

Towards an efficient Prediction Model of Malaria Cases in Senegal

Ousseynou Mbaye, Mouhamadou Lamine Ba

Université Alioune Diop de Bambey, Bambey, Senegal
{ousseynou.mbaye,mouhamadouamine.ba}@uadb.edu.sn

Abstract. One of the most deadly disease in the world, Malaria remains a real flail in Sub-saharan Africa in particular. In countries like Senegal, such a situation is acute due to the lack of high quality healthcare services and well-formed staffs able to perform accurate diagnosis of diseases that patients suffer from. This calls for the need of finding automated tools to help medical actors in their decision making process. In this paper, we present first steps towards an efficient way to automatically diagnosis Malaria occurrence or not based on patient signs and symptoms, and the outcome from the quick diagnosis test. Our prediction approach is built on the logistic regression function. First experiments on a real world patient dataset, as well as a semi-synthetic dataset, show promising performance results regarding the effectiveness of the proposed approach.

Keywords: Malaria · Diagnosis · Data imputation · Prediction Model.

1 Introduction

Malaria is one amongst the most deadly disease in the world, especially in sub-saharan Africa countries such as Senegal. Malaria is caused by parasitic single-celled microorganisms belonging to the Plasmodium group; it is an infectious disease which is transmitted to human being through bites from infected female Anopheles mosquitoes. Someone who suffers from Malaria may present symptoms that typically include fever, tiredness, vomiting, and headaches. In its severe form, the disease can cause yellow skin, seizures, coma or death.

Studied problem and motivations. According to the last report [15] about the propagation of Malaria disease around the world, published in November 2017 by the World international Health Organization (WHO in short), 216 millions of cases have been reported in 2016. As a result, the number of cases has significantly increased when compared to the 211 millions of reported Malaria patients in 2016. As for the number of death due to Malaria, it does not decrease between 2016 and 2017 (446.000 vs. 445.000) despite the huge effort made by governments and non-governmental organization to improve healthcare services and the awareness strategies, especially in critical areas. When analyzing the statistics above in details, one can easily notice that the burden of the Africa region of the World international Health Organization is colossal. Indeed, 90% of Malaria

cases and 90% of deaths due to the disease were located in this area in 2016. More specifically, 80% of the burden in terms of morbidity is distributed in fifteen countries, all located in Sub-saharan Africa except India. This demonstrates that Malaria is a real flail in Sub-saharan Africa states and Senegal is not spared at all. We investigate in this study an efficient approach to predict, using machine learning, the occurrence or not of Malaria when a patient has to be diagnosed. Given the patient signs and symptoms, as well as the result from the quick diagnosis test, our solution should be to automatically tell if she suffers from Malaria or not with a high accuracy.

Malaria is an acute problem in Senegal due mainly to the lack of high quality healthcare services and well-formed staffs able to perform accurate diagnosis of diseases that patients suffer from. Over the past years, the government with the help of international organizations have tried to eradicate Malaria by implementing various proactive and reactive solutions to fill the gap in terms of services and human resources. However, the mortality rate is still very high, e.g. in underserved areas, areas without required healthcare needs, uneducated people, population with low income, etc. Most of these deaths cases are reported to be caused by inaccurate diagnosis, sometimes incomplete leading to a bad prediction of the exact type of Malaria. On the other hand, Malaria occurrence or complication can often occur during popular events (for instance religious events) which group thousands of persons from everywhere in the country during a short time period. During those popular events, non-permanent medical points are set in order to assist and treat ill persons; the staff in a given health point can consist sometimes of only volunteers with no medical skills. Every medical point can have to receive hundreds of patients each day with some of them potentially suffering from Malaria. This appeals for the need of finding automated tools to help medical actors in their decision making process, and thereby to improve provided healthcare services.

Proposed diagnosis approach. In this paper we present first steps towards an efficient manner to automatically diagnosis Malaria occurrence or not based on patient signs and symptoms, and the outcome from the quick diagnosis test. We define our diagnosis task as a classical binary classification problem by considering two classes: “Malaria” and “not-Malaria”. Given a patient data, our main goal is to properly find to which class the patient belongs. To solve this classification problem we rely on machine learning and use the logistic regression function as the basis of our prediction approach. Machine learning has been largely used in several domains (e.g. Health Informatics [5]) for various purposes whereas logistic regression has demonstrated its efficiency when dealing with a binary classification problem.

As an application scenario, we focus on predicting Malaria cases in Senegal. At this end, we use a large volume of patient record dataset collected during the most popular religious event in Senegal from the different installed health points, namely more than twenty points that deadly receive hundreds of patients. As an immediate result of this work, we introduce a data preparation pipeline in order to (i) explore the dataset for profiling purpose; (ii) only retain records

related to Malaria; (iii) clean and transform attributes, as well data values, into the extracted Malaria dataset; and (iv) impute missing values (there were lot of missing values in the collected health dataset as reported in Section3). Such a data preparation pipeline has been realized using *OpenRefine* (formerly Google Refine) to perform various cleaning and profiling tasks on our raw atient dataset and *missForest*, a robust algorithm for imputing missing data of diverser types; see Section3 for more details. Expermients on the real world patient dataset, augmenting with a semi-synthetic dataset, show promising performance results regarding the effectiveness of the proposed approach.

Paper organization. The remaining of the paper is organized as follows. We summarize the related work on data imputation and binary classification methods in Section 2. In Section 3 we introduce a data preparation pipeline on the raw collected patient records for the prediction phase. We then present our prediction model for Malaria cases in Section 4. Experiments and performance analysis on the collected real-world dataset, as well as a semi-synthetic dataset, are detailed in Section 5 before we conclude in Section 6.

2 Related work

In this section, we summarize the sate-of-the-art research on Malaria in general, and in particular the use of machine learning techniques to tackle the various aspects related to one of the major healthcare problems worldwide which is Malaria.

As it is well-known, Malaria is caused by the bite of the female Anopheles, the most dangerous of which is *Plasmodium falciparum*. Many early works have been consequently focused on the study of the evolution and the distribution of the responsible mosquito, mainly with the goal to detect or diagnosis the severity of the disease given an infected patient [7,3]. Recent research on Malaria have largely adopted machine learning and showed its ability to solve various aspects of the disease. Most of these machine learning based techniques are based on the analysis of blood data obtained from high-definition microscopic screenshots as in [8]. The authors in [8] propose an unsupervised learning algorithm that detects and determines the types of infected blood cells. Used prediction approach consists of quantifying the amount of plasmodium parasites in a blood smear. In the same research intuition of harnessing blood, the Jordan-Elman neural network classifier introduced in [4], on the other hand, to quickly determine the occurrence of Malaria and its severity level as well: the neural network analyzes the features of the blood data of the patients. Still using ML, DIAZ et al. have proposed in [6] a semi-supervised algorithm enable to quantify and classify the erythrocytes infected by Malaria parasistes through microscopic images. The orginality of this work comes from its usability even in the presence of thin blood drandruff infected by falciparum *Plasmodium* for the quantification and the classification tasks. Besides blood data, sign and symptom records were also used to study Malaria with ML methods. Indeed, decision trees based

approach has been proposed in Nigeria [14] to predict the occurrence of Malaria given diagnostic data. However a decision tree suffers from various limitations as a classifier. Indeed it can easily overfit or can be extremely sensitive to small perturbations in data for instance. Even though we both rely on signs and symptoms, the prediction model in [14] differs from ours on numerous facets: our model is built upon logistic regression and is trained using also inputs from the quick diagnosis test. In addition, we apply our method in the context of patients living in Senegal.

In [10], Pranav et al. propose Malaria likelihood prediction model built on a deep reinforcement learning (RL) agent. Such a RL predicts the probability of a patient testing positive for Malaria by asking question about their household. In their model the authors have also dealt with the problem of determining the right question to ask next as well as the length of the survey, dynamically.

3 Data Preparation

In this section, we detail the data preparation pipeline followed to obtain a proper Malaria dataset for the prediction phase. We start by presenting the used data cleaning and normalization techniques.

3.1 Data cleaning and normalization

In order to set up an efficient prediction model for Malaria cases in Senegal, we have relied on a real-world patient dataset for validation purposes. The dataset has been extracted by more than twelve health points during one of the biggest popular religious event in Senegal. Each of these health points dairly receives hundreds of patients, some of them suffering from Malaria.

In detail, the dataset consists of thousands of patient records having each 16 attributes. Some of these attributes (also knwon as features) comprise personal data about the patient, but also patient signs and symptoms reported by the doctor who took in charge the patient. The other attributes describe clinical data such as information about the final diagnosis of the doctor (the disease that the patient suffers from), the income of the quick diagnosis test, and the status (i.e. admission, dead or put under observation) of the patient. For privacy concerns and some restrictions in data use, we have disregarded personal data about the patient during this work. Due to the fact that patient records have been collected manually in registers, we have noticed many inconsistencies such as misspellings, same attribute values with different writings (e.g., “DIARRHEE INFECTIEUSE” and “INFECTIEUSE DIARRHE”), and multi-valued attributes (e.g. sign and symptom reported values). We use OpenRefine [9,1] to first clean and then normalize values in the patient dataset.

OpenRefine (formerly called Google Refine) is a powerful open source tool that allows researchers or scientists to accomplish the data wrangling activity, i.e. working with messy data: cleaning it; transforming it from one format into another; and extending it with Web services and external data. We used the following methods provided by OpenRefine to pre-treat our raw dataset.

- **Text filter function:** text filter enables to expore attribute values, clean them, and to identify those that may have many variants.
- **Transform functions:** OpenRefine provides two different Transform functions: preset transformations for resolving trivial formatting issues like trimming whitespaces and advanced transformations based on the OpenRefine Expression Language (GREL) to normalize data in batch or split them. This second class of transformations is very useful, especially when the number of piece of data values to normalize is very important (doing the same task manually would be time-consuming and prone to errors). For instance, GREL allows to use a simple regular expression all variants of a symptom in the Symptom column.
- **Cluster and edit function:** Clustering option in OpenRefine also provides users with methods to merge and normalize variations across the dataset. The power of clustering is that it is able to automatically detect small data variations which follow a certain pattern.

As for the special case of multi-valued attributes such as symptom and diagnosis columns in our raw dataset, we splitted them into multiple values in distinct columns. Indeed, in the raw dataset information like the symptoms a given patient suffer from were stored in a single column, separated with the special character '+', e.g. "DOULEUR ARTICULAIRE" + "DOULEUR PELVIENNE" + "VOMISSEMENTS".

After this step of data cleaning and normalization, we have proceeded to the extraction of Malaria features.

3.2 Extraction of Malaria features

To properly study Malaria, one needs to have a patient dataset with the main features of the disease. Unfortunately, some of these Malaria features were not explicitly specified in our raw dataset. As a result, we have inferred twelve new attributes that better describe the signs and symptoms of Malaria according to experts in the health domain. Those new attributes are : *lack of appetite*, *tiredness*, *fever*, *cephalalgia*, *nausea*, *arthralgia*, *digestive disorders*, *dizziness*, *chill*, *myalgia*, *diarrhea*, and *abdominal pain*. We have then added the new attributes in our dataset and transformed this latter accordingly by filling the value of each new attribute based on the list of reported signs and symptoms for every patient.

A medical diagnostic is the results the analysis of the reported signs and symptoms; in general such a diagnostic is further confirmed by a medical test. Since our raw dataset does not contain only information about patients from Malaria, yielding to records with various diagnostics. For the purposes of our study, we replaced any diagnostic that is not Malaria by the class "Not-Malaria". At this step of our data preparaton pipeline, we came up with a patient dataset that contains required Malaria features. However, our Malaria was not yet complete and ready because of values missingness. As a last step, we have completed our dataset by using a robust data imputation approach.

3.3 Missing Data Imputation

As shown in Table 1, we observed many missing values in our dataset, affecting the majority of the data attributes. Such missing values should not be ignored as data completeness and quality are very important when dealing with a prediction problem; this could negatively impact the accuracy of our prediction and should be treated appropriately. One has to note that machine learning relies on complete dataset. The sources and types of missing values can be various [13]. In our context, missingness is *not completely random* and can be due to an incomplete knowledge of the patient data, the fact that the medical staff do not specify a attribute value when it is not observed, or a difficulty for the patients to properly describe some piece of information (e.g. related to the signs or symptoms of their diseases) at the diagnostic time. Since they might have a certain relationship between attribute values for the same patient, or even a correlation between patient records, we decide to solve our problem of missing values by using imputation algorithms instead of choosing arbitrary values or removing records with missing values.

Data imputation is often used in the machine learning field when dealing with missing information. Many algorithms have been proposed in the literature [11,13], depending on the nature of the missingness or the type of data. MissForest [12] has been proved to be efficient at the presence of various types (e.g. numerical data, string, categorical data, ect.) of data simultaneously as in our case. The algorithm missForest relies on Random Forest, a non-parametric prediction method that is able to deal with mixed-type data and allows for interactive and non-linear regression effects. Such a imputation algorithm aims at handling any type of input dataset by minimizing (when possible) assumption about the structural aspects of the data. Given an input dataset, missForest solves the missing data problem using an iterative imputation scheme by training a Random Forest on observed values in a first step, followed by predicting the missing values and then proceeding iteratively until convergence.

We have applied missForest on our Malaria patient dataset by using its open-source Python implementation [2]. We shall study and prove in Section 5 the accuracy of the prediction made by the algorithm with the help of the normalized root mean squared error metric.

Attribute name	#missing_values
Lack of appetite	21068
digestive disorders	21062
Loss of weight	21017
Arthragia	20940
Chill	20925
Nausea	20874
Myalgia	20870
Tiredness	20713
Diarrhea	20481
Vomit	20051
Abdominal pain	19770
Dizziness	19628
Fever	18245
Temperature	17636
Arterial pressure	16924
Cephalalgia	15370
Diagnostic	2875
Quick diagnostic test	76

Table 1. The number of missing values per attribute

4 Prediction Model

5 Experimentation and results

5.1 Experimentation setting

5.2 Performance measures

5.3 Analysis of the results

6 Conclusion

References

1. Openrefine. <http://openrefine.org/>, online; accessed 30 Octobery 2018
2. Python implementation of missforest. https://pypi.org/project/predictive_imputer/, online; accessed 31 October 2018
3. AS, A., AM, V., SH., K.: Malaria parasite development in the mosquito and infection of the mammalian host pp. 195–221 (2009)
4. Chiroma, H., Abdul-kareem, S., Ibrahim, U., Ahmad, I.G., Garba, A., Abubakar, A., Hamza, M.F., Herawan, T.: Malaria severity classification through jordan-elman neural network based on features extracted from thick blood smear. In: Neural Network World (2015)
5. Dua, S., Acharya, U.R., Dua, P.: Machine Learning in Healthcare Informatics. Springer Publishing Company, Incorporated (2013)

6. Daz, G., Gonzalez, F.A., Romero, E.: A semi-automatic method for quantification and classification of erythrocytes infected with malaria parasites in microscopic images. *Journal of Biomedical Informatics* **42**(2), 296 – 307 (2009)
7. Ferguson, H.M., Mackinnon, M.J., Chan, B.H., Read, A.F.: Mosquito mortality and the evolution of malaria virulence. *Evolution* **57**(12), 2792–2804 (2003)
8. Kunwar, S.: Malaria Detection Using Image Processing and Machine Learning. ArXiv e-prints (Jan 2018)
9. Kusumasari, T.F., Fitria: Data profiling for data quality improvement with open-refine. In: 2016 International Conference on Information Technology Systems and Innovation (ICITSI). pp. 1–6 (Oct 2016)
10. Rajpurkar, P., Polamreddi, V., Balakrishnan, A.: Malaria likelihood prediction by effectively surveying households using deep reinforcement learning. CoRR **abs/1711.09223** (2017), blue<http://arxiv.org/abs/1711.09223>
11. Silva, L.O., Zárate, L.E.: A brief review of the main approaches for treatment of missing data. *Intell. Data Anal.* **18**(6), 1177–1198 (Nov 2014)
12. Stekhoven, D.J., Bhlmann, P.: Missforest: non-parametric missing value imputation for mixed-type data. *Bioinformatics* **28**(1), 112–118 (2012)
13. Swalin, A.: How to handle missing data. <https://towardsdatascience.com/how-to-handle-missing-data-8646b18db0d4>, online; accessed 31 October 2018
14. Ugwu, C., Onyegbu, N.L., Obagbuwa, I.C.: The application of machine learning technique for malaria diagnosis. *Int. J. Green Comput.* **1**(1), 68–77 (Jan 2010)
15. WHO: World malaria report in 2017 (2017)