SUPPORT VECTOR MACHINES COMBINED WITH FEATURE SELECTION FOR DIABETES DIAGNOSIS

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Abstract: *Clinical Decision Support Systems (CDSS) are used as a service software which provides huge support to clinical decision making process where the main properties of a patient are matched to a tangible clinical knowledge. Within this gathered important information about patients, the medical decisions can be made more accurately. In this paper we present a CDSS that uses four physiological parameters of patients such as Pre-prandial Blood Glucose, Post-prandial Blood Glucose, Hemoglobin A1C (HbA_{1c}) and Glucose in Urine to produce a prediction about the possibility of being diabetic. According to collected reference data provided from hospitals, the disease can be predicted by comparing the input data of patients. If the system cannot procure a prediction about patients' status with these parameters, then the second phase which uses soft computing techniques is put into process with requesting additional data about patients. Our conducted experiments show that the diagnosis can be established in a breeze by getting the patients information with %80 accuracy. Support Vector Machines were applied to achieve maximum success rate with nine different physiological parameters such as; Pregnancy, glucose, blood pressure, skin fold, insulin, Hemoglobin A1C, body mass index, family tree and age. Four different Kernel Functions are implemented in case studies and classification process is optimized by reducing attributes with feature selection algorithms. This represents an improvement in classification of CDSS, while reducing computational complexity.*

Keywords: *Decision Support System, Support Vector Machine, Sequential Forward Search, Feature Selection.*

1. Introduction

Diabetes is a common disease that affects people at all points in our environment [1]. In this section it is simply explained what is diabetes, what kind of things can cause diabetes shall be answered to understand the concept of our Clinical Decision Support System (CDSS). If the patient has high blood sugar, because of inadequate of insulin production, it is apparent that diabetes occurs. In fact, two types of diabetes are considered frequently. Type 1 that is named as insulin-dependent diabetes or early-onset diabetes forms 5-10% of all diabetes cases. In this type of diabetes, the body of human does not produce insulin so that the people who are affected by type 1 of diabetes should take insulin injections for their rest life. Another type of diabetes which is Type 2 causes that the body of human does not produce enough insulin. Approximately 90-95% of people shall encounter this type of a diabetes [2][3]. In addition to these situations, it can be shown that death's risk of women because of the diabetes is higher than man in the world [4]. For our research, Decision Support Systems are suitable to generate solutions about diagnosis of diabetes' types.

Decision Support Systems enable decision maker to designate the alternative solutions and the re-revision of data while trying to solve the problems [5]. In today's world, Healthcare Organizations benefit from Information Systems [6] in the fields of management services, diagnosis of a patient, the decisions to be made about the patients by the doctors, being a guide for both physicians and nurses, interpreting on signals, laboratory services, and patient management and so on. That's why the most preferred system in this field is the Clinical Decision Support Systems that are the computer based systems supporting the physicians and other personnel in the process of clinical decision making [7].

In the proposed system, four physiological parameters of a patient that are Pre-prandial Blood Glucose, Post-prandial Blood Glucose, HbA_{1c} and Glucose in Urine are procured by a hospital in accordance with the official permission and personal rights and personnel information are kept secret. Thanks to these values, the system gives information to the patients whether they are diabetics or not.

Developing a CDSS for a hospital in Istanbul provides some benefits to patients, nurses, physicians so that our goals for the CDSS for Diabetes are;

- To support physicians in order to determine diagnosis of patient data.
- To support physicians in the process of patient's management.
- To be clear in diagnosis of patient data.

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- To help physicians in their determining diagnosis of patient data and prevent them in order not to make a mistake and if it is possible, to minimize the mistakes as these physicians work under the hard conditions.
- To create a cost cutting atmosphere in the hospitals in their process of diagnosis of patient data.
- To create more reliable physicians for the patients and enhance the relationship between the patients and physicians.

The remaining sections of this paper are organized as follows: section two introduces the background and related work, section three explains the approach in detail, section four shows the details of the experiments, and section five provides the conclusion and future work.

2. Related Work

CDSS is used as a software that provides a huge aid to clinical decision making where the main properties of a patient are matched to a tangible clinical knowledge, then the information are gathered by the clinicians or patients to notify the decision. Furthermore, CDSS decrease medical errors and raise strength and quality of health have become a favorite area in the not too distant past [8].

Below, some further studies handled so far with regards to the subject of Clinical Decision Support Systems have been outlined.

In the study of Kostic et. al. CDSS are used to improve the quality of healthcare delivery. They build a module that is a developed part of KardioNet system whose purpose is providing clinical decision making support for patients' treatment with Acute Coronary Syndrome [9].

El-Fakdi et. al. study is a detailed work that is about the work-flow-based CDSS that aims to give case-specific evaluation to clinicians during the complex surgery. Based on the workflow that was gathered, the software will use a Case-Based Reasoning methodology to get similar past cases from a case base [10].

In the study of Kamaleswaran et. al. thanks to CDSSs, clinicians provide accurate data analysis and recommendations to support health care of patients. They present the process web service as a new method that provides contextual information to a data stream processing CDSS [11].

Kunhimangalam et. al. constructs a system that has 24 input fields that consist of clinical values of diagnostic test and whose output field is the diagnosis of disease whether it is Motor neuropathy, sensory neuropathy, mixed type or normal case. The results were gathered are compared with the clinician's opinion. The system provides clinicians to make prediction of a better diagnosis [12].

Another study is about computerized epilepsy treatment CDSS whose purpose is to aid the clinicians about selecting the best anti-epilepsy treatments. Standridge et. al. has evaluated the system in three areas that are the preferred anti-epilepsy drug choice, the top three recommended choices, and the rank order of the three choices [13].

In the study of King et. al. they build the Genetic Smart Alarm(GSA) that is a framework for the design, analysis, and implementation of CDSS. Their aim was that showing how a GSA can be used to adapt a smart alarm for specific patient populations [14].

Kemppinen et. al. study is CDSS of the diagnosis of ADHD that is a complex neuropsychiatric disorder. The system supports the implementation of the new adult ADHD patient evolution, diagnosis and treatment process [15].

In the study of Karim et. al. they build a virtual telemedicine that uses CDSS is used as a rural station. The system provides diagnosis of patient's disease and it sends an e-mail to clinicians and when the response is received, the CDSS is updated for the future values [16].

The Bayesian Network was built by using systematic response syndrome criteria, mean arterial pressure, and lactate levels for sepsis patients in the study of Gultepe et. al. the resulting network brings to light a clear relationship between lactate levels and sepsis. Bayesian network of sepsis patients hold the show of providing a CDSS in the future [17].

In the study of Mattila et. al. they present a clinical decision support system that takes as an example of a patient's disease situation from heterogeneous multiscale data. Several medical datasets are applied to the system and the system is asserted by implementing a new clinical decision support tool for early diagnosis of Alzheimer's disease [18].

3. Methodology

Our proposed system is implemented as a web application to be used from anywhere in the hospital without making any install processes. Also, doctors can reach to the system from thin clients like PDAs easily.

The reference data is received from Yalova Public Hospital in Turkey. All data is about patients that are treated between the years 2013 and 2014 kept secret, because according to Turkish Rights of Patient Law, 21th clause [19], the information of patients must be kept confidential. Hereinbefore, four parameters Hemoglobin A1C, Pre-prandial Blood Glucose, Past-prandial Blood Glucose and Glucose in Urine are taken from the patients respectively.

Decision support process start with acquiring three main properties of patients as age, gender and health complaints as symptoms. Users may choose any 13 complaints from the system such as; frequent urination, excessive thirst, blurred vision, weakness, fatigue, unexpected weight loss, the feeling of hunger, nausea, vomiting, breath odor, frequency urinary tract infections, dry and itchy skin, slow healing of wounds and total deduction due to their conditions. Possibility of being a diabetic is categorized into 3 levels. First two levels can make a prediction directly without using any soft computing technique. On the contrary, level 3 type patients can be only graded with using Support Vector Machines (SVM). Those predictions are used at the moment of decision.

Our proposed system helps medical crew in order to have necessary information about their patients in a long term. This system consists of sequential stages that are generally compares the inputs that are coming from the patients and values as knowledgebase from the hospital called reference values. The methodology of main flow and the architecture of entire operations are indicated in Algorithm 1.

Algorithm 1: Pseudo code for disease prediction

```
Input: n = Symptom Quantity, k=Cluster Quantity, a = Patient Age, g = Patient Gender, S⃗n = Symptom Vector, W⃗n = Symptom weights Vector, C⃗k = Symptom Cluster Vector,

Output: Level of Disease ← ('Healthy', 'Potential Diabetes', 'Possible Diabetes')

Initialize:
   i:= 1….n, lim←loadUplerLowerLimits(),
f←getTestData(), Threshold:=3

for i=1: n
     W⃗n ← f(n)/ sum(f(n))
end for
α ← CalcFirstDiagnoseRef (n,a,g, W⃗)
if α < Threshold
   Print "Healthy"
end if
else if α ≥ Threshold
    result ← Diagnose(lim)
end else if
```

Weight of the symptoms within the given model is calculated by dividing the number of symptom frequency corresponding to the reference data into the total number of symptom frequency, when calculating the symptom's disease probabilities.

CDSS for Diabetes is used for the diagnosis of the diabetes and the information about the diagnosis is calculated by using reference data. The system works with some comparison to achieve the results and the gaps of comparisons are common information that can be found in some researches [20].

When the system is investigated in depth, the patient's information such as name, surname, age, gender is taken. According to gender some symptoms are shown in the startup screen of the system. Users asked to check these symptoms to evaluate their conditions. If the result that means the symptoms from the patients is less than our threshold (3), it means that person is healthy.

Potential patients are grouped under 7 categories. If the user cannot match one of these categories, then the classifier produces a prediction about patient's medical condition.

However, if the frequency of the symptoms is greater than or equal to 3, patient's pre-prandial glucose is requested, and the system is navigated to Pre-prandial stage. System takes the pre-prandial blood, and then compare with reference function. If the pre-prandial blood glucose value is smaller than 110, the results are compared with reference values. If the given value is less than the reference value, it means that the person is healthy. On the other hand, if the given value is greater than this reference value, patient's post-prandial glucose value is requested as additional information. Another condition is that if the pre-prandial value is greater than 110 but less than 126, post-prandial blood glucose value is requested and average blood sugar is calculated. The results are compared to reference values and according to results, the amount of glucose in the urine of patients is requested.

Algorithm 2: Pseudo code for Diagnose

```
Initialize:
r ← GetPrePrandialBG()
if r < 110 /*Case 1*/
   if r ≥ lim
     r ← GetPostPrandialBG()
           if r < 140
             Print "Healthy"
           else
              Print "Possible Diabetes"
           end else
           end if
     else Print "Healthy"
     end else
     end if
 end if
 if r > 126 /*Case 2*/
      r ← GetPostPrandialBG ()
      if 140 < r < 200
         Print "Potential Diabetes"
      else
         if r < lim
            Print "Potential Diabetes"
         else
            Print "Possible Diabetes"
         end else
         end if
      end else
      end if
 end if
 if 110 ≤ r ≤ 126 /*Case 3*/
   r ← GetPostPrandialBG ()
   if r > 140
       Print "Possible Diabetes"
   else
       Print "Potential Diabetes
   end else
   end if
end if
```

When pre-prandial value is greater than 126, the post-prandial blood glucose value is requested. If post-prandial value is greater than 140 but less than 200, average blood sugar is calculated and then the results are compared to reference values. If the pre-prandial value is less than 110 and post-prandial value is less than 140, the results are compared to reference values and if the results are less than reference value, it means that person is healthy. Another two situations are the same that if the pre-prandial value is greater than 110 but less than 126, post-prandial value is less than 140, and if the pre-prandial value is greater than 126, post-prandial value is between 140 and 200, the results are compared to reference values, and it means that the person will be potential diabetes and average blood sugar is calculated.

As the third case detailed in Algorithm 2, if the pre-prandial value is greater than 126, the post-prandial blood glucose value is greater than 200, person is a potential diabetes. In order to diagnose the patient, SVM that is soft computing technique is used as classifier. This classifier uses 9 different physiological parameters such as; Pregnancy, glucose, blood pressure, skin fold, insulin, Hemoglobin A1C, body mass index, family tree and age to determine a prediction about the possibility of being diabetic.

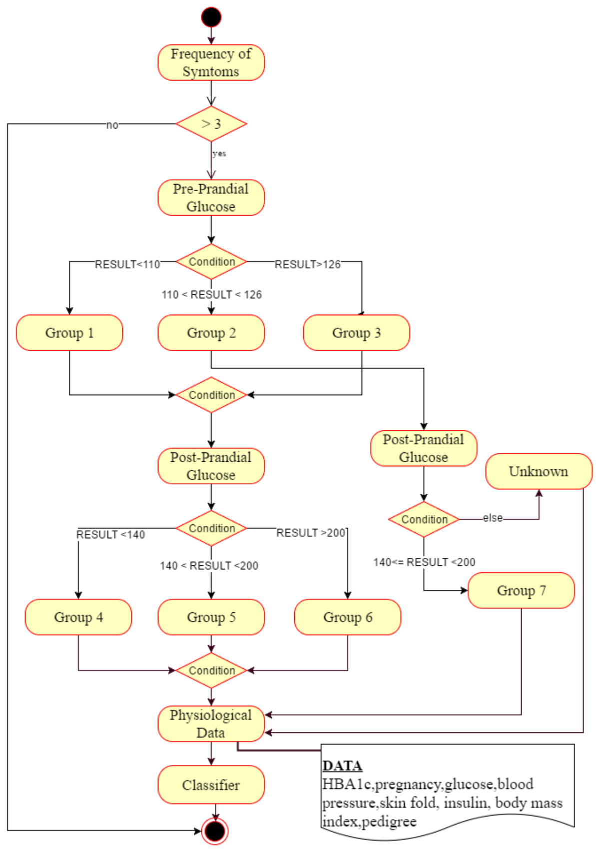

Figure 1. Activity Diagram of Diagnosis Process

4. Experiments and Results

Our reference data is consisting of 242 patients' physiological parameters. We used 10-fold cross validation technique to train and test classifier in our experiments.

The first factor in the success of the selected classifier is the effectiveness of the identified attributes. The goal in attribute selection is to find the subclass that most effectively expresses an achievement measure. Various search approaches such as genetic algorithm are used in the identification of subclass. Among these approaches are mostly preferred; Best Individual Feature, Sequential Forward Search, Sequential Floating Forward Search, Plus-L-Minus-R.

In recognition problems, each feature component has a certain recognition coefficient. The effects of these feature components should be analyzed in order to increase the performance of the recognition. One of the simplest way to learn the attributes' components for recognition is to evaluate the recognition performance of each component separately. For the best recognition, the set of attributes consisting of the highest coefficients should be determined and classified. In the advanced selection search algorithm, the highest coefficient components are included in the attribute set. At each iteration, the contribution of the newly included component to the overall performance of the system is validated to determine whether it is in the cluster.

The experiments are composed at two phases. In the first step, all values of attributes belonging to the database were classified with using SVM and the results were evaluated. In the second phase, the number of inputs are reduced by using the Sequential Forward Search (SFS) algorithm and the classification is repeated with the help of the SVM method.

Experiments using SFS have used 4 different kernel functions such as Linear, Polynomial, Gaussian Radial Basis Function Kernel (GRBFK) and Multilayer Perceptron Kernel (MPK). Physiological parameters were indexed as pregnancy (1), glucose (2), blood pressure (3), skin fold (4), insulin (5), body mass index (6), pedigree (7) and The reduced subsets of the indexed attributes in the specified kernel functions are shown in Table 1.

Table 1 – Reduced attribute sub-sets according to Kernel Functions

Kernel	Attribute Sub-sets
Linear	1,2,4,6,7
Polynomial	1,2,3,6,7
GRFBK	1,2,5, 6
MPK	1,2,3,5,6,7

Accuracy, sensitivity, specificity, ROC domain, and F-measure parameters were chosen as criteria in the analysis of the classification success. The functions used in the calculation of these parameters follow as;

$$\text{Accuracy} = (TP + TN)/\ (TN + TP + FP + \ FN)$$

$$\text{Sensitivity} = TP/(TP + FN)$$

$$\text{Specificity} = TN/(TN + FP)$$

$$\text{F Measure} = 2 * (\text{Accuracy} * \text{Sensitivity})/(\text{Accuracy} + \text{Sensitivity})$$

Sensitivity and originality are the parameters used to verify the classification ability of the system. Sensitivity is calculated by matching the correct samples to the correct classes. Accuracy is known as the percentage of correct matching. Table 2 presents the classification performance of the two stages based on the criteria. When the results are examined, it is seen that Linear kernel function has higher success rates than other functions before and after the feature reduction.

Table 2 – The Accuracy, Sensitivity, Specificity, ROC Domain and F Measure values of Kernel Functions

	Accuracy		**Sensitivity**		**Specificity**		**ROC Domain**		**F Measure**		**Confusion Matrix**			
Attribute Reduction	Off	On	Off	On	Off	On	Off	On	Off	On	Off		On	
Linear	0,78	0,78	0,81	0,78	0,72	0,77	0,76	0,80	0,76	0,77	TP 180	FN 33	TP 172	FN 27
											FP 41	TN 84	FP 49	TN 90
Polynomial	0,74	0,77	0,75	0,77	0,71	0,76	0,62	0,77	0,73	0,76	TP 166	FN 34	TP 171	FN 28
											FP 55	TN 83	FP 50	TN 89
GRBFK	0,72	0,72	0,71	0,75	0,74	0,68	0,5	0,5	0,72	0,71	TP 158	FN 31	TP 165	FN 37
											FP 63	TN 86	FP 56	TN 80
MPK	0,67	0,70	0,64	0,70	0,71	0,73	0,42	0,51	0,68	0,71	TP 142	FN 33	TP 154	FN 32
											FP 79	TN 84	FP 67	TN 85

The criterion values of the ROC curves (AUC) of SVM classifier are given in Figures 1, 2, 3 and 4 respectively. In the first test SVM is used with Linear Kernel. Results showed that the Attribute Reduction (AR) technique, increases the classification rate by 3% on Figure 2.

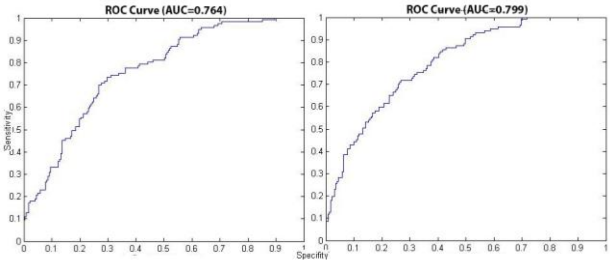

Figure 2. ROC Curves that are computed with Linear Kernel (a) Advanced lookup search algorithm w/o using AR (b) with using AR

Polynomial Kernel exhibits much appreciable success with AUCs of AR-On (0,77) and AR-Off (0,62) are shown on Figure 3.

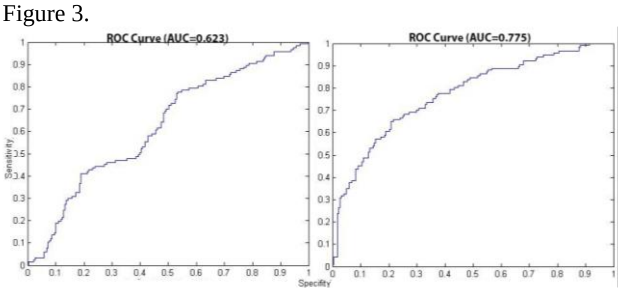

Figure 3. ROC Curves that are computed with Polynomial Kernel (a) Advanced lookup search algorithm w/o using AR (b) with using AR

The usage of with Gaussian Radial Basis Function Kernel plays no significance on classification even with RA.

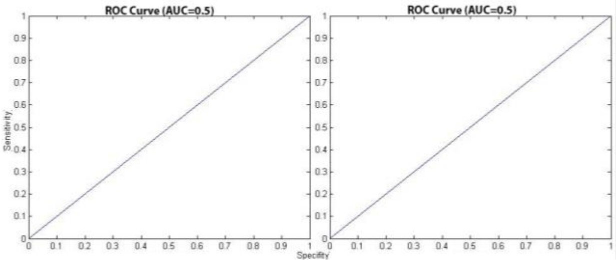

Figure 4. ROC Curves that are computed with Gaussian Radial Basis Function Kernel (a) Advanced lookup search algorithm w/o using AR (b) with using AR

As the last case study, Multilayer Perceptron Kernel is used to demonstrate the classification performance as displayed on Figure 5. AUCs of the AR-On (0,51) results in higher value according to AR-Off (0,42).

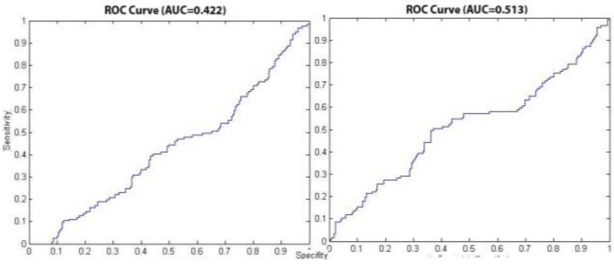

Figure 5. ROC Curves that are computed with Multilayer Perceptron Kernel (a) Advanced lookup search algorithm w/o using AR (b) with using AR

Referring to all four case studies, we showed that enabling AR increase the classification rate in a positive way. The highest dissimilitude is gained with using Polynomial Kernel with AR. However, Linear Kernel with AR gives the best AUS as (0,79).

5. Conclusions

This article has aimed at making a prediction about the diabetes and thanks to Clinical Decision Support System we developed, the diagnosis can be established by getting the patients information and comparing them reference data coming from the hospitals with rapidly.

A model that classifies patients' physiological data to predict the possibility of being diabetic was described. Patient’s physiological parameters such as Hemoglobin A1C, Pre-prandial Blood Glucose, Past-prandial Blood Glucose and Glucose in Urine are requested to compare and decide whether the patient is diabetic or healthy. These inputs guide the system into three level prediction. First two levels generate the output with traditional computing methods. For the patients that are fell into third category, system uses a soft computing approach to compute prediction rates instead of traditional comparisons.

Several tests have been applied to give success rate of the achievement in the third category so that numerous learning algorithms in Support Vector Machine concept were used. In the proposed method, 9 physiologic parameters (Pregnancy, glucose, blood pressure, skin fold, insulin, Hemoglobin A1C, body mass index, family tree and age) of 242 diabetic patients were used. In these experiments in which the support vector machines are run as classifiers, the performance subdivisions of the 9 attributes and the feature subset of the forward search algorithm are classified separately and the performance analysis is performed. It is determined that the system predict the patients' possibility of being diabetic with around 80% success rate.

As a future work, it is aimed to train the system with more verified data to increase prediction rate and optimizations for the computational parts are planned.

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