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SVM Computer Aided Diagnosis for Anesthetic Doctors

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Abstract— ***The application of machine learning tools has shown its advantages in medical aided decisions. The purpose of this study is to construct a medical decision support system based on support vector machines (SVM) with 30 physical features for helping the Doctors Specialized in Anesthesia (DSA) in pre-anesthetic DSA examination or preoperative consultation. For that, in this work, a new dataset has been obtained with the help of the DSA. The 898 patients in this database were selected from different private clinics and hospitals of western Algeria.***

The medical records collected from patients suffering from a variety of diseases ensure the generalization of the performance of the decision system.

In this paper, the proposed system is composed of four parts where each one gives a different output. The first step is devoted to the automatic detection of some typical features corresponding to the American Society of Anesthesiologists scores (ASA scores). These characteristic are widely used by all DSA in pre-anesthetic examinations. In the second step, a decision making process is applied in order to accept or refuse the patient for surgery. The goal of the following step is to choose the best anesthetic technique for the patient, either general or local anesthesia. In the final step we examine if the patient's tracheal intubation is easy or hard.

Moreover, the robustness of the proposed system was examined using a 6-fold cross-validation method and the results show the SVM-based decision support system can achieve an average classification accuracy of 87.52% for the first module, 91.42% for the second module, 93.31% for the third module and finally 94.76 % for the fourth module.

Index Terms— ***Doctors Specialized in Anesthesia, Support vector machines, American Society of Anesthesiologists scores, machine learning, pre-anesthetic examination.***

I. INTRODUCTION

The risks of anesthesia and the mortality rates are pretty low these years. As a matter of fact, not only have errors become relatively uncommon, but experts say that anesthesia is one of the safest areas of health care today thanks to the works being done in the medical decision support in the field of anesthesia. In the world, very few medical students are ready to specialize in the field of anesthesia, therefore the number of DSA's tends to decrease very disturbingly.

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In Algeria there are about 7,000 DSA's, a number which is insufficient to insure all the tasks that have to be performed for the safety of the patients. [1] The main problem is that despite their small number, their presence is indispensable in each hospital or clinic. Indeed, they have to insure the pre-anesthetic examinations of all patients who need general or local anesthesia. Moreover, they have to be present in the operating room during surgery and after that during the post-operative period of the hospitalization.

The realization of these different tasks is really hard to perform. That is why, we propose in this work an artificial intelligence based approach allowing to bring assistance to the DSA's.

The related works in preoperative patient classification were carried out by Peter et al. in [2]. The authors have developed an automatic instrument used for grading the level of anesthetic patient risk, with a modified version presented by Hussman and Russell [2]. So far, the risk prediction has been carried out using statistical analysis tools, which lacks the desired precision [3].

In the same field, another work was done in [4]. The authors proposed a Support Vector Machine -SVM- based decision system for clinical aided tracheal intubation and predication with multiple features. The experiments used 264 medical records and only one technique of classification while in this research, we used the same technique of classification (SVM) and we took into consideration 30 basic and anthropometrical features for our 898 patients.

The Support vector machine (SVM) was applied to build an aided decision support system to estimate the ASA physical status in the first step. In the second step, a decision making process is applied in order to accept or refuse the patient for surgery. The goal of the following step is to choose the best anesthetic technique for the patient, either general or local anesthesia. The final step examines if the patient's tracheal intubation is easy or hard. Furthermore, a 6-fold cross-validation method was used to test the robustness of the proposed system and the results showed that the SVM-based decision support system with 30 features could achieve a high classification accuracy in each step.

In this paper, we target two distinct objectives: the database construction and the data classification. For this aim, we divide this work as follows. In section II, we describe the database used and we discuss its different parameters. After that, in section III, we review some basic SVM concepts, and we propose our prototype. Section IV presents the experimental results and the discussion. Finally, we summarize the main points of our prototype and we provide a conclusion.

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II. DATA COLLECTION

In this section we present the creation of the dataset. The dataset has been obtained with the help of DSA's. The patients in this database were selected from different private clinics and hospitals of western Algeria (TLEMCEN hospital, ORAN CANASTEL hospital, ORAN HAMMOU BOUTELILIS clinic, ORAN NOUR clinic, TLEMCEN LAZOUNI clinic).

We have to notice that the unavailability of a standardized database in this field forced us to create this personal database. On the whole 898 patients were taken into consideration in this data collection, among whom 488 males and 410 females.

Our database is divided into four sub-bases. Each sub-base has a specific task to achieve. The first sub-base (SB1) is devoted to the detection of the ASA physical status. It is characterized by 17 parameters presented in table1.

Sex	488 males and 410 females
Age	between 2 months and 105 years
Medical Background	Diabetes
	Hypertension
	Respiratory failure
	Heart failure (HF)
ECG	Heart rate 1 (beat/min)
	Heart rate 2 (beat/min)
	Heart rate3 (beat/min)
	Steadiness of heart rate
	Pace maker
	Atrioventricular block
	Left ventricular hypertrophy
Oxygen saturation (%)	This measure is taken by a pulse oximetry device
Blood sugar or blood glucose level (g/l)	This mesure is taken by an glucometer device
Blood pressure (mmHg)	Systole
	Diastole
Classes	The ASA physical status during the pre anesthetic examination by the DSA

Table.1. SB1 dataset parameters

The ASA physical status classification system is a system for assessing the fitness of patients before surgery.

In 1963 the American Society of Anesthesiologists (ASA) adopted the five-category physical status classification system. A sixth category was later added. These characteristics are presented in table2 [3].

ASA Physical Status 1	A normal healthy patient
ASA Physical Status 2	A patient with mild systemic disease
ASA Physical Status 3	A patient with severe systemic disease
ASA Physical Status 4	A patient with severe systemic disease that is a constant threat to life
ASA Physical Status 5	A moribund patient who is not expected to survive without the operation
ASA Physical Status 6	A declared brain-dead patient whose organs are being removed for donor purposes

Table.2. ASA Physical Status

The ASA physical status allows to evaluate the anesthetic risk and to obtain a predictive parameter of surgical mortality. We have selected patients with ASA Physical Status 1, 2, 3 and 4. We could not select patients with ASA Physical Status 5 and 6 because they were dying. The output (classes) for the database takes the values '1', '2', '3', or '4'. The ASA score in our data base is summarized in table3.

- '1' means the patient is in ASA physical status 1.
- '2' means the patient is in ASA physical status 2.
- '3' means the patient is in ASA physical status 3.
- '4' means the patient is in ASA physical status 4.

There are 219 patients, that is (24.38%) of the cases in class '1', 395 patients (43.98%) of the cases in class '2', 232 patients (25.84%) of the cases in class '3', and only 52 patients (05.80%) of the cases in class '4'.

ASA Physical Status	1	2	3	4
Number of patients	219	395	232	52
Mean age (year)	57,62	67,49	65,35	79,07
Mean heart rate 1 (bpm)	79,18	79,05	97,29	109
Mean heart rate 2 (bpm)	78,45	79,67	99,35	110
Mean heart rate 3 (bpm)	79,32	80,32	100,57	109
Mean oxygen saturation	98,58	98,75	93,58	89
Mean blood glucose level	1,25	1,48	2,89	3,42
Mean blood pressure (systole)	123	135	155	169
Mean blood pressure (diastole)	81	95	102	110

Table.3. Clinical data of all 898 patients and their distribution according to ASA class

The second sub-base (SB2), which is characterized by three attributes: the first one is the result of the first classifier (ASA Physical Status), the second is the cerebrovascular accident (CVA) and the third one being the myocardial infarction (MI). These three parameters are exposed in table4. SB2 aims at detecting if the patients are accepted or refused for surgery.

ASA physical status	The output of the first classifier ASA1, ASA2, ASA3, ASA4
CerebroVascular Accident (CVA)	The CVA is a very serious condition in which the brain is not receiving enough oxygen (O_2) to function properly. Cerebrovascular accidents are the second leading cause of death worldwide. If the duration of the deficit is less than 24 hours, it is defined as a transient ischemic attack. If the deficit persists for a longer period, it is defined as a stroke. [5]
Myocardial Infarction (MI)	The Myocardial Infarction (MI), commonly known as a heart attack, results from the interruption of blood supply to a part of the heart, causing its cells to die. [6]
Classes	•Accept patient for surgery •Refuse patient for surgery

Table.4. SB2 dataset parameters

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If the patient has been subject to an MI and/or a recent CVA (less than 6 months), he is automatically refused or his surgery is put off to a later date.

As far as the first parameter of the second classifier is concerned, the ASA Physical Status, it can have the score 1, 2, 3 or 4 according to the physical status of the patient.

Concerning the second and third parameters, they are classified into three categories:

- Category 0 is for patients who have never been subject to any CVA and/or MI.
- Category 1 is for patients who have been subject either to a CVA and/or an MI at least 6 months ago.
- Category 2 is for patients who have been subject either to a CVA and/or an MI less than 6 months ago.

The output or classes for SB2 take the values '0' or '1'.

- '0' means a patient is refused for surgery
- '1' means a patient is accepted for surgery.

There are 136 patients, that is (15%) of the cases in class '0', and 762 patients, (85%) of the cases in class '1'.

The third sub-base (SB3) is devoted to the detection of the most suitable anesthetic technique for the patient (general anesthesia or local anesthesia). It is characterized by four attributes: the first one is age, the second is the state of patient, the third is the body mass index (BMI), and finally the type of surgery. These four parameters are exposed in table5.

Age	Newborn, Child, Young, Adult, Old
State of patient	Normal, Mental illness, Hyper stressed, Down syndrome
Types of surgery	They are 25 types of surgery
Body Mass Index (BMI) (kg/m^2)	BMI =A person's weight / height^2
classes	• General anesthesia • Local anesthesia

Table.5. SB3 dataset parameters

The output or classes for SB3 take the values '0', '1'.

- '0' means the technique of surgery for the patient is general anesthesia.
- '1' means the technique of surgery for the patient is local anesthesia.

There are 198 patients, that is (22%) of the cases in class '0', and 700 patients, (78%) of the cases in class '1'. The fourth part of our work deals with a fourth classifier. It aims at detecting if the patient's tracheal intubation is easy or hard.

The patient's tracheal intubation is a medical procedure in which a flexible plastic tube or is placed into the windpipe (trachea), through the mouth or endotracheal tubes the nose. In most emergency situations it is placed through the mouth. The endotracheal tubes can be connected to ventilator machines to provide artificial respiration. This can help when a patient is unconscious and by maintaining a patent airway, especially during surgery

The learning of this classifier is done by Sub-based 4 (SB4) which is characterized by five features which are exposed in table6.

Mallampati score	1, 2, 3, 4
Bigonial distance	mm
Distance between the thyroid cartilage and the chin	mm
Background of hard tracheal intubation	Yes or no
Patient dentition	Normal, Toothless, Upper dentures, Lower dentures, Brace
Mouth opening	mm
Classes	• Easy tracheal intubation • Hard tracheal intubation

Table.6. SB4 dataset parameters

The Mallampati score is used to predict the ease of intubation.[7] It is determined by looking at the anatomy of the oral cavity; specifically, it is based on the visibility of the base of uvula, faucial pillars (the arches in front of and behind the tonsils) and soft palate. Scoring may be done with or without phonation. A high Mallampati score (class 3 or 4) is associated with more difficult intubation as well as a higher incidence of sleep apnea.[8]

The output for SB4 take the values '0' or '1'.

- '0' means the patient's tracheal intubation is easy.
- '1' means the patient's tracheal intubation is hard.

There are 700 patients, that is (78%) of the cases in class '0', and 198, of the cases patients (22%) cases in class '1'.

As we have seen previously the database has been divided into four sub-bases (SB1, SB2, SB3 and SB4). In this work we deal with 10 classes and 30 features as shown in table 7.

Dataset	*898 patients*	
SB1: ASA Physical Status	4 classes	17 features
SB2: Accept or refuse patient for surgery	2 classes	3 features
SB3: General or local anesthesia	2 classes	4 features
SB4: Easy or hard tracheal intubation	2 classes	6 features
Total	10 classes	30 features

Table.7. Recapitulation of database

III. THE SUGGESTED PROTOTUPE AND SVM TECHNIQUES

In this section we present the proposed prototype (figure1), and the basic concept of the SVM classifier. This process allows to classify patients according to the ASA score, to accept or refuse patient for surgery, to choose the best anesthetic technique for the patient either general or local anesthesia, and also to evaluate if the patient's tracheal intubation is easy or hard.

A. The suggested prototype:

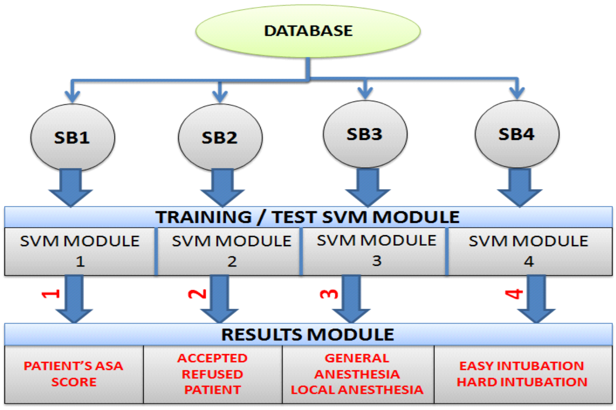

Fig.1. Functioning of the prototype

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Our prototype is divided into four parts as shown in figure 1. Each of them uses a sub-based dataset (SB1, SB2, SB3, and SB4) as shown in the previous section. These ones were used for learning and test with the SVM technique.

The first part is devoted to the detection of the ASA physical status by the SB1 dataset. The second part uses the SB2 dataset. Its role is to decide if the patients are accepted or refused for surgery. The third part is devoted to the detection of the most suitable best anesthetic technique, either general or local anesthesia by the SB3 dataset. And finally the fourth part works with the SB4 dataset. Its objective is to determine if the patient's tracheal intubation is easy or hard.

Each part contains three units. The first one is the dataset (SB1, SB2, SB3, and SB4), the second one is the training/test based module with the SVM classifier (SVM module1, SVM module2, SVM module3, and SVM module4) and finally the results module.

B. Basic concepts of SVM classifier:

The Support vector machines (SVMs, also called support vector networks [9] are supervised learning models with associated learning algorithms that analyze data and recognize patterns. They are used for the classification and regression analysis. This technique is based on the Vapnik statistical learning theory and the current standard incarnation (soft margin). This technique was proposed by Vapnik and Coinna in 1995 [9].

More formally, a support vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general, the larger the margin is the lower the generalization error of the classifier is.

In case we have two classes, the goal of the classification is to decide in which class a new data point will be, either in the first class or in the second one. Data point is viewed as a p-dimensional vector (a list of p numbers), and we want to know whether we can separate such points with a $(p-1)$ dimensional hyperplane. This is called a linear classifier (as shown in Fig 2). There are many hyperplanes that might classify the data; the best choice is when the hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose this the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin or equivalently, the perceptron of optimal stability. (as shown in Fig 3)

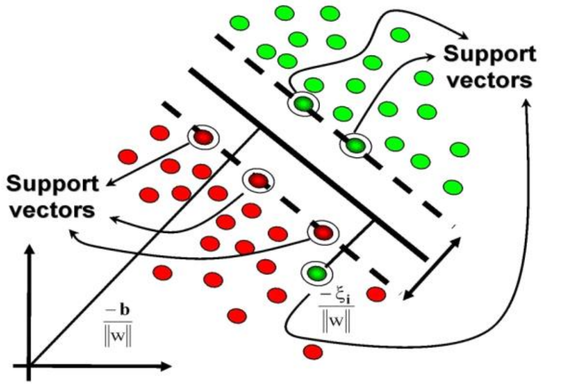

Fig.2. The sketch map of two class problem with SVM

[10]

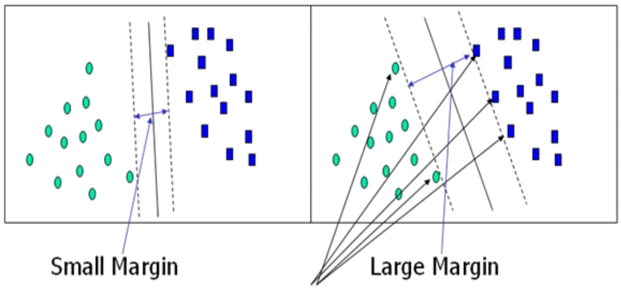

Fig.3. Maximum-margin hyperplane and margins for an SVM trained with samples from two classes [11]

It often happens that the classifications are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mappings used by the SVM schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function K(x,y) selected to suit the problem (as shown in Fig 4) [12], knowing that there are different types of kernel functions.

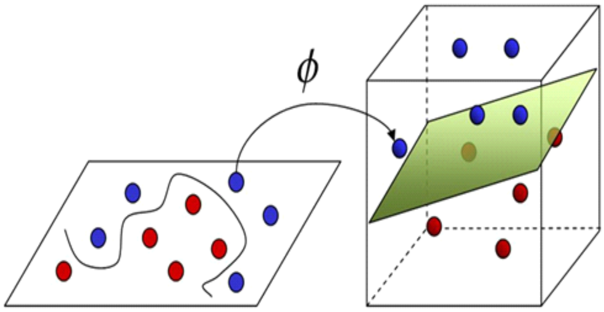

Fig.4. Kernel machine for an SVM trained with samples from two classes

IV. EXPERIMENTS RESULTS AND DISCUSSION

A. Classification accuracy:

The 6-fold cross-validation accuracy of each subset and average accuracy are listed in Table8.

B. Confusion matrix:

Each part of our prototype is presented as a confusion matrix (Table 8; 9; 10; 11). Usually, a confusion matrix contains information about actual and predicted classifications performed by a classification system. In this study, there are 10 diagnostic classes: in the first part, four classes (ASA physical status 1; 2; 3; and 4), in the second part, two classes (accepted or refused patient for surgery), in the third part, two classes (general or local anesthesia), and finally in the fourth part, two classes (easy or hard patient's tracheal intubation). In the confusion matrix, the rows represent the test data, while the columns represent the labels assigned by the classifier. Several indices of classification accuracy can be derived from the confusion matrix.

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	part 1					
Model	#1	#2	#3	#4	#5	#6
Accuracy (%)	88.18	84.36	91.55	83.62	93.74	83.67
Accuracy average	87.52%					
	part 2					
Model	#1	#2	#3	#4	#5	#6
Accuracy (%)	86.31	94.25	91.77	95.71	85.49	94.99
Accuracy average	91.42%					
	part 3					
Model	#1	#2	#3	#4	#5	#6
Accuracy (%)	90.36	93.61	89.75	96.81	96.59	92.77
Accuracy average	93.31%					
	part 4					
Model	#1	#2	#3	#4	#5	#6
Accuracy (%)	93.11	96.53	90.59	94.62	96.30	97.41
Accuracy average	94.76%					

Table.8. The testing accuracy for the our prototype via 6-fold cross-validation

The cross-validation classification accuracy can be determined as:

part 1: (201+335+207+43) / 898 = 87.52%
part 2: (723+98) / 898 = 91.42%
part 3: (165+673) / 898 = 93.31%
part 4: (670+181) / 898 = 94.76%

From the confusion matrix of the first part shown in Table 9, 201 patients with ASA physical status 1 among 219, 335 patients with ASA physical status 2 among 395, 207 patients with ASA physical status 3 among 232 and 43 patients with ASA physical status 4 among 52 were recognized correctly by the SVM classifier.

Output / **desired**	*ASA 1*	*ASA 2*	*ASA 3*	*ASA 4*	*Row sum*
ASA1	201	16	2	0	219
ASA2	22	335	38	0	395
ASA3	3	12	207	10	232
ASA4	0	1	8	43	52
Column sum	226	364	255	53	898

Table.9. Confusion matrix for part 1 via 6-fold Cross-validation method

From the confusion matrix of the second part shown in Table 10 we notice that 723 patients accepted for surgery among 762 patients and 98 patients refused for surgery among 136 patients were recognized correctly.

Output / **desired**	*Accepted patient*	*Refused patient*	*Row sum*
Accepted patient	723	39	762
Refused patient	38	98	136
Column sum	761	137	898

Table.10. Confusion matrix for part 2 via 6-fold cross-validation method

*Output / **desired***	*Easy patient's tracheal intubation*	*Hard Patient's tracheal intubation*	*Row sum*
Easy patient's tracheal intubation	670	30	700
Hard Patient's tracheal intubation	17	181	198
Column sum	687	211	898

From the confusion matrix for the third part shown in Table 11 we have 165 patients whose general anesthesia technique is the best for surgery among 198 patients and 673 whose local anesthesia technique is the best for surgery among 700 ones were recognized correctly by the SVM classifier.

Table.11. Confusion matrix for part 3 via 6-fold cross-validation method

Output / **desired**	*General anesthesia*	*Local anesthesia*	*Row sum*
General anesthesia	165	33	198
Local anesthesia	27	673	700
Column sum	192	706	898

Table.12. Confusion matrix for part 4 via 6-fold cross-validation method

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From the confusion matrix for the fourth part shown in Table 12, 670 patients who tracheal intubation is easy among 700 patients and 181 who tracheal intubation is hard among 198 ones were recognized correctly by the classifier.

V. CONCLUSION

Our prototype gives a medical decision support system based on the SVM for helping Doctors Specialized in Anesthesia in pre anesthetic consultation in four steps. The first one is the detection of the ASA physical status, the second to choose if the patients are accepted or refused for surgery, the third is the detection of the best anesthetic technique either general or local anesthesia, and the fourth one is to determine the patient's tracheal intubation.

A pre-anesthetic database consisting of 898 patients was collected locally from different hospitals and private clinics of western Algeria. This system has been developed with 30 input features and 10 classes.

Furthermore, the robustness of the proposed system was examined using a 6-fold cross-validation method and its results showed that the SVM-based decision support system could achieve an average classification accuracy at 87.52% in the first multiclass one, 91.42% for the second one, 93.31% for the third one and finally 94.76% for the fourth.

The results obtained are promising and we wish to ameliorate our databases and to test other techniques of classification for giving more precise output.

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