

On the efficiency of Machine Learning Models in predicting Malaria using Symptôm Data

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Abstract.

Background Malaria is a major health problem in Senegal where it is endemic with a seasonal upsurge, therefore they represents about 35% of the reasons for consultation. This is mainly due to inappropriate medical care support coupled with an often late and error-prone diagnosis from the medical staff. In addition, largely used diagnostic standards such as the Rapid Diagnosis Test is not fully reliable. With the development and increasing adoption of automated tools in the health field, machine learning applications might help medical actors in their decision-making process.

Methods: In this study we test the efficacy of six machine learning algorithms for the prediction of Malaria in Senegal. These algorithms aim at predicting whether or not a given patient suffers from Malaria based on his signs and symptoms. The performance of the algorithms have been extensively tested and evaluated over real data sets about signs and symptoms of patients in Senegal that suffer or not from Malaria. The algorithms are evaluated using four criteria: accuracy, Recall, F-measure, Precision and Specificity.

Results and conclusions: The results show that overall of ML algorithms perform as well as for predicting occurrence or not of the malaria according the dataset used. However that there is not necessarily a single best classification tool, but instead the best performing algorithm will depend on the dataset to be analysed. Hence the need to build prediction model by combining the best classifiers among those studied

Keywords. Malaria, Prediction, ML algorithm, L^AT_EX, book, layout

1. Introduction

Malaria is a life-threatening disease caused by parasites that are transmitted to people through the bites of infected female *Anopheles* mosquitoes. It is preventable and curable. Malaria is an acute febrile illness. In a non-immune individual, symptoms usually appear 10–15 days after the infective mosquito bite. The first symptoms – fever, headache, and chills – may be mild and difficult to recognize as malaria. If not treated within 24 hours, *P. falciparum* malaria can progress to severe illness, often leading to death. Chil-

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dren with severe malaria frequently develop one or more of the following symptoms: severe anaemia, respiratory distress in relation to metabolic acidosis, or cerebral malaria. In adults, multi-organ failure is also frequent. In malaria endemic areas, people may develop partial immunity, allowing asymptomatic infections to occur. In 2019, there were an estimated 229 million cases of malaria worldwide. The estimated number of malaria deaths stood at 409 000 in 2019. The WHO African Region carries a disproportionately high share of the global malaria burden. In 2019, the region was home to 94% of malaria cases and deaths, thanks to the 2019 World Malaria Report [1]. Over the past years, many efforts have been done by governmental and non governmental organizations to eradicate Malaria: actions continuously conducted by the WHO are real examples of those. In the research field, many studies, aiming at understanding the disease from the Plasmodium mosquito point of view or proposing automated detection tools, have been conducted [2,3,4,5]. The Rapid Diagnostic Test (RDT) [5] is one of the most successful and prominent introduced tool to automatically predict whether or not a given patient suffers from Malaria. It relies on the detection of specific Plasmodium proteins, PfHRP2, pLDH and aldolase. The RDT is largely used and adopted as a standard in many health structures in Sub-African countries because of its simplicity to utilize and does not require any specific domain knowledge. However as highlighted in [5] the RDT is not fully reliable: in Section 2 we show that the precision of the RDT is about 90% for the real datasets used in this study. With the development and increasing adoption of automated tools in the health field, machine learning (ML) [6,7] applications might help medical actors in their decision-making process. In this paper, we propose an extensive comparative study of six machine learning algorithms, among the most popular for the prediction of Malaria in Senegal. The evaluated and compared ML algorithms are Naive Bayes (NB), Logistic Regression(LR) , Decision Tree(DT), Support Vector Machine(SVM) , Random Forest(RF), and Artificial Neural Network(ANN). We conducted experiments on five datasets based on the two real world datasets about Senegalese citizens that suffer or not from Malaria. These two datasets have been collected in two different contexts and contain clinical data such as sign, symptom and final diagnostic of patients living in distinct locations in Senegal (for the first dataset) or within the same area (for the second dataset). Those patients have been examined by doctors in given health services and their clinical data recorded: for each patient the final diagnostic is provided with the corresponding signs and symptoms. The outcome of the RDT is also provided. The rest of the paper is structured as follows. First we give detail explanation of machine learning methods and the different data sets methods used for this study in section 2. In section 3 our different results are presented. Section 4 and 5 includes discussion of our results and conclusions of this paper.

2. Methods

2.1. Machine Learning algorithms in healthcare

There are already some attempts to apply ML techniques for the prediction or a better understanding of various diseases, e.g. logistic regression has been tested in [8] for the prediction of Malaria and provides promising results.

2.2. Datasets

In order to carry out our experiments in a real setting we have collected two real world datasets about patients living in Senegal. We describe each of them in the sequel.

Data collection. Our first dataset, that we refer to it as DT1, contains medical records about patients living in distinct places in Senegal. It has been collected in 2016 during the **Grand Magal of Touba** which is one of the most popular religious event in Senegal. Such an event gathers every year several millions of persons that come from various areas around the country [21]. During the event several fixed and mobile health points are set up to enable the examination and treatment of ill persons. The second dataset, denoted by DT2, has been collected by drawing our attention on medical records about patients living in the same area. We focused on the district of Diourbel, Thies and Fatick² where the prevalence of Malaria is very high and collected patient records from its different health structures.

Data features. Table 1 contains the main characteristic of each dataset. Some of these variables (also called features or attributes) include personal data about the patient, but also signs and symptoms (e.g. lack of appetite, tiredness, fever, cephalalgia, nausea, arthralgia, digestive disorders, dizziness, chill, myalgia, diarrhea, and abdominal pain) of the patient reported by the doctor who treated this later. The other attributes describe clinical data such as information about the doctor's final diagnosis (the patient's disease), the outcome of the Rapid Diagnosis Test and the patient's status (i.e. admission, death or observation). For privacy reasons and certain restrictions in the use of the data, we have ignored patient personal data during this study. In addition, we can observe that both datasets are unbalanced because the proportion of observations per class is largely unequal. As an example for dataset DT1 we have 614 observations in the first class and 5108 observation in the second class. Finally, we remarked that the precision of the Rapid Diagnosis Test is around 90% for both datasets, meaning that the systematically performed RDT in Senegal is not fully reliable.

| Dataset | Variables | Observations | Variables types | | Classes | | Precision of RDT |
|---------|-----------|--------------|-----------------|---------|---------|-------------|------------------|
| | | | Numeric | Boolean | Malaria | not Malaria | |
| DT1 | 16 | 21083 | 2 | 14 | 614 | 20469 | 90.23% |
| DT2 | 16 | 5809 | 2 | 14 | 5108 | 701 | 90.49% |

Table 1. Raw Data characteristics

From DT1 and DT2 we built three news datasets DT3, DT4 and DT5 data sets as below.

²https://en.wikipedia.org/wiki/Diourbel_Region

DT3: It is obtained by concatenating the DT1 and DT2 datasets. Thus it concerns 37,175 patients of which 9,837 are diagnosed positive for malaria.

DT4: It is obtained by considering the 16,092 patients in the DT2 data set (including 9,223 patients with malaria). Since this DT2 is unbalanced, we randomly selected 2354 patients who tested negative for malaria from the DT1 data set at the end of the rebalance. Thus it concerns 18,446 patients, 9,223 of whom are suffering from malaria.

DT5: is obtained by the over sampling of DT1 by the SMOTE method of python. This method consists first of dividing DT1 into two parts, one for training (train set) and the other for testing (test set). The train set being unbalanced, then we apply the SMOTE method to remedy it. Thus we obtain a new train set comprising 30,369 patients, half of whom tested positive for malaria.

2.3. Machine Learning algorithms studies

In the following we discuss about some of these methods. Those algorithms are chosen among the most used ones in the health field according to studies[9,10].

Decision tree (DT)[11] is a supervised classifier which is obtained by recursively partitioning the labelled set of observations. It is one of the most adopted classifiers, thanks to its simplicity and its straightforward interpretation. For CART algorithms, hyperparameters are the impurity criteria (entropy and gini), the maximum depth, the minimum samples to split and the minimum samples at a leaf

Random Forest (RF) [12]: RF is an ensemble approach built upon many decision tree classifiers. It is a supervised classifier which requires the same hyper parameters as DT, plus the number of trees to create and the random number of features to look at when splitting the labelled data during the training step [12].

Naive Bayes classifier (NB): NB[13] is a *supervised* machine learning algorithm, i.e. requires to be trained, used for classifying observations to given distinct classes based on *input explanatory variables* (a.k.a feature or attribute). It is a classification technique based on the well-known *Bayes' theorem*³ with strong and naive assumptions. It simplifies learning by assuming that features are independent of given class.

Logistic regression (LR: LR [14] is a statistical model used in the machine learning domain as a supervised classifier for binary classification [15]. It is based, in its basic form, on a logistic function to describe a binary dependent variable[16,9] by considering as input qualitative or/and ordinal explanatory variables in order to measure the probability of a given class label.

Support Vector Machine (SVM): SVM [17] is a supervised classification approach whose intuition is to represent input data in a space and to determine the optimal hyper-plane that divides that space in two regions depending on the targeted value.

Artificial Neural Network (ANN): ANN [18] is a computational approach also referred to as a Connectionist System used in Machine Learning. ANNs are loosely modeled after the biological neural network in an attempt to replicate the way in which we learn as humans. Think of it as a computing system, structured as a series of layers, each layer consisting of one or several neurons. The types of the layers comprise *input*, *output* and *hidden* layers [19,20].

³https://en.wikipedia.org/wiki/Bayes%27_theorem

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2.4. Experimentation Setting

In this section data is available for applying classification algorithm. After model creation from training data, classification operation is performed on test data. All the performed tests have been done in the same machine and the same operating system. To test the performance of our six chosen ML algorithms, we relied on their Python implementations available through the scikit-learn library. Scikit-learn is an open source simple and efficient tool for predictive data analysis that implements most of the existing ML algorithms. For the details about the description of each parameter of ML we refer to the official documentation of the implementation of these algorithms in scikit-learn⁷. Concerning the segmentation of both datasets for the training of our ML algorithms and their testing we have considered the stratified-5-fold cross-validation in classification model construction and efficiency evaluation. This method is very useful to handle data with an unbalanced class distribution, increases the validation of classification and prevents from random and invalid results.

2.5. Measurement

To evaluate the performance of every considered algorithm we have considered common measures of the accuracy of a prediction system that are *Precision*, *Recall*, *F1-score*, *True Positive Rate*, and *False Positive Rate* on both datasets augmented with semi-synthetic datasets which are obtained after imputation in order to deal with missing values.

3. Results of the experiments

Table 2 presents the results of the experiments with the different algorithms on our data on Malaria. More specifically, Table 2 contains the precision, the recall, the specificity, the AUC measure, the score and F-measure of each algorithm tested while Figure 1 shows their respective ROC curve.

3.1. Discussion

In this study, the algorithms DT, RF, LR, NB, SVM and ANN were applied on five datasets concerning patients with or without malaria and living in regions of Senegal namely: Diourbel, Thies and Fatick. Indeed, in order to offer a new technique for diagnosing and predicting malaria, it is important to know the performance of those existing through our datasets. Analysing in details the performance of our six classifiers across the five datasets, the results show that there is not necessarily a single best classification algorithm, but that the best performing algorithm will depend on the characteristics of the dataset to analyze. Indeed we notice that all the algorithms produce their best precision on the DT1, DT3, and DT5 data sets. These values, which reach 97% at times, outperform the Rapid Diagnosis Test which is the standard diagnostic tool largely adopted in the healthcare system in Senegal. However, on these same datasets, the algorithms often present very low specificities, for example 0.05 on DT1. This shows that our best performing classifiers are only able to predict a single class: either the patient has malaria or he does not, but not in both spots. This is because the DT1 and DT3 datasets are very unbalanced. In fact in these datasets either the number of patients with malaria is greater

| ML Algorithms | Datasets | Precision | Recall | F1-score | AUC | Score | Specificity |
|-----------------------------|----------|-----------|--------|----------|------|-------|-------------|
| Decision Tree | DT1 | 0.97 | 1 | 0.98 | 0.78 | 97.04 | 0.05 |
| | DT2 | 0.59 | 0.48 | 0.48 | 0.64 | 63.01 | 0.80 |
| | DT3 | 0.89 | 0.85 | 0.87 | 0.86 | 80.86 | 0.69 |
| | DT4 | 0.68 | 0.57 | 0.62 | 0.70 | 65.60 | 0.74 |
| | DT5 | 0.99 | 0.84 | 0.91 | 0.76 | 83.41 | 0.58 |
| Random Forest | DT1 | 0.97 | 1 | 0.99 | 0.81 | 97.13 | 0.07 |
| | DT2 | 0.63 | 0.34 | 0.44 | 0.64 | 63.33 | 0.85 |
| | DT3 | 0.89 | 0.85 | 0.87 | 0.87 | 80.86 | 0.70 |
| | DT4 | 0.68 | 0.56 | 0.62 | 0.70 | 65.82 | 0.74 |
| | DT5 | 0.99 | 0.84 | 0.91 | 0.76 | 78.35 | 0.60 |
| Logistic Regression | DT1 | 0.97 | 1 | 0.99 | 0.79 | 97.19 | 0.05 |
| | DT2 | 0.58 | 0.36 | 0.44 | 0.63 | 61.96 | 0.81 |
| | DT3 | 0.85 | 0.88 | 0.86 | 0.86 | 79.59 | 0.55 |
| | DT4 | 0.98 | 0.56 | 0.92 | 0.70 | 65.82 | 0.72 |
| | DT5 | 0.90 | 0.78 | 0.88 | 0.84 | 81.86 | 0.75 |
| Naive Bays | DT1 | 0.97 | 1 | 0.99 | 0.81 | 97.13 | 0.00 |
| | DT2 | 0.60 | 0.34 | 0.43 | 0.63 | 62.86 | 0.83 |
| | DT3 | 0.86 | 0.87 | 0.86 | 0.85 | 79.94 | 0.60 |
| | DT4 | 0.68 | 0.59 | 0.63 | 0.70 | 65.63 | 0.73 |
| | DT5 | 0.99 | 0.82 | 0.90 | 0.84 | 85.61 | 0.71 |
| Support V Machine | DT1 | 0.97 | 1 | 0.99 | 0.84 | 97.13 | 0.00 |
| | DT2 | 0.58 | 0.05 | 0.09 | 0.62 | 62.86 | 0.97 |
| | DT3 | 0.57 | 0.86 | 0.86 | 0.85 | 79.94 | 0.64 |
| | DT4 | 0.68 | 0.58 | 0.62 | 0.70 | 65.63 | 0.73 |
| | DT5 | 0.99 | 0.86 | 0.92 | 0.80 | 85.61 | 0.62 |
| Artificial N Network | DT1 | 0.97 | 1 | 0.99 | 0.84 | 97.15 | 0.04 |
| | DT2 | 0.59 | 0.40 | 0.48 | 0.65 | 62.86 | 0.80 |
| | DT3 | 0.89 | 0.85 | 0.87 | 0.87 | 86.68 | 0.69 |
| | DT4 | 0.68 | 0.58 | 0.62 | 0.70 | 0.70 | 0.75 |
| | DT5 | 0.99 | 0.84 | 0.91 | 0.79 | 83.26 | 0.65 |

Table 2. Performances measures of our classifiers over all datasets

than those who are not or the opposite is true. Furthermore, we note that on the DT2 and DT4 datasets all the algorithms present specificities and Sensivity that are significant and quite similar. Contrary to what is quoted a little above, on these datasets the algorithms are efficient on the prediction tasks of the two classes. Looking closely at the results in terms of precision, recall and F-measure we observe that the classifiers RF, LR, SVM and ANN generally outperform the others for each dataset. Indeed, for the dataset DT1, which contains observations on patients living in different regions of Senegal, these four classifiers have an accuracy of 99%, a recall greater than 92% and an F-measure greater than 95%. We note the same trend with the DT2 dataset which contains observations on patients living in the same area in Senegal. It can also be noted that RF, LR, SVM and ANN have better precision than the rapid diagnostic test carried out and systematically used in the majority of health structures in Senegal. This observation remains true with DT4 which is a perfectly balanced dataset. In conclusion, it is very difficult or even impossible for us to say definitively which algorithm is more efficient for the task of pre-

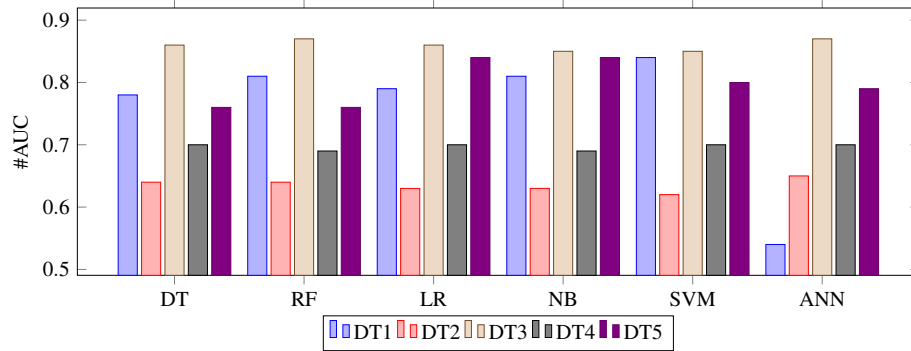
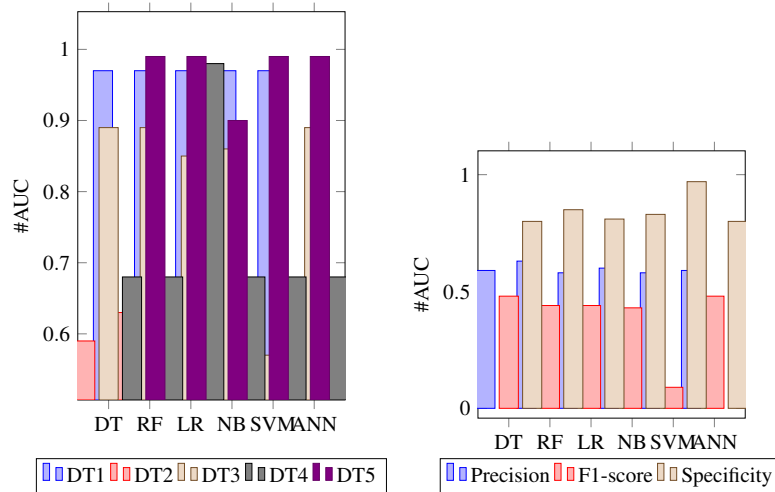


Figure 1. Comparison of the ROC Curves of the classifiers on different datasets

dicting malaria, but the choice of this one will strongly depend on the choice of the data set. However, this study shows that our classification problem has been taken care of. A method integrating several models and various datasets is necessary



(a) Precision values of compared classifiers on different datasets (b) Precision, F1-score, specificity values of the classifiers on DT1

4. Conclusion

In this study, six classifiers using a wide variety of operating procedures have been extensively tested and compared over real world health datasets in order to evaluate their performance for the task of predicting the occurrence or not of Malaria in a patient knowing his signs and symptoms. The results obtained show that the algorithms RF, LR, SVM with Gaussian kernel and ANN present the best performances in predicting the occurrence or not of Malaria. In addition those four algorithms outperform the Rapid Diagnosis Test which is the standard diagnostic tool largely adopted in the health system in

Senegal. This research has indicated that in practice there is no single best classification tool, but instead the best technique will on the characteristics of the dataset to be analysed. Future work consists in the study and the implementation of an ensemble method for predicting the occurrence or not of malaria based on the classifiers offering the best performances in our present study. But also to compare these performances with the ensemble methods for their validation

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