosis of diabetes mellitus and intermediate hyperglycemia, Report of World Health Organization and International Diabetes Federation.
[2] International Diabetes Federation (2013). Diabetes atlas (6th ed.). Brussels, Belgium (Available from https://www.idf.org/sites/default/files/EN_6E_Atlas_Full_0.pdf. Accessed 04 January 2016).
[3] International Diabetes Federation (2009). Diabetes atlas (4th ed.). Brussels, Belgium. Available at https://www.idf.org/sites/default/files/IDF-Diabetes-Atlas-4th-edition.pdf. Accessed on 04 January 2016.

classification of diabetes are very important. So, especially WHO, IDF and lots of other scientists are working on these issues.

The use of computer technology in various fields immediately brings in mind the concept of computer-supported systems. Computer-supported systems and the activity of computers solution are noted as a factor in increasing the productivity and performance with a revolutionary direction. At this point, the computer-supported system holds the possibility of widespread use in many areas. One of these areas has found widespread use in the medical possibilities of computer-supported systems. Accordingly, the approach is performed in the medical field on a computerized support system based on obtained results with high success rates and it is becoming more attractive day by day. It is also undoubtedly one of the points of interest in computer-supported systems of the various elements involved in the work conditions in different areas of science and research. When we examine the approaches, methods, and techniques in the Artificial Intelligence research field, it can be said that the classification is receiving the highest degree of attention. When today's applications are examined, the Artificial Intelligence techniques in the computer-supported medical system in question can be seen particularly often used in diagnosing various diseases (Szolovits et al., 1988; Muralidaran et al., 2015). On the other hand, it is also an important factor to have Artificial Intelligent-based software solutions especially in real-world based problems. It can be said that not only the medical field but also many other fields of modern life often benefit from intelligent software-oriented applications in order to save time and reduce costs (Pătruț & Tomozei, 2010).

In this study, a diabetes diagnosis approach, which is formed via both Support Vector Machines (SVM) and Cognitive Development Optimization Algorithm (CoDOA) is proposed. Along the training of SVM, CoDOA was used for determining the sigma (σ) parameter of the Gauss (RBF) kernel function, and eventually, a classification process was made over the diabetes data set, which is related to Pima Indians and obtained from the University of California at Irvine (UCI) Machine Learning Repository. It is important that there are lots of studies which used the same dataset for diagnosis diabetes. For example, Santhanam and Padmavathi have classified the dataset to detect diabetes. In their work, they have used K-Means to remove the noisy data and genetic algorithms for finding the optimal set of features with Support Vector Machine (SVM) as classifier for classification. They have used reduced dataset of Pima Indians Diabetes from the related UCI repository (Santhanam & Padmavathi, 2015). Another classification application of the diagnosis of diabetes has made by Aslam and friends. They have also used reduced dataset of Pima Indians Diabetes from the same repository. In this research, a Genetic Programming (GP) based method has been used for diabetes classification. GP has been used to generate new features by making combinations of the existing diabetes features, without prior knowledge of the probability distribution (Aslam, Zhu, & Nandi, 2013). In the final example of work, Kahramanli and Allahverdi have used Fuzzy Neural Network to classify dataset for diagnosis diabetes. They have also used the UCI dataset (Kahramanli & Allahverdi, 2008).

According to all the works briefly mentioned above, the approach proposed in this study offers an alternative solution to the field of Artificial Intelligence-based diabetes diagnosis and contributes to the related literature on diagnosis processes.

In the context of the explanations above, the organization of the paper is as follows: the next section is devoted to essential information on employed dataset, and also Artificial Intelligence techniques. Following that, the third section is based on details regarding the applied approach on determining diabetes. After the third section, an application for determining diabetes from the employed dataset and also obtained results are briefly presented. Finally, the paper ends with conclusions and discussion on future works.

2. Essentials of the Diabetes Determining Approach

In order to have a clearer idea about the proposed diabetes determining approach, it is necessary to focus first on the employed dataset and on the Artificial Intelligence techniques that are related to the following research work.

2.1. Diabetes Dataset

As previously noted, the data used in this study has been obtained from the University of California at Irvine (UCI) Machine Learning Repository. The datasets are based on Pima Indians diabetes (Frank & Asuncion, 2010). Several constraints were placed on the selection of these instances from a larger database. In particular, all the patients here are at least 21 years old females of Pima Indian heritage. There are 768 instances and 8 attributes in the related dataset. Furthermore, there are available 2 results as healthy (negative diabetes) and diabetes (diabetes positive) in this dataset. The attributes included in the dataset are given in Table 1.

Table 1. Attributes included in the dataset of Pima Indians diabetes.

Attribute No	Attribute Subject
1	Number of pregnancy
2	Plasma glucose concentration a 2 hours in an oral glucose tolerance test
3	Diastolic blood pressure (mm Hg)
4	Triceps skin fold thickness (mm)
5	2-Hour serum insulin (mu U/ml)
6	Body mass index [weight in kg/(height in m)^2]
7	Diabetes pedigree function
8	Age (years)

More details regarding the Artificial Intelligence techniques employed in this study have been briefly explained under the next sub-titles.

2.2. Support Vector Machines

Vector Machines (SVM) was designed in 1979 by Vapnik and Lerner. In 1995 it was recommended for classification and regression by Vapnik and Lerner (Comak, Arslan, & Turkoglu, 2007; Vapnik, Golowich, & Smola, 1997). Since a SVM is known to have the advantage of offering solid performance of classification with even smaller learning data, we can expect that the proposed algorithm, with relatively small learning data, would demonstrate better performance than other classifiers and be implemented faster on account of the reduction of feature dimensions. For a cross-validation procedure, this algorithm was compared with Multi-Layer Perceptrons (MLP) and Fuzzy Inference System (FIS) classifiers (Song et al., 2005).

The SVM method provides an optimally separating hyper-plane in the sense that the margin between two groups is maximized. Support Vectors are defined as subset of data instances used to define the hyper-plane. The distance between the hyper-plane and the nearest support vector is called margin. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. There are two types of SVMs: (a) Linear SVM is used to separate the data points using a linear decision boundary and (b) Non-linear SVM separates the data points using a nonlinear decision boundary (Santhanam & Padmavathi, 2015; Tamura & Tanno, 2009).

SVM is a supervised learning algorithm, which is recommended for classification and nonlinear function approaches. Starting to be widely used over the last few years, SVMs have been used in pattern recognition applications like text recognition, object recognition, sound recognition and face recognition (Comak, Arslan, & Turkoglu, 2007). The main idea on the background of SVM is based on the formation of the equation of Lagrange multipliers. The goal of SVM is to find the

optimum separating hyper-plane, which is able to classify data points as well as possible and to again separate them into two classification points as much as possible. In other words, it aims to find the state in which the distance between the two classes is the maximum. The hallmarks of this classification reasoning are the support vectors chosen from the training set, and they are located on the closest points of both classes (Javed, Ayyaz, & Mehmood, 2007). In Figure 1, an example of support vectors and a maximum margin hyper-plane (in other words, an optimum separating hyper-plane) is shown (Cortes & Vapnik, 1995).

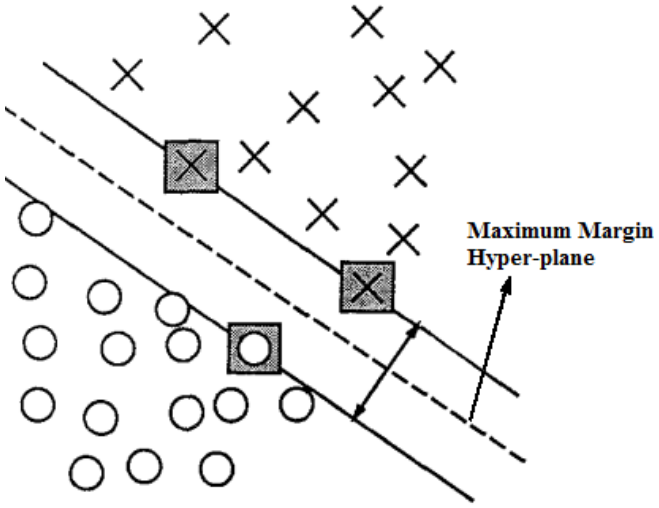

Figure 1. Maximum margin hyper-plane (Cortes & Vapnik, 1995).

The optimum separating hyper-plane is defined as:

$$w^T x_i + b \geq 1 - \xi_i \; y_i = 1 \tag{1}$$

$$w^T x_i + b \leq -1 + \xi_i \; y_i = -1 \tag{2}$$

$$\xi_i \geq 0 \; \forall i \tag{3}$$

whereξ_i approximates the number of misclassified samples. For a training data set with input vector $x_i \in R^n$, $i=1,...,l$ and output labels y_i, $y \in \{1,-1\}$, SVM needs to find solution to the following optimization problem:

Minimize: $$\frac{\|w\|^2}{2} + c\sum_{i=1}^{l} \xi_i \tag{4}$$

subject to: $$y_i(w^T x_i + b) \geq 1 - \xi_i \; \xi_i \geq 0 \tag{5}$$

where$c>0$ represents the penalty parameter between the error term and the margin of hyper-plane. By using Lagrange multipliers, we can represent this problem in its dual form as

Maximize: $$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1, j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{6}$$

subject to: $$\alpha_i > 0, \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{7}$$

α_i's are all zero except for those training patterns close to the separating plane which are called support vectors (Cao et al., 2003). All other α_i's are zero, so the data points which are not support vectors will have no effect on the solution. From here we can understand that the all information required to reconstruct the hyper-plane are in support vectors (Tamura & Tanno, 2009).

In most practical applications the data of two classes linear indistinguishable, and thus data can be accessed by the mapping results in a higher dimensional space. The idea of a non-linear support vector of the original input space can be mapped in a higher dimensional feature space that can be divided into training data. In such cases, the SVM kernel function is activated and n-dimensional data set of m>n, including m-dimensional transformed into a new data set is made of high dimension linear classification. Core functions, an important position in the SVM algorithm. Choosing the correct core function considerably affects the performance of classification. Some kernel functions used in SVM are given under Equation 8, 9, and 10.

Linear : $K(x_i, x_j) = x_i^T x_j$ (8)

Polynomial : $K(x_i, x_j) = (1 + x_i^T x_j)^p$ (9)

Gauss (RBF) : $K(x_i, x_j) = e^{\frac{\|x_i - x_j\|^2}{2\sigma^2}}$ (10)

2.3. Cognitive Development Optimization Algorithm

Cognitive Development Optimization Algorithm (CoDOA) is an Artificial Intelligence oriented optimization approach designed and developed by Kose and Arslan, in 2015 (Kose & Arslan, 2015). After the first introduction, it also had some improvements so far and applied in different fields. It is important that CoDOA employs simple equations and it was developed as inspired from Piaget's Theory on Cognitive Development. The concept of Cognitive Development can be briefly defined as a natural development process related to each individual. Piaget has expressed that individuals go through different stages like maturation, social interaction, balancing while learning new concepts and eventually improving cognitive infrastructure (Kose & Arslan, 2015; Singer & Revenson, 1997).

Briefly, CoDOA includes some steps regarding the following phases: Initialization Phase, Socialization Phase, Maturation Phase, Rationalizing Phase, and Balancing Phase. These phases are some kind of calculation steps, which have been formed as a result of inspirations from stages of cognitive development. The phases are repeated until the stopping criterion is met (Kose & Arslan, 2015).

Algorithmic details of the CoDOA can be expressed briefly as follows (Kose & Arslan, 2015; Kose & Arslan, 2016):

- **Step 1 (Initialization Phase):** Set initial parameters (*N*: number of particles; initial interactivity rate (*ir*) and experience (*ex*) values for each particle; max. and min. limits (min. limit is 0.0) for *ir* value (*max_ir* and *min_ir*); *ml* for the maturity limit; and *r* for the rationality rate.

  Also, set other values related to the function, problem…etc. (e.g. dimension, search domain…etc.).
- **Step 2:** Place the particles randomly in the solution space and calculate fitness values for each of them. Update the *ir* value of the particle with the best fitness value by using a random value (Equation 11).

  *best_particle_ir_(new) = best_particle_ir_(current) + (rand. * best_particle_ir_(current))* (11)

  Also, increase *ex* value of this particle by 1.

- **Step 3:** Repeat the loop steps below until the stopping criterion (e.g. iteration number) is met:
  - **Step 3.1 (Socialization Phase):** Decrease (by 1) *ex* value of each particle, whose fitness value is equal to or above the average fitness of all particles (if the problem is minimization).

    Also, increase (by 1) the *ex* value of each particle, whose fitness value is under the average fitness of all particles (if the problem is minimization). Finally, Update the *ir* value of these particles by using a random value (Equation 12).
    $particle_j\_ir\_(new) = particle_j\_ir\_(current) + (rand. * particle_j\_ir\_(current))$ (12)
  - **Step 3.2:** Update the *ir* value of all particles by using the Equation 13:

    $particle_i\_ir\_(new) = rand. * particle_i\_ir\_(current)$ (13)
  - **Step 3.3:** Update position of each particle (except from the best particle so far) by using the Equation 14:

    $particle_i\_pos.\_(new) = particle_i\_pos.\_(current) + (rand. * (particle_i\_ir\_(current) * (global\_best\_pos. - particle_i\_pos.\_(current))))$ (14)
  - **Step 3.4:** Calculate fitness values according to new positions of each particle. Update the *ir* value of the particle with the better / best fitness value by using a random value (Equation 15).

    $best\_particle\_ir\_(new) = best\_particle\_ir\_(current) + (rand. * best\_particle\_ir\_(current))$(15)
    Also, increase ex value of this particle by 1.
  - **Step 3.5 (Maturation Phase):** Update *ir* value of each particle, whose *ex* value is equal to or under the *ml* value by using the Equation 16:

    $particle_j\_ir\_(new) = particle_j\_ir\_(current) + (rand. * particle_j\_ir\_(current))$ (16)
    Calculate fitness values according to new positions of each particle. Update the *ir* value of the particle with the better / best fitness value by using a random value (Equation 17).
    $best\_particle\_ir\_(new) = best\_particle\_ir\_(current) + (rand. * best\_particle\_ir\_(current))$(17)
    Also, increase ex value of this particle by 1.
  - **Step 3.6 (Rationalizing Phase):** Update *ir* and positions of each particle, whose *ex* value is under 0, by using the following equations:

    $particle_j\_ir\_(new) = particle_j\_ir\_(current) + (rand. * (best\_particle\_ir\_(current) / particle_j\_ir\_(current)))$ (18)
    $particle_i\_pos.\_(new) = particle_i\_pos.\_(current) + (rand. * (particle_i\_ir\_(current) * (global\_best\_pos. - particle_i\_pos.\_(current))))$ (19)
    Update *ir* of each particle, whose*ex* value is equal to or above 0, and repeat this *r* times; by using the Equation 20:
    $particle_j\_ir\_(new) = particle_j\_ir\_(current) + (rand. * (best\_particle\_ir\_(current) / particle_j\_ir\_(current)))$ (20)

- **Step 3.7 (Balancing Phase):** Update the *ir* value of all particles by using the Equation 21:

  $particle_i\_ir\_(new) = rand. * particle_i\_ir\_(current)$ (21)

  Calculate fitness values according to new positions of each particle. Update the *ir* value of the particle with the better / best fitness value by using a random value (Equation 22).

  $best\_particle\_ir\_(new) = best\_particle\_ir\_(current) + (rand. * best\_particle\_ir\_(current))$(22)

  Also, increase *ex* value of this particle by 1. For big problems, perform in-system optimization.Return to the Step 3.1. if the stopping criteria is not achieved yet.

- **Step 4:** The best values obtained within the loop are related to the optimum solution.

The related algorithm steps can be visualized with a flow chart as shown in Figure 2 [26].

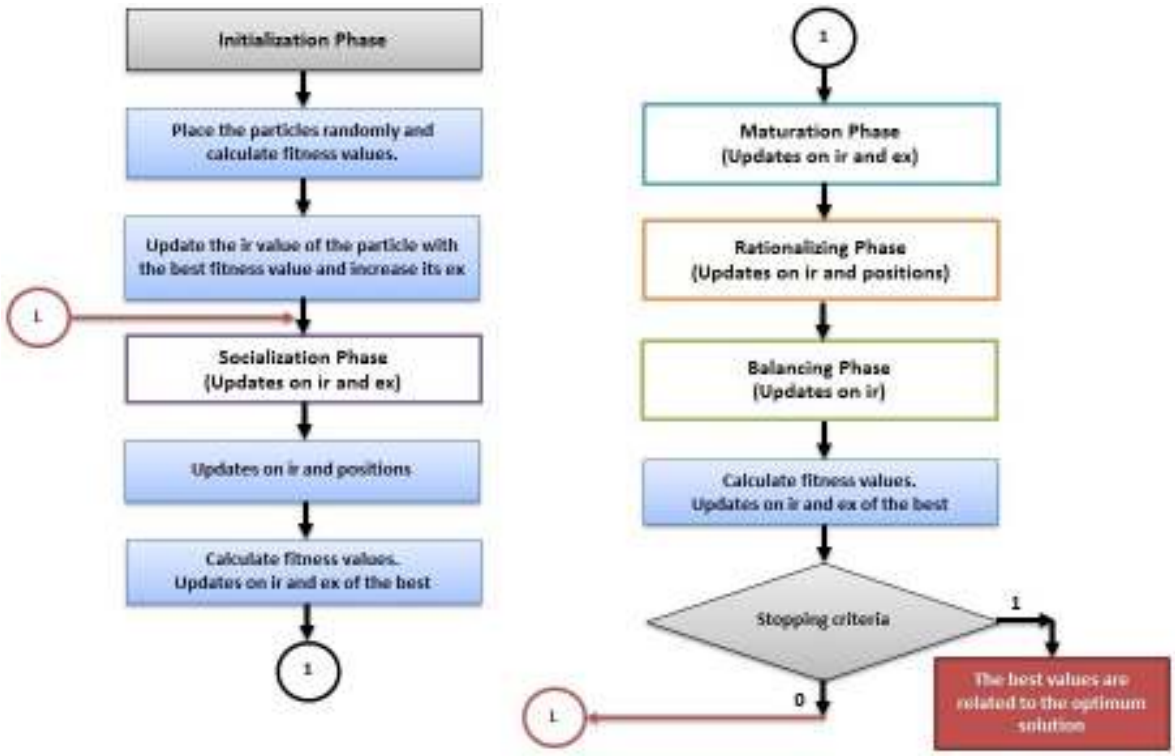

Figure 2. Flow chart of the CoDOA (Kose & Arslan, 2015).

3. CoDOA- SVM Approach forDetermining Diabetes

The related solution steps within CoDOA-SVM approach for determining diabetes can be explained briefly as follows:

- Each particle provided to the solution space within the CoDOA represents the value of sigma (σ) to be used in the Gauss (RBF) kernel function of the SVM.
- CoDOA runs according to a determined iteration number. In every new iteration the value of each particle is used in the SVM and after the training process, the locally best and globally best (in all iterations run so far) particles are determined according to the accuracy of the values calculated according to the Equation 23.

$$\frac{TP+TN}{TP+FP+TN+FN} * 100 \quad (23)$$

In the Equation 23, TP stands for true classified diabetes positive individuals; TN stands for true classified diabetes negative individuals; FP stands for false classified diabetes positive individuals and finally, FN stands for false classified diabetes negative individuals.

- After determining good (optimum) particles, default CoDOA steps are run.
- After achieving the total iteration number, it is allowed to train the SVM via optimum Gauss (RBF) kernel function parameters, by using the optimum particle value [sigma (σ) value].
- The trained SVM is now ready for the classification and so is diabetes determination process.

A brief schema of the CoDOA-SVM approach is also provided in Figure 3.

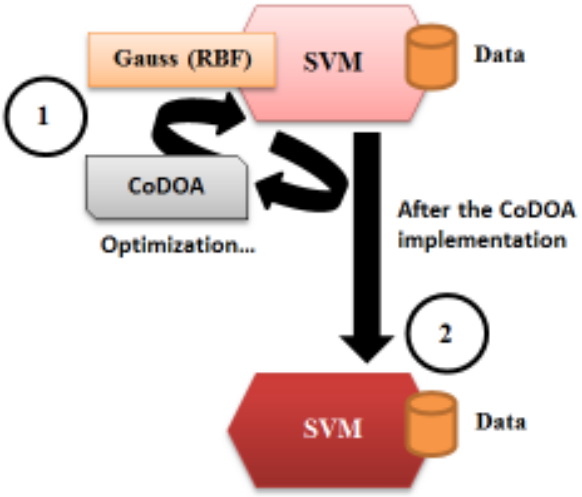

Figure 3. A brief schema of the CoDOA-SVM approach.

4. Application and the Results

CoDOA-SVM approach was applied over the related Pima Indians diabetes dataset with different particle and iteration number settings in the context of CoDOAprocess. The dataset used in the application employs a total of 768 data, as 500 of them belong to diabetes negative individuals, and also the remaining 268 ones belong to diabetes positive individuals. During the application, half of this data was used along the training process, while the other half was devoted to the testing process. At this point, the calculated accuracy rates have been taken into account for evaluating the effectiveness of the applied CoDOA-SVM approach. In the CoDOA, initial interactivity rate (*ir*) was 0,50; max. interactivity rate was 10; maturity limit (*ml*) was 3; and finally rationality rate was 2.

The findings obtained from the related application processes on five different particle numbers and six different iteration numbers are presented in Table 2.

Table 2: Findings obtained from the application processes.

N	Iteration	Sigma (σ)	Accuracy (%)
25	2000	9,5062	76,56
40	2500	7,2388	75,26
40	3000	3,9547	74,48
50	4000	0,9107	76,04
75	5000	0,8377	81,25
90	5000	0,7405	87,50

Table 2 presents the results about sigma (σ) and accuracy rates for different application processes performed. According to the findings, it can be expressed that the CoDOA-SVM approach is good enough at classification on diabetes determination.

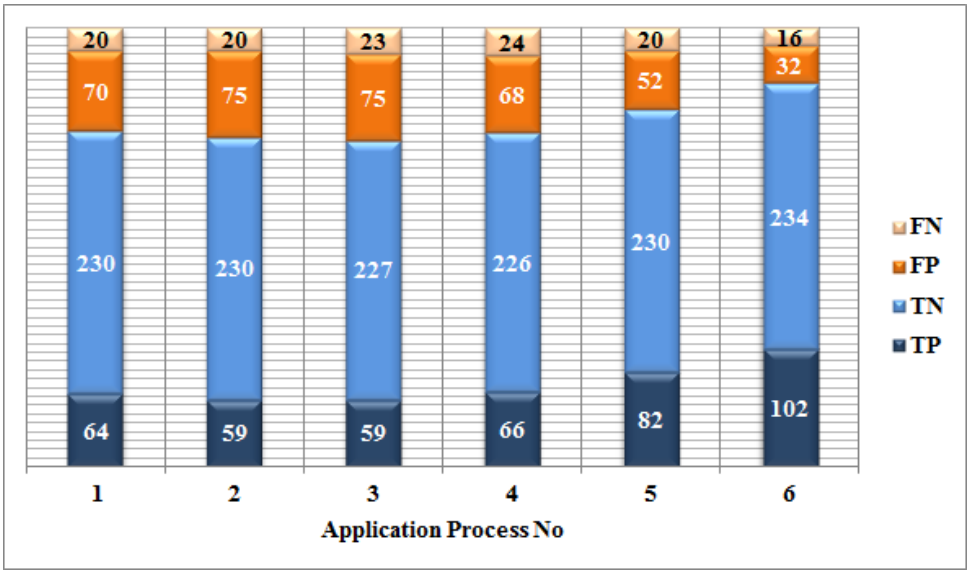

Figure 4. A graphic on values of TP, TN, FP, and FN for each different application process.

In addition to the finding provided in Table 2, Figure 4 provides a graphic on values of TP (true positive), TN (true negative), FP (false positive), and FN (false negative) on each different application processes.

5. Conclusions and Future Work

This study has proposed a diabetes diagnosis system, which is formed via both Support Vector Machines (SVM) and Cognitive Development Optimization Algorithm (CoDOA). In this approach, the training process of the SVM has been supported with the CoDOA and after determining the most optimum sigma (σ) parameter of the Gauss (RBF) kernel function (so the most optimum SVM), a better classification formation has been tried to be achieved. In the context of the study, diabetes data set, which is related to Pima Indians, has been used for evaluating effectiveness of the proposed approach and after six different application processes, it was seen that the approach is well-enough on classification, which means being capable of determining diabetes.

There are also some future works regarding the developed CoDOA-SVM based approach. In this context, there will be some more works for improving classification accuracy and also setting different optimization plans on i.e. different parameters of the kernel function. Additionally, it is aimed to evaluate the approach with datasets belonging to different diseases.

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