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Towards an Intelligent Surgical Preoperative Decision Support System: An Approach Based on Decision Trees and the Random Forest

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ABSTRACT

In recent years, Artificial Intelligence has experienced significant growth thanks to technological advances such as high performance computing and massive data processing. This evolution has led to a new reflection as well as a serious interest on the part of managers of hospital structures, who are beginning to take an interest in the automation and optimization of surgical processes. Machine Learning finds its place as a preferred technique for developing intelligent decision support systems in the operating room. In this aisle, it has become crucial to automate and optimize preoperative procedures. Through this paper, we focus on the development of an intelligent decision support system for the surgical preoperative phase, using the Random Forest model, which is an extension of the decision tree algorithm, to analyze a variety of preoperative predictive data such as hypertension, body temperature, ECG, hemoglobin, etc. We use a dataset previously approved by an institutional review board, while validating our model in a development environment dedicated to the field of Artificial Intelligence.

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1. INTRODUCTION

The operating room is of vital importance in a hospital establishment, as it brings together various material and human resources. Hospital managers are therefore concerned with the optimization and automation of its operation; hence the preoperative phase begins to take on crucial importance in the surgical process for the purpose of good patient care and adequate management of the operating room. In this study, we are interested in the proposal for the development of an intelligent preoperative surgical decision support system, which aims to reduce the risks of patients before any surgical intervention, and to optimize the planning of the operating room, by using Machine Learning models, in particular decision tree, while moving towards the Random Forest model. We detail the principle of the decision tree, which is a widely used model in the field of Machine Learning and serves as the basic foundation of the Random Forest, a powerful method for processing large amounts of data. By applying the decision tree to our preoperative database [12], [15]. We demonstrate the advantages of Random Forest in terms of reliability and accuracy, and its contribution in an intelligent decision support system for the surgical preoperative phase.

The structure of this article includes several sections; we start with a section relating to the surgical field, of which particular attention will be paid to the preoperative phase. In a second section, we present the key concepts of Artificial Intelligence (AI), particularly Machine Learning, with an emphasis on Decision Tree and Random Forest algorithms. Our approach will then be detailed in a separate section, guided by the presentation of a case study. Finally, we conclude with a general conclusion and perspectives for future work.

2. Operating Room

The operating room is a capital and essential element of any hospital center or hospital structure, involving a multitude of resources and constantly interacting with different sectors and medical services such as surgery, obstetrics, anesthesia, functional explorations, radiology and biology. Thanks to advances in Artificial Intelligence, the surgical field has undergone a significant transformation, for example: the diagnosis of patients is now based on radiological, pathological, endoscopic, ultrasound and biochemical examinations, allowing increased precision and a reduction workload for healthcare professionals. During the surgical process, the preoperative, operative and postoperative phases have also been improved thanks to new, more efficient techniques, which has led to significant benefits [14],[15].

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2.1. Preoperative Phase

Our approach will focus on the preoperative phase, the importance of which is justified as follows:

• Risk reduction: The preoperative phase aims to reduce the risk of perioperative complications and death by assessing the patient's preoperative medical status, identifying risk factors for cardiac and pulmonary complications, and optimizing the patient's health before surgery.

• Preparation: Appropriate preoperative preparation involves the implementation of specific procedures depending on the nature of the operation indicated, the results of the diagnostic work-up and the preoperative evaluation. This preparation ensures that the patient is optimally prepared to undergo the procedure.

• Postoperative follow-up: The preoperative phase also includes follow-up of the patient after the operation, from his exit from the recovery room to his transfer to his room. This makes it possible to monitor any complications and take the necessary measures, such as transfer to an intensive care and resuscitation unit if necessary [8],[19].

We can illustrate this phase through the following figure (see Figure 1):

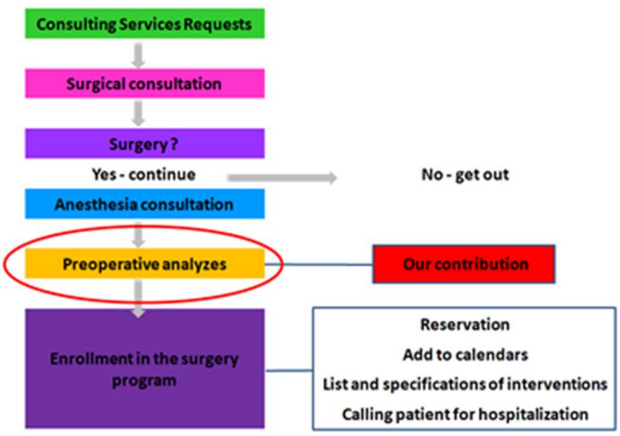

Figure 1. Management of the Preoperative Phase

3. Machine Learning

Machine Learning refers to the development of algorithms that can learn from data and improve their performance over time. These algorithms are used in various sectors such as health [1], [5]. Machine Learning includes a set of commonly followed steps to build a Machine Learning model [11].

These steps can be summarized as follows:

• Data acquisition.
• Data pre-processing.
• Data augmentation.
• Data processing.
• Feature extraction.
• Division of data.
• Classification.
• Model evaluation using metrics.
• Model testing.
• Refinement of the model.

These steps provide a structured process for developing and improving Machine Learning models.

3.1 Random Forest and decision tree

The Random Forest has been selected as a modern model based on Machine Learning and can be considered as an extension of traditional decision tree based classifiers [3],[10]. Random Forest was chosen over other Machine Learning techniques (e.g. neural networks, KNN...) because of its similarity to CART [9] and advantages in data management. The Random Forest attempts to mitigate the limitations of decision tree through an ensemble-based technique using multiple decision trees. Each tree is built from a random subset of the original training data. At each split node, a random subset of the total number of variables is analyzed. By taking the decision mode of a large number of these randomly generated trees (using the law of large numbers) [13], random forests are able to minimize the problem of overfitting. Some additional advantages of random forests include efficient execution on large samples with thousands of input variables, ability to scale to different scales of data, and robustness to inclusion of irrelevant items.

4. Proposed approach

Through this manuscript, we propose an intelligent decision support system for the surgical preoperative phase using Machine Learning. We rely on the Random Forest algorithm for reliable and accurate exploration and classification of preoperative patient assessments. Our goal is to improve patient care and optimize the use of the operating room by trying to move towards dynamic and real-time planning.

The general principle of our approach is also to move from a culture of "assessment for all" to "thoughtful action", Rather than being content with a systematic assessment, our system uses a predefined preoperative assessment, unified across all the units and hospital structures that adopt this new system. Using a large preoperative dataset, we train our model to predict the operative case of each new patient (see Figure 2).

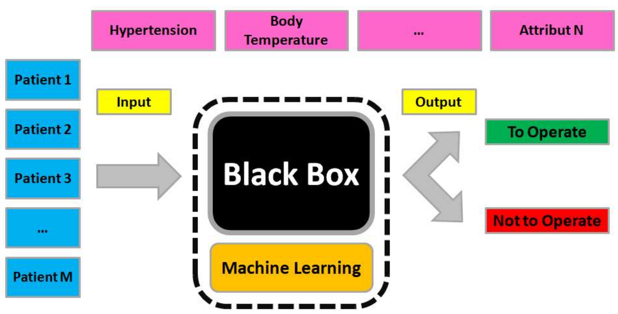

Figure 2. General Description of the Approach

5. Detailed Description of the Approach

We will try to give a detailed description of our approach using the Random Forest, which is an extension of the decision tree, whose objective is to predict the cases of patients from preoperative data.

The sequence of the process is as follows:

• Acquisition of information: Preoperative patient information is required from the various hospital units.

• Data pre-processing: Pre-operation data undergoes pre-processing including cleaning, normalization of values and handling of missing values. Relevant features are extracted to guide accurate prediction.

• Dividing the dataset: The dataset is divided into two parts: one for training the model and the other for testing to evaluate performance.

• Decision tree: A decision tree is used as the basis in the Random Forest. It makes decisions based on conditional rules represented in the form of a tree. Each node represents a feature, each branch represents a possible value of that feature, and the leaves represent the results or classification labels.

• Random Forest: The Random Forest combines several decision trees to improve prediction performance. Trees are constructed using different subsets of training data generated by random sampling with replacement. Moreover, each node division constitutes a random subset of the characteristics, thus introducing randomness in the construction of the trees.

• Prediction: Each Random Forest decision tree makes an individual prediction. Then, an aggregated decision is obtained using a majority vote or an average, exploiting the diversity of trees for a more reliable and accurate prediction. The final prediction is obtained by aggregating the tree predictions by majority vote.

By using Random Forest, our approach combines the advantages of tree diversity and aggregation to obtain a robust and accurate prediction of preoperative data, applying in the final phase a majority vote (See Figure 3).

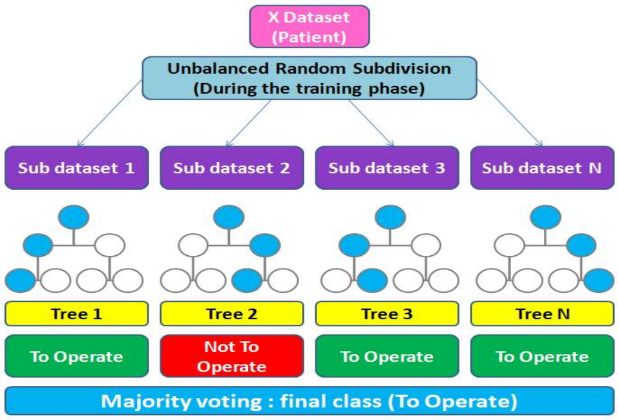

Figure 3. Detailed Description of the Approach

6. Case Study

In order to show the feasibility of our approach, we will use a database (Dataset) approved by the Institutional Review Board of Seoul National University Hospital (H-1408-101-605). The study has also been registered on clinicaltrials.gov (NCT02914444). Data collection was performed in accordance with the relevant guidelines and regulations of the institution's ethics committee [12]. For simplicity, we will generate a small part (as seen in Table 1) of this database, which will be preprocessed beforehand to simulate our approach.

Table 1. Used Part of the Dataset

ID	Age	Gender	Preop Hypertension	Body Temperature	Preop ECG	Preop Hemoglobin	Preop Glucose	Operate
1	63	M	120/80 mmHg	36.1°C	Worrisome	13.5 g/dL	100 mg/dL	Yes
2	34	M	100/65 mmHg	37.1°C	Normal	13.8 g/dL	130 mg/dL	Yes
3	52	F	Elevated	37.8°C	Worrisome	10.0 g/dL	70 mg/dL	No
4	77	F	115/70 mmHg	38.1°C	Worrisome	14.9 g/dL	85 mg/dL	Yes
5	84	M	Elevated	38.6°C	Normal	17.2 g/dL	115 mg/dL	Yes
6	66	M	118/78 mmHg	36.4°C	Normal	16.3 g/dL	96 mg/dL	Yes
7	81	M	105/65 mmHg	37.5°C	Normal	15.5 g/dL	126 mg/dL	Yes
8	72	F	115/75 mmHg	38.0°C	Worrisome	10.5 g/dL	132 mg/dL	No
9	75	F	Stage 1	38.1°C	Normal	12.9 g/dL	119 mg/dL	Yes
10	83	F	Stage 2	37.3°C	Normal	13.2 g/dL	122 mg/dL	Yes
11	51	M	Elevated	36.5°C	Worrisome	13.9 g/dL	114 mg/dL	No
12	65	M	Elevated	39.1°C	Normal	14.1 g/dL	128 mg/dL	Yes
13	80	F	117/68 mmHg	36.9°C	Worrisome	11.0 g/dL	90 mg/dL	No
14	20	F	Stage 2	37.7°C	Normal	15.4 g/dL	75 mg/dL	Yes
15	86	M	Elevated	38.8°C	Normal	15.5 g/dL	88 mg/dL	Yes
16	79	F	Stage 1	36.8°C	Normal	12.9 g/dL	121 mg/dL	Yes
17	93	M	110/70 mmHg	40.1°C	Worrisome	13.5 g/dL	125 mg/dL	No
18	17	F	Stage 2	39.2°C	Normal	15.0 g/dL	73 mg/dL	Yes
19	69	F	119/79 mmHg	37.5°C	Worrisome	11.3 g/dL	80 mg/dL	No
20	23	M	Elevated	39.7°C	Normal	13.7 g/dL	95 mg/dL	Yes

We notice that each attribute has multiple values, which is why we will use a binary recursive partitioning algorithm, such as CART [9], to build each decision tree in our Random Forest. For this, we need to discretize our continuous attributes by creating thresholds (as seen in Table 2), and this to divide the data into two binary categories. This will allow us to build a binary tree using the discrete values of each attribute.

Table 2. Attribute Threshold Repository

Age	Young	< 50 Y
	Old	> 50 Y
Hypertension	Normal	Less than 120/80 mmHg
	Worrisome	More than 120/80 mmHg (Elevated, Stage 1, Stage 2)
Body temperature	Normal	36.0°C - 38.1°C
	Worrisome	> 38.1°C
Hemoglobin	Normal	Men : 13.5 - 17.5 g/dL - Women : 12.9 - 15.5 g/dL
	Worrisome	10.0 - 12.9 g/dL
Glucose	Normal	70 - 100 mg/dL
	Worrisome	> 126 mg/dL

Thereafter, we perform a step of dividing the data set into training and test sets to evaluate the performance of our model.

The training set is used to fit the individual decision trees in the Random Forest, while the test set is used to assess the accuracy of the predictions made by the model, (as seen in Table 3)

6.1. Application of the Random Forest Algorithm on our Dataset

In the Random Forest, the first tree is constructed using a combination of bagging and sampling. Bagging stands for bootstrap aggregation, which involves randomly sampling the training data with replacement to create multiple new datasets. Each of these datasets is the same size as the original dataset, but they contain different cases due to replacement sampling. After creating the new datasets, a decision tree is built for each of them using a random subset of the features. The number of features to use is specified by a hyper parameter. This is called feature sampling (as seen in Table 4). The tree is built by recursively dividing the data into smaller subsets based on the values of the selected features, until a stopping criterion is satisfied [2].

Table 3. Attribute Threshold Repository with Binary Values and Split of the Dataset into Training Set and Testing Set

ID	Age	Gender	Preop Hypertension	Body Temperature	Preop ECG	Preop Hemoglobin	Preop Glucose	Operate
1	O	M	Normal	Normal	Worrisome	Normal	Normal	Yes
2	Y	M	Normal	Normal	Normal	Normal	Worrisome	Yes
3	O	F	Worrisome	Normal	Worrisome	Worrisome	Normal	No
4	O	F	Normal	Normal	Worrisome	Normal	Normal	Yes
5	O	M	Worrisome	Normal	Normal	Normal	Worrisome	Yes
6	O	M	Normal	Normal	Normal	Normal	Normal	Yes
7	O	M	Normal	Normal	Normal	Normal	Worrisome	Yes
8	O	F	Normal	Normal	Worrisome	Worrisome	Worrisome	No
9	O	F	Worrisome	Normal	Normal	Normal	Worrisome	Yes
10	O	F	Worrisome	Normal	Normal	Normal	Worrisome	Yes
11	O	M	Worrisome	Normal	Worrisome	Normal	Worrisome	No
12	O	M	Worrisome	Worrisome	Normal	Normal	Worrisome	Yes
13	O	F	Normal	Normal	Worrisome	Worrisome	Normal	No
14	Y	F	Worrisome	Normal	Normal	Normal	Normal	Yes
15	O	M	Worrisome	Worrisome	Normal	Normal	Normal	Yes
Training Set ↑ - Testing Set↓								
16	O	F	Worrisome	Normal	Normal	Normal	Worrisome	Yes
17	O	M	Normal	Worrisome	Worrisome	Normal	Worrisome	No
18	Y	F	Worrisome	Worrisome	Normal	Normal	Normal	Yes
19	O	F	Normal	Normal	Worrisome	Worrisome	Normal	No
20	Y	M	Worrisome	Worrisome	Normal	Normal	Normal	Yes

Table 4. Bagging and Sampling

ID	Age	Gender	Preop Hypertension	Body Temperature	Preop ECG	Preop Hemoglobin	Preop Glucose	Operate
1	O	M	Normal	Normal	Worrisome	Normal	Normal	Yes
2	Y	M	Normal	Normal	Normal	Normal	Worrisome	Yes
3	O	F	Worrisome	Normal	Worrisome	Worrisome	Normal	No
4	O	F	Normal	Normal	Worrisome	Normal	Normal	Yes
5	O	M	Worrisome	Normal	Normal	Normal	Worrisome	Yes
6	O	M	Normal	Normal	Normal	Normal	Normal	Yes
7	O	M	Normal	Normal	Normal	Normal	Worrisome	Yes
8	O	F	Normal	Normal	Worrisome	Worrisome	Worrisome	No
9	O	F	Worrisome	Normal	Normal	Normal	Worrisome	Yes
10	O	F	Worrisome	Normal	Normal	Normal	Worrisome	Yes
11	O	M	Worrisome	Normal	Worrisome	Normal	Worrisome	No
12	O	M	Worrisome	Worrisome	Normal	Normal	Worrisome	Yes
13	O	F	Normal	Normal	Worrisome	Worrisome	Normal	No
14	Y	F	Worrisome	Normal	Normal	Normal	Normal	Yes
15	O	M	Worrisome	Worrisome	Normal	Normal	Normal	Yes

↓↓↓

ID	Preop Hypertension	Preop ECG	Preop Hemoglobin	Preop Glucose	Operate
1	Normal	Worrisome	Normal	Normal	Yes
8	Normal	Worrisome	Worrisome	Worrisome	No
11	Worrisome	Worrisome	Normal	Worrisome	No
13	Normal	Worrisome	Worrisome	Normal	No
15	Worrisome	Normal	Normal	Normal	Yes

6.1.1. Construction of the First Tree in the Random Forest Model

We can explain the process followed, according to the steps below:

• Selection of the partitioning variable: The algorithm starts by evaluating each available attribute to determine which would be the best choice to partition the data, (as seen in Table 5):

Table 5. Selection of the Partitioning Variable

Hypertension	ECG	Hemoglobin	Glucose	Operate
Normal = 1	Normal = 1	Normal = 2	Normal = 2	Yes
Normal = 2	Normal = 0	Normal = 1	Normal = 1	No
Worrisome = 1	Worrisome = 1	Worrisome = 0	Worrisome = 0	Yes
Worrisome = 1	Worrisome = 3	Worrisome = 2	Worrisome = 2	No

The Gini index [17] (as seen in Equation 1) is calculated for each attribute in order to measure the impurity of the possible partitions.

$$\text{Gini-index (Attribute = Value)} = 1 - \sum (P_i)^2$$
$$\text{Gini-index (Attribute)} = \sum P_v * GI(V) \quad (1)$$

The attribute that minimizes the Gini index is selected as the partitioning variable (as seen in Table 6).

• Creation of the partition: Once the partitioning attribute has been selected, the algorithm divides the data into subsets according to the different values of this attribute, (as seen in Table 7):

Table 6. Partitioning Variable Selection

Attribute	GINI index calculations	Value
Preoperative hypertension	$[(1-((1/3)^2+(2/3)^2))*(3/5)]+[(1-((1/2)^2+(1/2)^2))*(2/5)]$	0,4666
Preoperative ECG	$[(1-((1/1)^2+(0/1)^2))*(1/5)]+[(1-((1/4)^2+(3/4)^2))*(4/5)]$	0,3000
Preoperative hemoglobin	$[(1-((2/3)^2+(1/3)^2))*(3/5)]+[(1-((0/2)^2+(2/2)^2))*(2/5)]$	0,2666
Preoperative glucose	$[(1-((2/3)^2+(1/3)^2))*(3/5)]+[(1-((0/2)^2+(2/2)^2))*(2/5)]$	0,2666

Table 7. Creation of the Score

Preoperative Hemoglobin = Normal			
Hypertension	ECG	Glucose	Operate
Normal	Worrisome	Normal	Yes
Worrisome	Worrisome	Worrisome	No
Worrisome	Normal	Normal	Yes

Preoperative Hemoglobin = Worrisome			
Hypertension	ECG	Glucose	Operate
Normal	Worrisome	Worrisome	No
Normal	Worrisome	Normal	No

Each subset represents a node or a branch of the tree (see Figure 4).

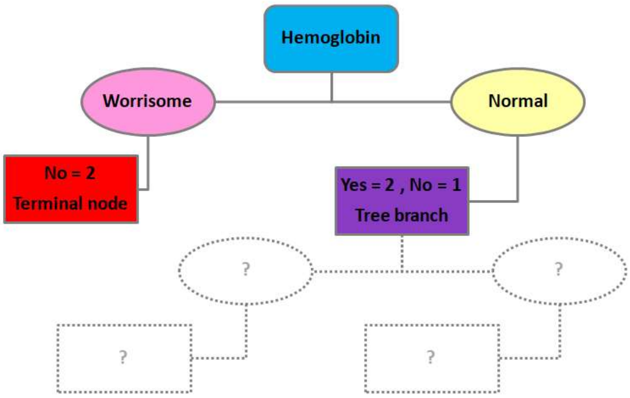

Figure 4. First Knot

• Calculation of the Gini index for each subset: For each created subset, the Gini index is calculated to evaluate the impurity of the class of labels in this subset. The Gini index measures the probability that a randomly selected item if misclassified would be randomly labeled based on the distribution of classes in the subset.

• Repetition of previous steps: Steps 1 to 3 are repeated recursively for each subset until a stopping criterion is reached. The stopping criterion can be a maximum depth of the tree, a minimum number of instances in the nodes or a minimum impurity.

• Creation of tree leaves: Each leaf represents a specific output class or value that is assigned to data instances during the prediction phase.

After generating several decision trees, the result is a set of decision trees, each of which is constructed using a different set of data and a random subset of the features (as seen in Figure 5):

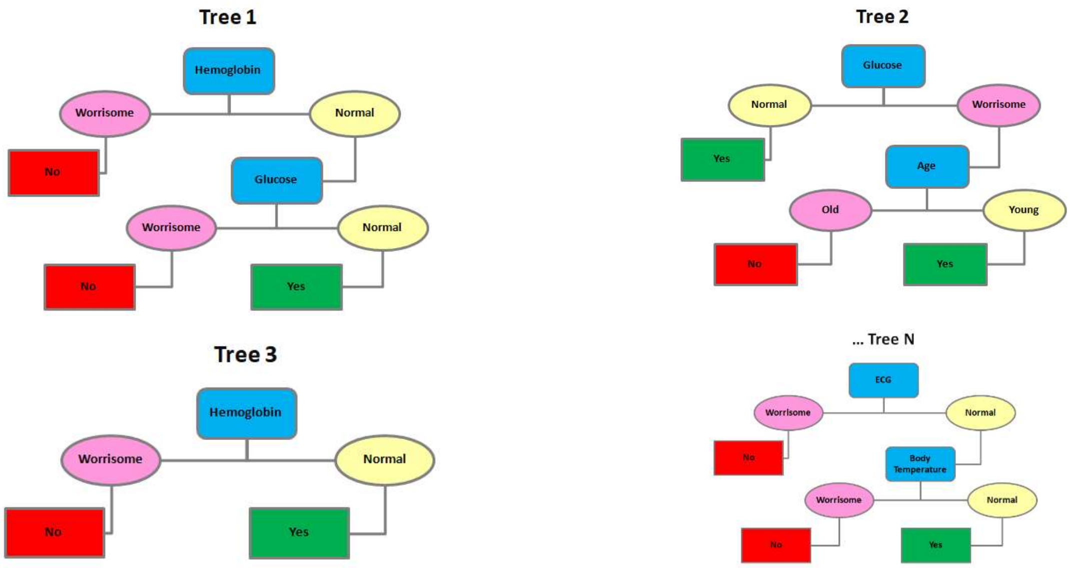

Figure 5. A Set of Decision Trees

To make a prediction about a new instance, which will be calculated relative to each individual tree, the final prediction is obtained through a majority vote (as seen in Figure 6).

ID	Age	Gender	Preop Hypertention	Body Temperature	Preop ECG	Preop Hemoglobin	Preop Glucose	Operate
X	O	M	Normal	Normal	Worrisome	Normal	Normal	???

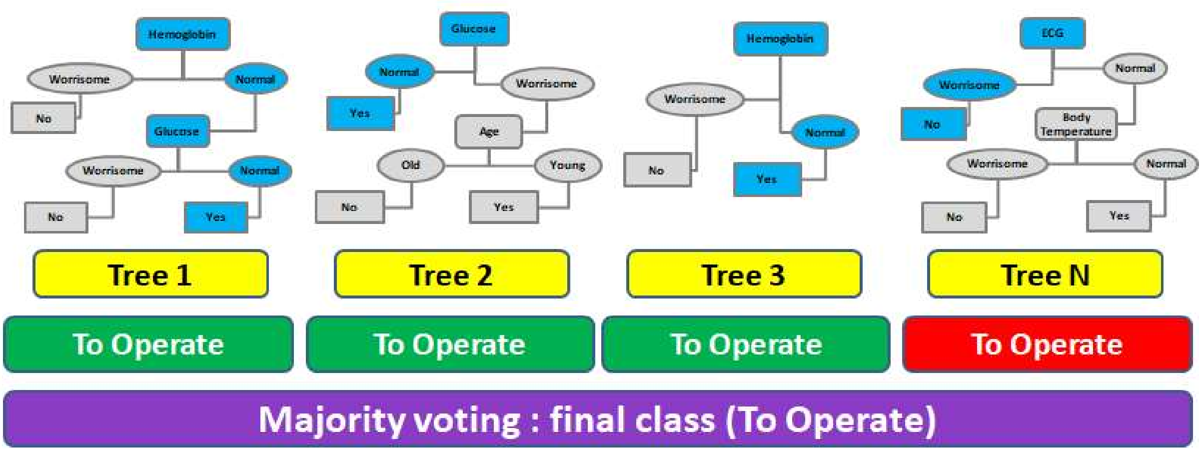

Figure 6. Prediction of a New Instance

7. Results and Discussion

In our study, we explored the use of Random Forest and CART (decision trees) algorithms, for preoperative decision making regarding the need for surgery. After having implemented and evaluated these two algorithms using the previous Dataset [3], [16], and in an environment dedicated to Artificial Intelligence:

- Runtime environment: Google Colab
- IDE: Spyder
- Python version: 3.10
- Libraries:

Pandas: (data import and manipulation)

NumPy: (scanning)

Scikit-Learn: (Machine Learning)

We obtained promising results with very favorable precision and accuracy (see Figure 7). These results improved the ability of the model to detect patterns present in the data and to generalize on new observations, which argued the interest of our approach for preoperative surgical decision-making.

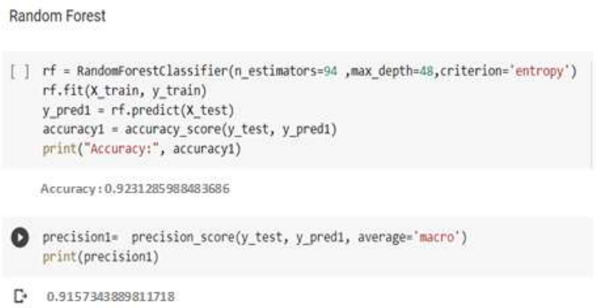

Figure 7. Some Evaluation Metrics of the Random Forest Model

8. Conclusion

This paper has been the subject of a presentation of a new approach, which is based on Machine Learning, using two models: Random Forest and decision trees, with the aim of developing an intelligent system decision support for the preoperative surgical phase. The approach taken was presented in general and then in detail. The results obtained have demonstrated the reliability and accuracy of our approach, the latter which has been validated through a renowned Dataset and in an environment dedicated to Artificial Intelligence. This work offers new advances for more accurate and reliable decision-making in the surgical field. Future perspectives of this research include comparing our model to other Machine Learning models, while considering addressing the next surgical phases: perioperative and postoperative; through appropriate Deep Learning models.

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