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Binary Classification Model of Adult Patients Deserting the Orthopedic Traumatology Department of a Reference Hospital: A Machine Learning Approach to Strengthen Traditional Medicine

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ABSTRACT: The phenomenon of leaving against medical advice remains a significant issue in public reference institutions in Côte d'Ivoire. Thus, one out of twelve adult patients hospitalized in the Orthopedics – Traumatology department of the Treichville University Hospital often interrupts their treatment in favor of traditional Bone-Setters or other destinations. However, despite recent advances in machine learning, it is still challenging to predict what type of destination these absconding patients will choose. Therefore, this article first aims to sequentially establish two datasets based on medical records: one original and the other after feature selection. Then, based on these datasets, this research involved four supervised machine learning models (Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and Gradient Boosting (GB)). The results obtained from performance metrics during testing, after five cross-validations, show that Random Forest is the most robust model for both datasets. Finally, a second analysis indicates that the Random Forest built on the original dataset remains the best model overall, with an AUC-ROC of 96%, an accuracy of 86%, a precision of 84%, a recall of 100%, and an F1-Score of 91%. These results suggest that this model offers hope for early and accurate prediction of the destination the absconding patient will opt for, thus positively impacting their care.

KEYWORDS: Cross validation, datasets, destinations, Discharge Against Medical Advice, Orthopedics – Traumatology, supervised machine learning.

1 INTRODUCTION

Unintentional injuries remain a significant issue in sub-Saharan African countries. In 2023 alone, according to the report from the national commission for the suspension and withdrawal of driving licenses, road traffic accidents (RTA) resulted in over 1,000 deaths on Ivorian roads [1]. This, despite all the efforts made in recent years by the authorities responsible for this sector. Consequently, when severe trauma cases arise, patients are taken to dedicated public hospitals. Unfortunately, once admitted, some patients consciously and emphatically decide to interrupt the treatments suggested to them and leave these public hospitals in favor of Traditional Bone-Setters (TBS) or other destinations [2].They act disregarding all explanations provided by the attending physician regarding their condition, completely unaware of the complications and potential risks associated with their decision.And this despite the serious consequences for their health and daily life, such as limb shortening, amputations, and often death [3, 4]. As reported by [5] and [3], the fundamental reasons quoted by these patients include, among others, the high cost of treatment, religious or ethnic beliefs, pressure from friends and family members, trust in the effectiveness of traditional treatment, fear of plaster casts or surgical intervention, and finally, the slowness in patient care. Thus, as a public health issue, this phenomenon of Discharge Against Medical Advice (DAMA), which affects nearly all state healthcare facilities to varying degrees, represents a significant problem for any formal healthcare system worldwide, particularly in Africa [2]. This scourge, which spares no area of medicine, is also observed in the orthopedic-traumatology department of the Treichville University Hospital Center (T-UHC). For this reason, it has long been the focus of particular attention in the field of traumatology in sub-Saharan countries, as reflected in several related studies. Unfortunately, it is evident that most research focusing on DAMA in West Africa primarily highlights the frequency and identification of factors promoting this desertion, followed by potential complications arising from the health of patients who desert in favor of TBS, and finally some suggested solutions that remain, till now, ineffective [5].

However, in order to stand out from their peers in Black Africa and especially with the aim of optimizing the diagnosis of a patient in a multidisciplinary situation, [6] developed a data model based on machine learning, without taking into account the issue of hospital stay for patients suffering from physical trauma. Fortunately, a promising development has come from researchers in the Maghreb. In this regard, [7], in their master's thesis, established a machine learning model for the exclusive prediction of hospital stay duration. This model will help practitioners better optimize the allocation of hospital resources while significantly reducing medical care costs. However, this model is not applicable to all pathologies, since the length of stay can vary from one illness to another. To address this gap, [8] focused their study on predicting the duration of long-term stays for geriatric patients suffering from upper femoral fractures. In order to achieve their stated objective, the study concluded with the identification of key risk factors (delayed surgery, type of surgery, and sex), after several cross-validations, adopting support vector machine and logistic regression models as those with better predictive performance.

Moreover, the review of related studies conducted within the framework of this research did not lead to the implementation of a machine learning model capable of appropriately predicting the destination of patients addict of Discharge Against Medical Advice (DAMA) from orthopaedic-traumatology services [9], which could explain the persistence of the problem. Although this situation leads to unfortunate consequences, it must be acknowledged that these traditional fracture treatment centers play an important role in managing certain injuries, which explains the enthusiasm of local populations for this practice in both rural and urban areas [2, 10]. Given what has been said previously, shouldn't we admit that this trend, which has received increasing attention over the last few decades, requires better regulation? In other words, wouldn't it be necessary to change the paradigm regarding the scourge of DAMA in order to create a consensus among all stakeholders in the field for better patient management when certain cases arise? Thus, this study which is a continuation of previous works on DAMA, primarily aimed at establishing a database resulting from a retrospective survey of DAMA patients in the orthopedics–traumatology department of the Treichville University Hospital Center (T-UHC) between 2015 and 2022. The next step involves implementing binary classification models based on machine learning (ML) algorithms capable of predicting the most likely destination of these patients, on one hand, based on a patient's profile and, on the other hand, the underlying reason for their discharge. Finally, performance evaluation criteria are applied to each of these algorithms to identify the one with the best predictive score, notably the random forest when handling the original database. Consequently, the main strength of this work is that it will enable traumatologists to early and accurately identify deserting patients in order to quickly redirect them to traditional healers based on their injuries. All of this aims to ensure effective care. This will lead to optimal management of hospital resources, foster cooperation between the two modes of medicine, and enhance the practice of traditional healers in orthopedics.

2 Materiels And Methods

2.1 Data Collection

This dataset was created to determine the factors influencing hospital abandonment among adult patients in the orthopedic-trauma department of CHU-T. Data were collected successively from two sources over five phases between July 2023 and January 2024. The first source is based on Physical Medical Records (PMR) of 402 patients out of the 4902 registered and subject to a DAMA. This represents a departure rate of 8.2% during the period from January 2015 to December 2022 [2]. The first step was to sort all the 402 medical records that had the notes "discharge" or "escaped" from the other remaining physical records. Then, for reasons of efficiency and especially accessibility to the archive room, we proceeded to individually scan the said records using a mobile phone via the CamScanner application. Finally, the collected data (age, sex, profession, place of residence, the facility that referred the patient, circumstances of the injury, location of the lesion, type of injuries, number of days of hospitalization, relationship with the person who influenced the DAMA, phone number of the patient or his relatives) mentioned in these files are recorded in the database once at home. It is obvious that at this point, the dataset contains some missing fields. Hence, there is a necessity to resort to the second source. This one involves conducting Individual Telephone Exchanges (ITE) with the 201 patients and/or their relatives who were willing to cooperate for the success of the study. The purpose of these ITEs is to gather additional information about the DAMAs patient: level of education, religion, reasons for leaving, and destination. The latter can be categorized as follows: to traditional healers, to other public hospitals, to private clinics, to modern hospitals outside the country, and finally to the patients' homes with his relatives as caregivers.

2.2 From Raw Data To Transformed And Normalized Data

On the evening of January 20, 2024, a first set of baseline raw data was obtained. Unfortunately, this dataset is unbalanced and seriously lacks coherence. Therefore, it is unsuitable for analysis and exploitation by ML algorithms. To address the elements that could hinder the performance of future models, we applied the main data preprocessing steps, namely data transformation and feature value normalization. The latter specifically aims to ensure that certain features of the variables do not overwhelmingly dominate the others, as illustrated in Fig.1 [11], [12.]

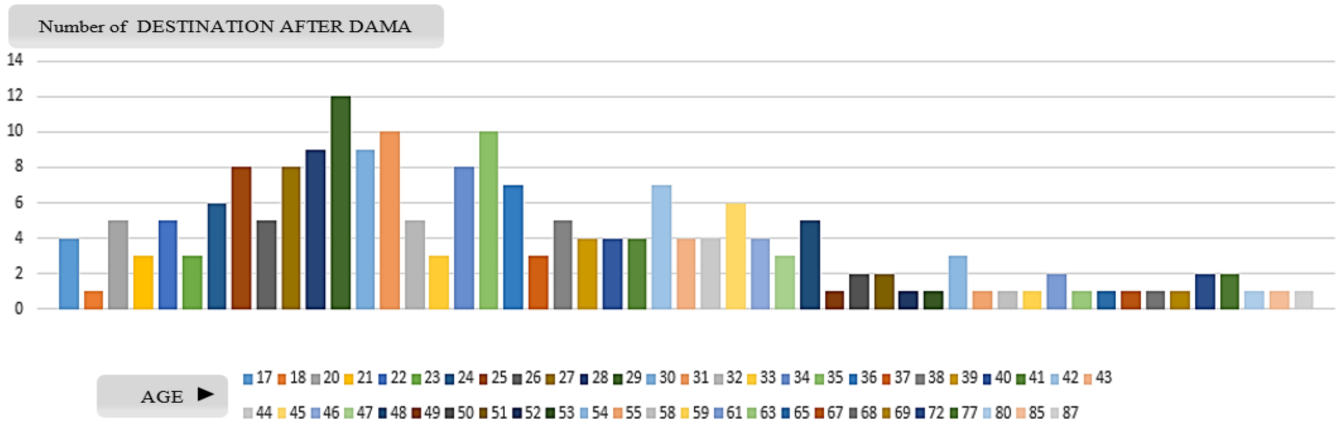

Fig. 1. Fragment representing the dominant and unbalanced character of certain ages based on destinations

2. In order to better address the imbalance issue that existed among certain features, we utilized various normalization criteria. Following this process, the selected data bank after labeling is represented in Table 1. This new dataset having taken into account issues of multiple fractures and traumas unit now having 269 patient observations compared to initially 201.

Table 1. Fragment of the characteristics of some DAMA patients after normalization: dataset original

age	gender	level_of_ instruction	religion	profession	proximity	circumstance	site_of_ lesion	classification_of_ lesion	length_ of hospitalization	influencing_ person_exit	factors_ motivating_ the_dama	destination_ after_dama
adult	M	primary	christian	agent	distant	wa	leg	CF	one day	parent	better care	0
adult	M	secondary	muslim	infom	distant	rta	foot	OF	one day	parent	costtt	1
young	M	secondary	christian	infom	close	rta	thigh	CF	two days	parent	costtt	1
young	F	primary	muslim	infom	close	rta	leg	OF	four days	parent	fgcast	1
young	F	secondary	muslim	infom	distant	rta	arm	OF	two days	parent	fgcast	1
young	F	primary	muslim	infom	vclose	rta	thigh	CF	two days	parent	costtt	1
adult	M	secondary	christian	agent	distant	rta	thigh	CF	three days	parent	costtt	1
young	M	secondary	christian	infom	close	rta	leg	OF	one day	parent	costtt	1
young	M	secondary	christian	infom	close	rta	arm	CF	one day	parent	costtt	1
young	M	primary	muslim	framew	close	rta	leg	OTHER	one day	parent	costtt	1

M : male ; F : femal ; infom : informal ; framew: framework ; vclose : very close ; vdistant: very distant ; wa : workplace accident ; rta : road traffic accident ; da : domestic accident ; CF : Closed Fracture ; OF : Open Fracture ; costtt : cost of treatment ; slownessc : slow response in care ; 1 : Traditional bone-setters ; 0 : other destinations

2.3 Choice Of Relevant Variables

On the evening of January 20, 2024, a first set of baseline raw data was obtained. Unfortunately, this dataset is unbalanced and seriously lacks coherence. Therefore, it is unsuitable for analysis and exploitation by ML algorithms. To address the elements that could hinder the performance of future models, we applied the main data preprocessing steps, namely data transformation and feature value normalization. Statistical analysis of potential characteristics. For that purpose, statisticians have a range of tests at their disposal, including the Chi-square test, which is applicable to categorical variables and is often performed alongside Cramer's V [8], [13]. The Chi-square is one of the best feature selection techniques that helps establish the correlation between variables. It remains a well-executed method for feature selection in statistical data sets [14].Based on this assertion, we employed the Chi-square test to check the null hypothesis (H0) of our model, which posits the existence of independence between the dependent variable, namely the destination, and each of the other explanatory variables. Thus, the results of this analysis are illustrated in Table 2.

Table 2. Results of chi-square test measures and cramer's V for the selection of variable

Tests	Âge	Gender	Level	Religion	Profession	Proximity	Circumstance	Site	Nature	Length hospi	Infl Per	Factors
Actual Chi-square value	8.76	0.01	16.39	5.05	26.97	15.05	10.70	4.74	9.12	3.70	2.32	102.90
Critical Chi-square value	7.81	3.84	7.81	5.99	11.07	7.81	7.81	14.06	7.81	11.07	5.99	12.59
The null hypothesis H_0 is rejected	Yes	No	Yes	No	Yes	Yes	Yes	No	Yes	No	No	Yes
Cramer'V coefficient	0.180	-	0.246	-	0.316	0.23	0.201	-	0.184	-	-	0.61

Consequently, the comparison of the actual Chi-square test values and the critical Chi-square values for each predictor, followed by the calculation of Cramer's coefficient in case of dependency, leads us to judiciously select the following variables as relevant: the age of the patient at the time of DAMA, their level of education, their profession, the proximity of their residence to the healthcare facility where they are hospitalized, the type of injury they are diagnosed with, and the main reason for their DAMA. Moreover, we can claim to construct a solid binary classification model that meets professional standards based on the characteristics of the patients who abandon treatment. Based on the previous tasks, we can assume that the issue of imbalance among certain characteristics is generally resolved. For example, Fig. 2 perfectly illustrates the proportion of age groups according to the destination of the patients who abandon treatment.

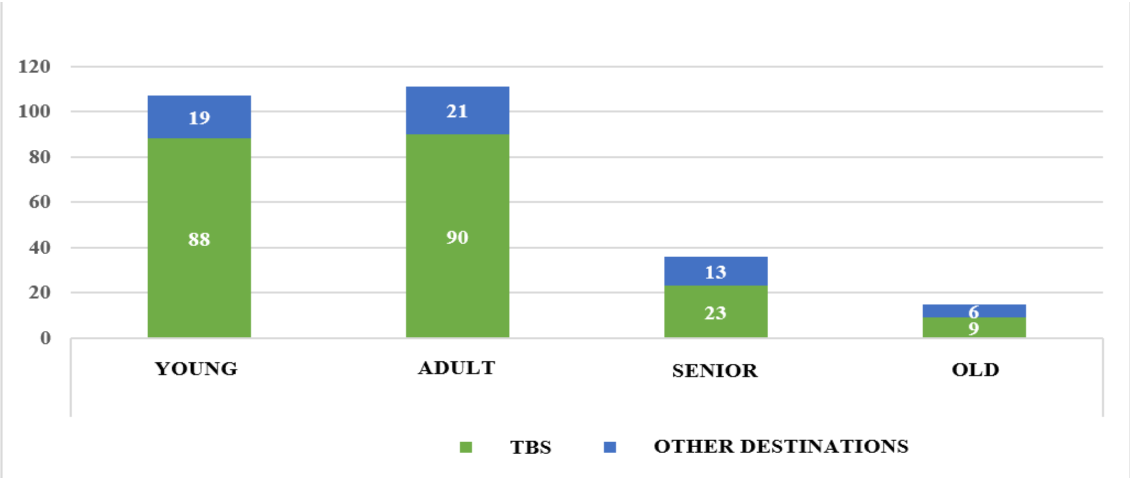

Fig. 2. Distribution of DAMA patients by age group according to destination

2.4 Machine Learning

The activity that involves describing the relationship between the prediction of the appropriate point of care and the profile of a patient who abandons the trauma services of a public reference healthcare facility is a binary classification problem. To adequately address this concern, we relied on four binary classification algorithms frequently used in the health sector and supported by a large number of researchers [15].

- The selection of these algorithms is based on the constraints and attributes of the assigned task. Among these attributes, we can mention, on one hand, the accuracy and interpretability of the results, and on the other hand, the scalability of the model. That is, its ability to adapt to new patient data while still providing good scores. Based on this, we chose the following algorithms.
- Logistic regression (LR): LR is commonly used in binary classification situations (1 for success and 0 for failure) and is particularly useful in cases where the relationship between the output variables and the input variables is linear. It provides the probability that an observation belongs to a particular category. Its effectiveness stems from its ability to use logistic functions to estimate the probability based on input features in contexts where the datasets are small to medium-sized [16].
- Decision Trees (DT): Decision trees remain one of the most robust tools for the classification and regression of nonlinear and outlier data. They are flexible to interpret. However, over fitting remains their weak point. In their operation, they split the dataset into two subsets based on the characteristics [17].

- Random Forest (RF): The Random Forest is characterized as an algorithm that combines multiple decision trees. Each tree is built on a randomly chosen representative fraction of the data. Furthermore, the predictions are aggregated to obtain a good final prediction. This model is very powerful and effective for regression and classification [18].
- Gradient Boosting (GB): GB are a family of supervised learning algorithms that build reliable prediction models step by step. G.B is commonly used for classification and regression tasks is technique that allows for the transformation of the most modest learners into robust learners. Hence the name 'Gradient Boosting. 'Thus, in this boosting environment, each new model is based on the errors of its predecessors that it has incorporated to refine its learning. It is particularly utilized for datasets that have a large amount of data. It is likely to produce better predictive performance [19].

2.5 Flowchart Of Our Modelling Approach

In this section, we have chosen to summarize our modeling process through Fig.3. Our modelling process deals with 7 steps. It begins with the compilation of our raw dataset obtained from field surveys and telephone interviews with the two hundred and one (201) cooperative patients for comparing the important characteristics of the best machine learning model in our study.

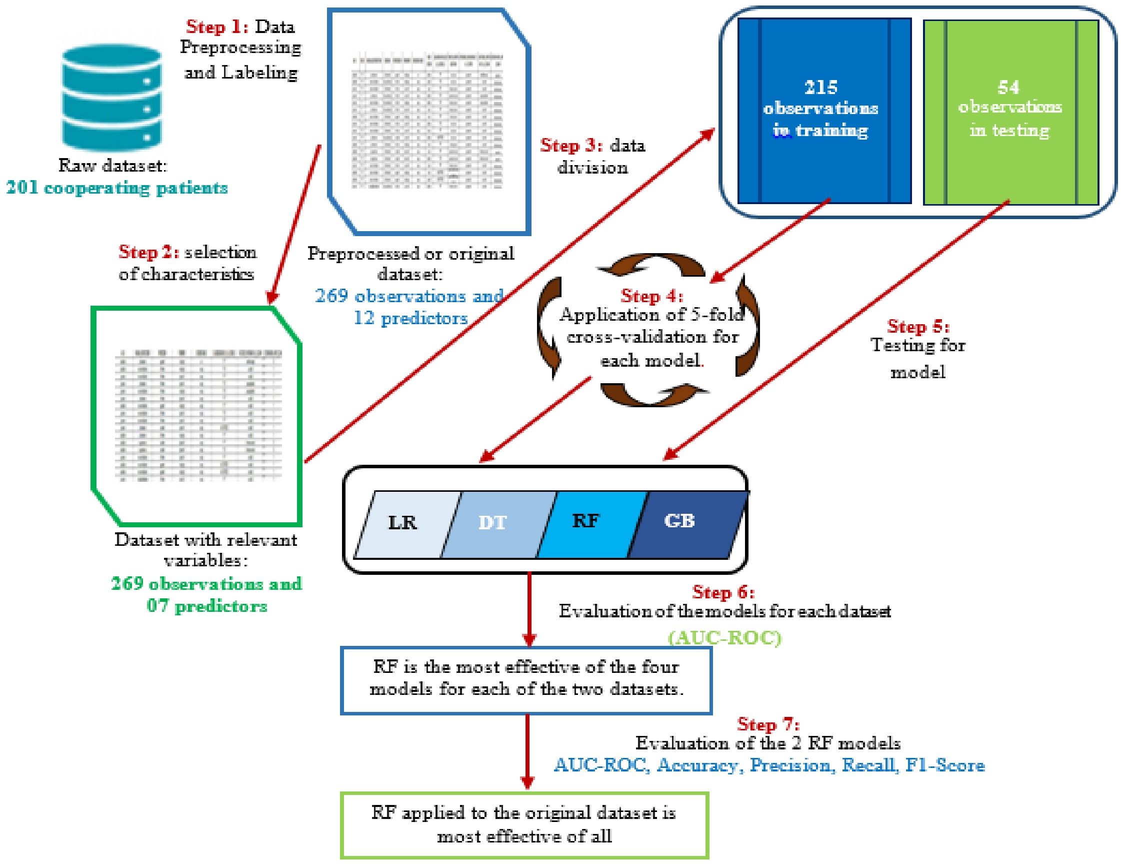

Fig. 3. Diagram of process of our research methodology

3 Results And Discussion

We will present the results of predicting the destination of DAMA patients, as well as our discussion section according to the two types of datasets at our disposal. In this context, the results from the dataset containing only the relevant characteristics will be presented. It goes for the original datasets. However, before any analysis, the performance measures that will allow us to assess the predictive power of the models will be highlighted.

3.1 PERFORMANCES METRIC

3.1.1 CONFUSION MATRIX AND CALCULATION OF PERFORMANCE METRICS FOR OUR STUDY

The confusion matrix is a double-entry table which allows us to understand, on the one hand, the different errors made by each of the four algorithms chosen for prediction. Its usefulness lies in clearly indicating the performance of each classification model based on the 54 test data whose original valid values are known from the start [20]. In other words, in our situation, this makes it possible to measure the predictive power of the algorithms constructed in our research. It is in this context that we chose to highlight the confusion matrix of the learning models using the original dataset (shown in Fig.4).

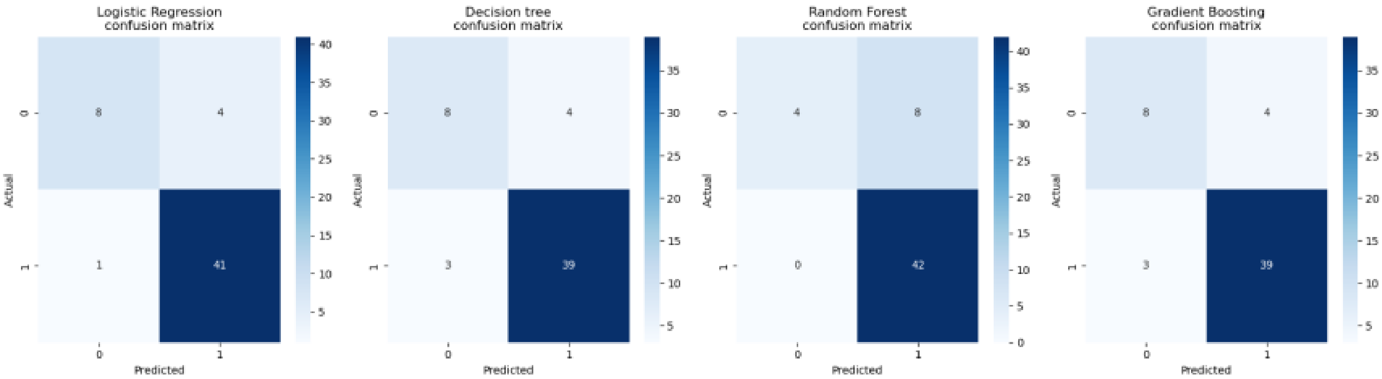

Fig. 4. Confusion matrix of all 04 techniques

3.1.2 CHOICE OF PERFORMANCE METRIC VALUES

The performance metrics employed to evaluate the degree of performance of the algorithms applied in our study are as follows: accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC) [21], [22], [23].

- Accuracy allows us to estimate the frequency of records that are well predicted.
- Precision measures the proportion of positive predictions that are deemed true.
- Recall is a metric used to determine the frequency of actual positive observations that are well predicted.
- The scalability of the model, or the area under the receiver operating characteristic curve, is an indicator that verifies whether the model remains performance as new data is gradually added to the dataset. In our context, this last metric represents the primary evaluation criterion for the performance of our model. Under the conditions mentioned above, the calculation method for each of our measures is described in Table 3 [24].

Table 3. The performance metrics

Accuracy = TP + TN / (TP +TN + FP + FN)
Precision = TP/ (TP + FP)
Recall = TP/ (TP + FN)
Specificity = TN/ (TN + FP)
F1-Score = 2 x (Precision x Recall)/ (Precision + Recall)
Area under the curve = (Recall + Specificity) / 2

TP: True Positive; FP: False Positive; TN: True Negative; FN: False Negative.

3.2 Evaluation Of The ML Model After 5 Cross-Validations

3.2.1 In The Original Data

3.2.1.1 Evaluation Of The Model

The information regarding the performance of the four (04) algorithms built from the original data is recorded in Table 4. At first glance, all performance indicators show that the four (04) models have very good results, with performance scores generally close to 80%. However, a detailed analysis of key metrics highlights that the Random Forest algorithm achieves the highest area under the curve (AUC-ROC = 0.96), indicating a margin of over 10% compared to the three other algorithms. This suggests that this Random Forest model is capable of adapting to 96% of new data while continuing to perform very well (see Fig. 5). This means that its scalability or overall behavior demonstrates very impressive performance. Furthermore, its accuracy is 86%, placing it in the second place for this metric. This indicates that 86% of the samples under its test are predicted correctly. Additionally, we can add an F-score of 9%, which corroborates an excellent balance between the precision and recall of this model.

Table 4. Performance of ML algorithms on the original data

Performance Measures	AUC-ROC	ACCURACY	PRECISION	RECALL	F1-SCORE
Logistic Regression	0.86	0.91	0.91	0.98	0.94
Decision Tree	0.80	0.87	0.91	0.93	0.92
Random Forest	0.96	0.86	0.84	1	0.91
Gradient Boosting	0.86	0.87	0.91	0.93	0.92

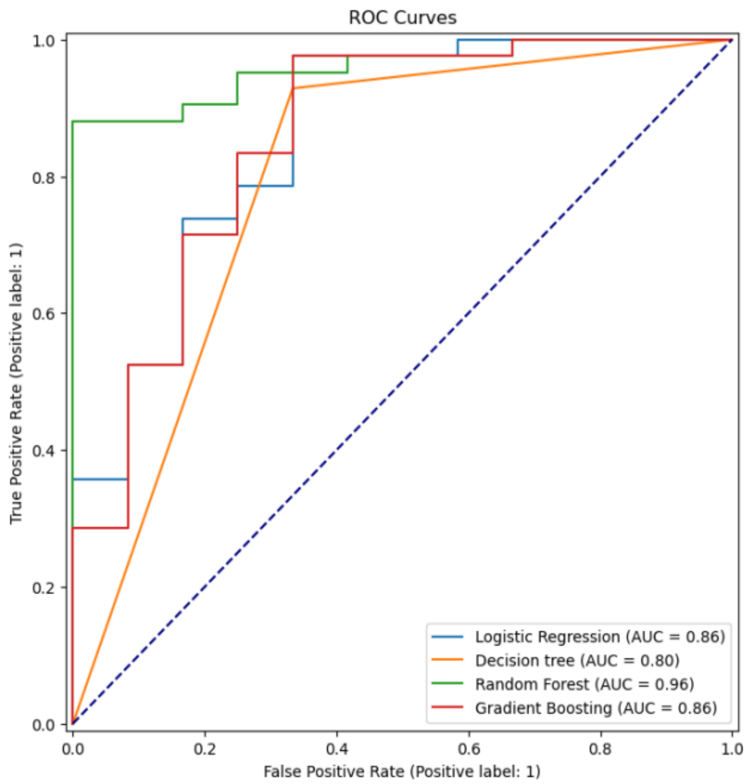

Fig. 5. Characteristic operating curve of the receiver for the algorithms applied with original data

To sum up, it follows that the Random Forest model remains, within the scope of our study, the one that presents the best performance and scalability indicators. Fig. 5 perfectly illustrates this achievement. Overall, our stance on the model's prowess is that the Random Forest is the best algorithm among the four (04) constructed.

3.2.1.2 IMPORTANCE OF MODEL CHARACTERISTICS

In terms of performance measures, the Random Forest algorithm maintains an outstanding overall performance. Furthermore, it is undeniable to recognize the characteristic importance of this model in order to determine its impact on the choice of destination of a patient fit to a DAMA among the patients in our study [8]. Fig.6 shows the weight of the characteristics in a gradual manner. Thus, it appears that according to our Random Forest model, the top five (05) characteristics are: the slowness of care in public facilities, the better care anticipated by the patient for his destination, the high cost of treatment, the patient with a higher level of education, and the fact that the patient is a worker in the informal sector.

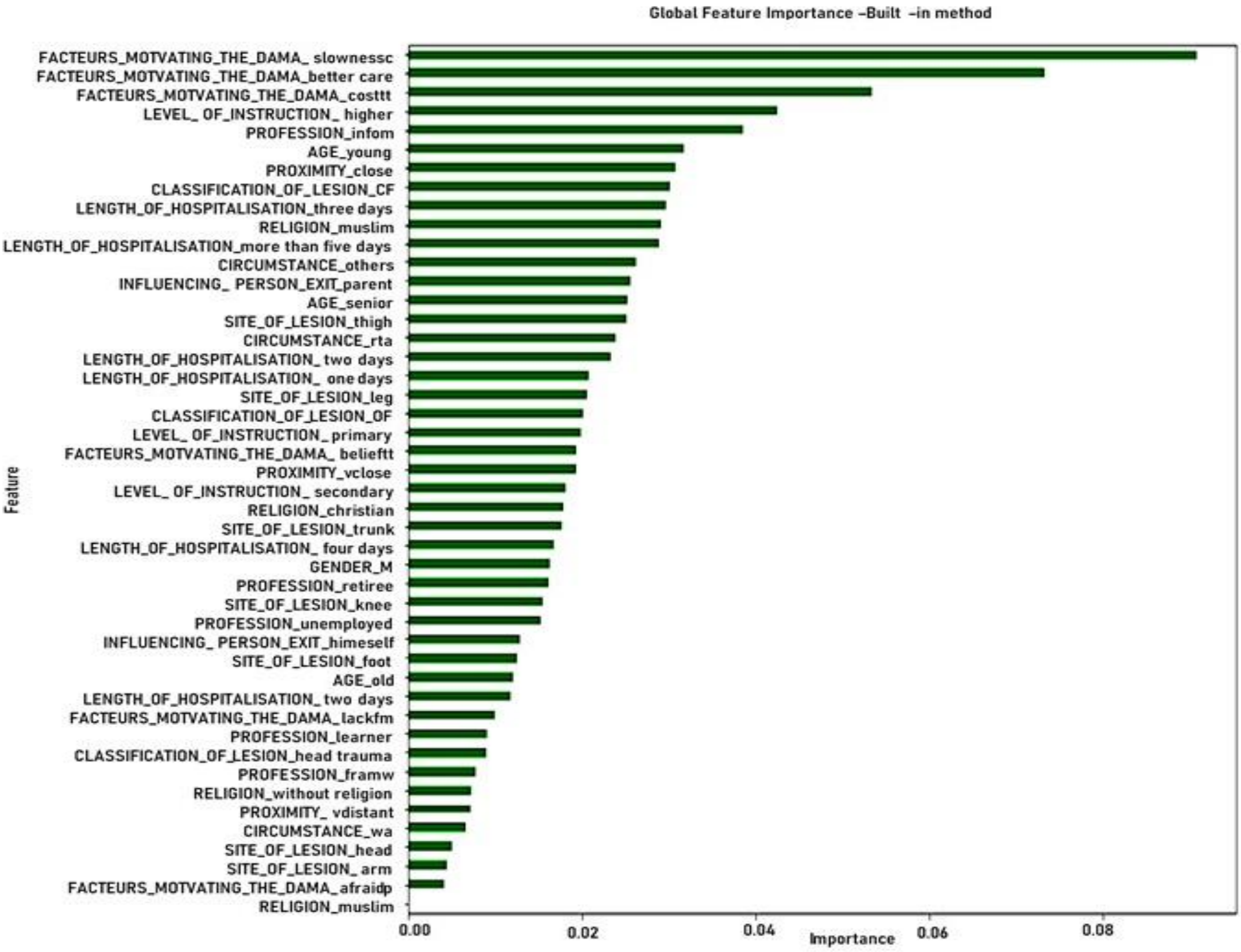

Fig. 6. Overall importance of the random forest model features in the original data

3.2.2 IN THE DATA WITH RELEVANT VARIABLES

3.2.2.1 THE MODEL EVALUATION

The information presented in Table 5 details the performance measures of the four (04) algorithms used in our patient tracking study following their DAMA. A thorough analysis of the key performance indicators shows that the random forest algorithm has the best overall performance compared to most other models, with the highest area under the curve (AUC-ROC = 0.92). This means that the constructed random forest algorithm indicates an excellent performance on the first dataset and tends to maintain this performance as the database expands. More, its accuracy of 85%, although behind other algorithms, shows that 85% of the observations submitted to it are predicted accurately. Furthermore, we can add its F-score of 91%, which combines recall and precision, reinforcing the perfect balance between these two essential metrics.

Table 5. Performance of ML algorithms on the data with relevant variables

Performance Measures	AUC-ROC	ACCURACY	PRECISION	RECALL	F1-SCORE
Logistic Regression	0.89	0.85	0.87	0.95	0.91
Decision Tree	0.79	0.91	0.91	1	0.94
Random Forest	0.92	0.85	0.84	1	0.91
Gradient Boosting	0.89	0.83	0.87	0.93	0.90

Based on the performance results obtained by the various algorithms and illustrated in Fig.7, we can conclude that the Random Forest model holds the top position in the classification activity of DAMA patients, with a 3% margin over the others.

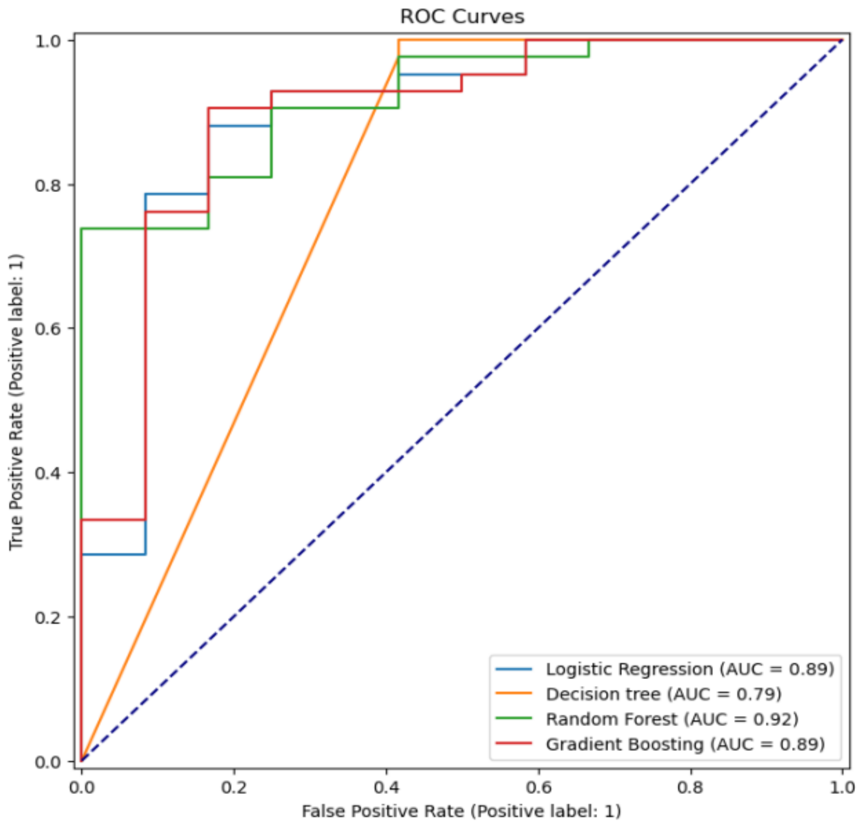

Fig. 7. Receiver operating characteristic curve for the algorithms applied with original data

3.2.2.2 Importance Of Model Characteristics

According to our later analyses, it is common knowledge that the Random Forest algorithm has the best performance record among the four (04) constructed for the binary classification task assigned to us. Therefore, it is important to highlight the list of significant features of the dataset that underpin this remarkable achievement. Thus, it emerges that the five (05) most useful features for our model in terms of patient dropout from DAMA are as follows: the slowness of care in public facilities, the hope for better care at the chosen destination, the treatment cost deemed unaffordable, the patient having a high educational level, and the fact that the patient works in the informal sector.

3.2.3 Comparative Study Of The Best Performances

In this study, the area under the ROC curve obtained from the various learning algorithms after five (05) cross-validations constitutes our main performance metric. An examination of this measure for the original data and that of the relevant variables shows that the random forest remains the most robust model for these two datasets, with respective AUC-ROC rates of 96% and 92%. Table 6 reflects this strong position. Furthermore, it is noteworthy that the RF constructed on these two datasets maintains almost identical performance across all four (04) remaining metrics. Thus, they demonstrate a precision of 84%, a recall of 100%, an F-score of 91%, and an accuracy of around 86%. All these values confirm that the RF constructed from the original data remains the most performant model of all (See Fig.8).

Fig. 7. Comparative summary of the performance of the RF on the two datasets.

Table 6.

Performance Measures	AUC-ROC	ACCURACY	PRECISION	RECALL	F1-SCORE
RF in the original data	0.96	0.86	0.84	1	0.91
RF in the relevant data	0.92	0.85	0.84	1	0.91

On the other hand, the two random forest models developed on both sides produce the same five (05) primary determinants in terms of feature importance: the slow pace of care in public facilities, the expectation of better treatment for the chosen destination, the treatment costs deemed unaffordable, the patient having a higher level of education, and the fact that the patient works in the informal sector. A detailed analysis shows that the order is preserved for the three (03) primary characteristics.

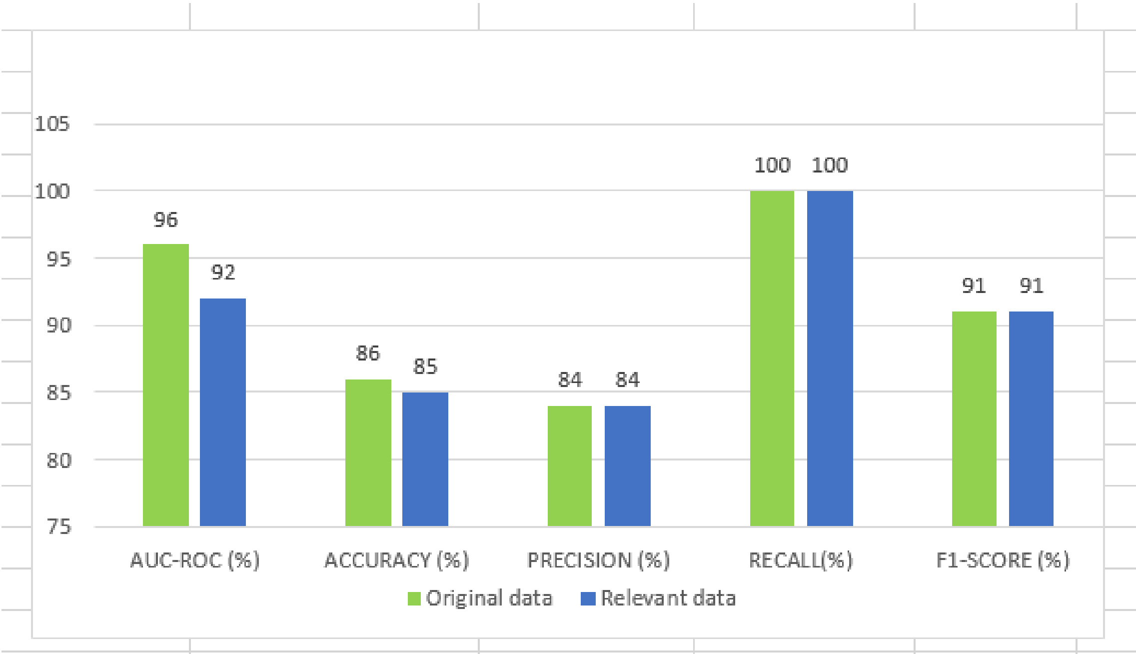

Fig. 8. Comparative histogram of random forest performance

4 Strengths And Limitations

This research conducted a new investigation in the orthopedic trauma department of T-UHC with the aim of developing and predicting the appropriate destination for a DAMA patient. Subsequently, two datasets were obtained, and four (04) models were developed. The performance analysis revealed that the random forest model produces results that surpass all other algorithms. Additionally, the frequency is impressive when the model is built from the original dataset. This endows the model with the capability to offer several advantages to trauma surgeons, traditional healers, and patients. For the former, it serves as a valuable decision-making support tool. Indeed, our model will enable them to detect early the destination of a DAMA patient. Thus, when our model predicts that a patient will abandon the trauma emergency department in favor of a traditional bone treatment center, the treating physician can, based on the algorithm for managing injuries proposed by traditional Bone-Setters [25], quickly discharge the patient so that he can be treated as soon as possible by a referred healer. This situation will potentially promote the patient's proper recovery and reduce future complications in his daily life while ensuring functional recovery of the injured limb (s). Furthermore, the traumatologist can work to keep the deserter patient by providing all necessary information about the inability of TBS to manage his condition when he insists on pursuing this dead-end path. In the second category, namely traditional healers, our model will enable them first to create a framework for cooperation [26], a climate of trust and tolerance towards their practices with traumatologists and other practitioners of modern medicine, who will no longer consider them as charlatans, but rather as partners who are eager to receive basic training from traumatologists. The immediate result of this cooperation is that public healthcare facilities will be decongested, allowing healthcare personnel to focus on genuinely critical cases. This will undoubtedly lead to better management of hospital resources (practitioners, hospitalization beds, operating rooms, implants, etc.). Furthermore, in centers dedicated to traditional bone treatment, we will see a reasonable influx of patients from public hospitals who have a probable diagnosis established for optimal care. This will allow this third category to avoid taking enormous risks (such as falling during escape, often late at night, worsening injuries, or having radiological examinations confiscated by healthcare agents at the time of DAMA that expose their already fragile health before their exit. Moreover, TBS will also be able to quickly decline the care of certain patients whose clinical presentation exceeds their competencies, as recommended by [25] and [26].

5 CONCLUSION

Machine Learning algorithms are impressive techniques that have made their way into the field of medical sciences to make predictions about diseases or phenomena related to public health issues. In this way, we operate under the assumption that tracking the destination of adult patients hospitalized in the orthopedic trauma department who choose to leave against medical advice will become possible with an appropriate predictive model. Based on this premise, we conducted a field survey that allowed us to successively establish two sets of data from which we adopted four (04) commonly used exploratory data techniques in a binary classification study. Furthermore, five (05) cross-validations of each of these models were performed during the training phase, which gives the generated models robust estimation power. Subsequently, we compared the performance measures, the main one being the area under the receiver operating characteristic curve, which is used to verify a model's ability to maintain impressive performance as the dataset grows. After evaluating this metric concerning the overall performance of the models, we can assert that the random forest proves to be the most suitable algorithm for predicting the most appropriate destination for a deserter patient, considering his profile and the factors motivating his DAMA. In order to distinguish between the two datasets, a thorough comparative analysis of other performance measures (accuracy, precision, recall, and F1-score) of the two random forest models allowed us to conclude that the model derived from the original database ranks first by producing the highest scores. Based on the ranking of our experimental results, we believe that predicting the appropriate destination for a patient who decides to interrupt and abandon his treatment will be more effectively achieved with the normalized database, which includes predictors such as age, gender, education level, religion, profession, proximity of residence to the hospital, cause of trauma, location and nature of the injury, reason for departure, duration of hospitalization, and finally, the person who influenced their exit. In light of these results, it is evident that the random forest remains the most effective of the four (04) models across the two datasets. Moreover, its position is strengthened when developed using the original database. Thus, it has proven to be the most suitable learning algorithm for predicting the medical endpoint of a patient leaving against medical advice from the orthopedic trauma services of T-UHC, especially when constructed on the original dataset.

In perspective, this model based on automatic prediction techniques promises to bring a glimmer of hope in the management of patients suffering from physical trauma and those who abandon healthcare facilities. In reality, the main strength of this model is to enable traumatologists to detect early and optimally the destination of DAMA patients. Thus, depending on the type of injury, they will be able to quickly release the victim to receive better care from TBS. Furthermore, this model will allow for optimal management of hospital resources while creating cooperation between the two healthcare systems. Ultimately, this learning tool will significantly help promote the practice of TBS.

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