Medical Tool for Assisting Patients in Kazakhstan Polyclinics

Shahriar Shamiluulu
Department of Computer Science,
Faculty of Mathematics and
Natural Sciences,
Suleyman Demirel University,
Kaskelen, KAZAKHSTAN, 040900
shahriar.shamiluulu@sdu.edu.kz

Moussa Mahamat Boukar
Department of Computer Science,
Faculty of Natural and
Applied Sciences,
Nile University of Nigeria,
Abuja, NIGERIA, 900001
musa.muhammed@nileuniversity.edu.ng

Zulfiya Yussupova
Department of Computer Science,
Faculty of Mathematics and
Natural Sciences,
Suleyman Demirel University,
Kaskelen, KAZAKHSTAN, 040900
zulfiya.yussupova@is.sdu.edu.kz

***Abstract*—The healthcare system in developing countries facing many challenges due to factors such as lack of doctors, medical equipment, overwhelmed hospitals, and increased number of refugees. The World Health Organization annually announces reports related to patients per doctor ratios, and according to reports even in many developed countries, it is low. The aim of this work was to develop a medical tool that will try to solve various issues and help assist patients as well as doctors. The tool is based on two machine learning algorithms for disease diagnosis which are rule-based method and decision tree algorithm. The tool also has several useful functionalities that help patients with their conditions. Using scikit-learn framework we were able to develop and integrate algorithms inside the tool. During the benchmarking study, the implemented machine learning algorithms achieved the following performance: an accuracy of 75% for the rule-based classifier, and 89% for the ID3 decision tree classifier.**

Keywords—Clinical Decision Support Systems, Machine Learning Algorithms, Mobile Computing and Android Platform

I. Introduction

Presently, the use of machine learning and artificial intelligence (AI) has become widely accepted in medical applications. This is manifested by an increasing number of medical devices currently available on the market with embedded various AI algorithms [1, 2]. The reason is due to the ratio of patients per doctor, which is even in the developed countries is low, in other words, an insufficient number of doctors. For evidence we have provided ratios in Figure 1, 2017 report provided by World Health Organization (WHO), where it shows the doctor per patient ratios in various developed and developing countries. The country ratios are provided in descending order.

In addition, the overwhelming working conditions of doctors makes increase diagnostic in false positive and negative rates. The Federal Agency for Healthcare Research and Quality of U.S. in 2009 prepared a report where states that it's found that 28 percent of 583 diagnostic mistakes reported by doctors were life-threatening or had resulted in death or permanent disability; the surveys were conducted anonymously [3]. There were a lot of diagnostic mistakes and delays, which are believed to affect 10 to 20 percent of cases. Thus, such incidents in healthcare result in about 80,000 to 160,000 patients suffering permanent disabilities each year in the USA. This is also creating a negative pressure on doctors [4]. Logically such problems are higher in developing countries like Kazakhstan as compare to developed ones where there is an issue of much unqualified medical personnel that lack professional expertise due to the corruption in the education system. From the patients' side, there are also many issues like patients who experience different symptoms' and do not know whether to contact a doctor or stay at home. In order to tackle these issues, we have developed a medical mobile prototype application called (SYMPTOMUS) that assists patients as well as doctors in solving different problems related to health.

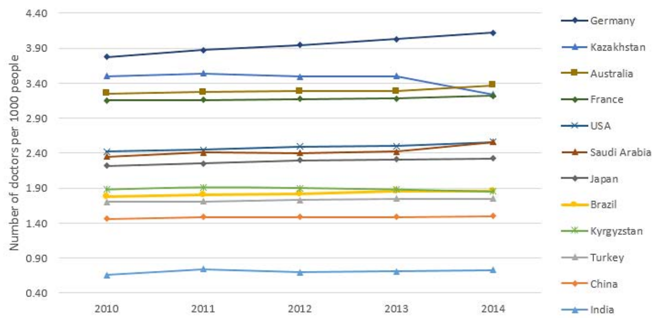


Fig. 1. Number of physicians per 1000 people in various countries (WHO Data repository, 2017)

Creating Clinical Decision Support Systems (CDSS) will help tackle several problems mentioned above and bring a lot of advantages listed below [5]. During the literature review, we have identified several studies that try to solve similar issues but using different approaches. These studies are using various machine learning algorithms such as; Regression models, Neural Networks, Support Vector Machines, and Kernels developed for other areas. The graduate at Stanford University Ron Gutman in 2011 developed a medical web-

978-1-5386-2501-9/17/$31.00 ©2017 IEEE

application called Healthtap™ which is intended to treat patients over the internet [6]. It can be accessed over different platforms and devices. Patients can be directly treated over the internet where he/she can communicate with the doctor. Another application that is called ISABEL™ is a web-based symptoms checker tool with embedded decision support component created by physicians in the USA in 2001. The tool is primarily designed for patients and covers major specialties like Internal medicine, Surgery, Gynecology & Obstetrics, Pediatrics, Geriatrics, Oncology, and Toxicology [7]. Also the big IT corporations like IBM investing in healthcare where they in collaboration with Cleveland Clinic and Pursuant Health Inc., developed an interactive medical station/kiosk called HealthKiosk™. The project developed under the governmental program of CHIP Obamacare scheme in the USA. There are many autonomous academic research projects that are being developed over the world. One of them is Neurologist expert system (NES), where researchers developed a medical diagnosis system for neurological disorders such as Alzheimer, Parkinson, Huntington's disease, cerebral palsy, meningitis, epilepsy, multiple sclerosis, stroke, cluster headache, and migraine. The system is assisting neurologist doctors and medical students, who are doing specialization and research in neurology and perform a preliminary diagnosis [8]. There are several research studies that use different rule-based and inductive machine learning algorithms like decision trees for disease diagnosis. The Fan et. al. developed a hybrid model by integrating a case-based data clustering method and a fuzzy decision tree for Breast Cancer Wisconsin and Liver datasets. The researchers achieved the average forecasting accuracy for breast cancer of 98.4% and for liver disorders 81.6% [9]. In order to get a grasp of an application side of decision tree algorithms in various fields, the authors present several case-studies where they use different rule-based and inductive methods for classification [10].

The goal of the tool is to solve the various issues and help assist patients as well as doctors. The SYMPTOMUS is based on two machine learning algorithms for disease diagnosis. The first method has a non-trivial rule-based logic which is based on nested conditions developed over disease and symptoms relations details are provided further in Section 3 of the paper. As a second method, we have used IDE3 decision tree classifier based on entropy homogeneity analysis. The tool has several modules and is under constant improvement. Currently, as a prototype version, the tool is being used by few patients and doctors in the governmental polyclinic.

II. Materials and Methods

The section contains the technical details information, which was used during the project development.

A. Data Collection

The medical data has been obtained from the No. 5th governmental polyclinic hospital which is located in Almaty city. It contains over 120 records and 22 symptomatic features and five disease groups. Generally, symptomatic features are represented as 0 or 1 which defines whether a patient has a particular symptom or not. The reason was to develop a simple prototype system which suggests patient which doctor he/she should see initially.

B. Machine Learning Methods

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations.

The classifiers used in the project are developed over Python 2.7.13 version and scikit-learn 0.18 platform.

i. Rule-based methods are intended to encompass any machine learning method that identifies, evolves 'rules' to process provided data [1, 2]. Such methods are considered the basic ones. The rules generally take the form of an IF-THEN conditional expressions, for example, *{IF 'symptom1 present' AND 'symptom2 present' THEN 'most probable disease'}*. The nested rules are easy to implement once problem range is known but can be complex to maintain due to the vastness of nested conditions. The other drawback of such methods is a low classification performance if there are not clear scope in analyzed features.

ii. Decision Trees (D-Tree) is a supervised learning method that is used for the classification purposes [1, 2]. The key point is to create a model that classifies the value of a target variable by learning simple decision rules inferred from the data features. D-trees are based on based on information theory paradigms like Entropy, Gini and Misclassification error in order to find best splitting feature. In this project, the ID3 method has been used based on entropy. The entropy equation is provided in Eq. 1 where it finds the overal information gain for all features in the dataset. Wherease information gain in Eq. 2, finds the gain for each feature.

$$E(S) = -\sum_{i=1}^{N} p_i \log_2 p_i \tag{1}$$

$$IG(S,A) = E(S) - \sum_{v \in Values(A)} \frac{|Sv|}{|S|} E(S) \tag{2}$$

This method has several advantages like being simple to understand and easy to interpret and also trees can be visualized and requires minor data preparation.

C. Mobile Development Platform

The SYMPTOMUS has been developed over Android Studio version 2.3 based on IntelliJ IDEA over Windows 7 OS. The Android Studio is an open source software stack created for a wide range of mobile applications based on Java programming language. It contains all needed components and tools to develop robust and full-featured mobile applications [11].

D. Performance Measures

Evaluation of the classifier to measure the quality is commonly evaluated using the data in the confusion matrix. Several standard measures have been defined for correct and incorrect classification results of the matrix. The most common practical measure to evaluate the performance is accuracy, which is defined as the proportion of the total number of instances that were classified correctly. Sensitivity is the mean proportion of actual positives which are correctly identified. Specificity is the mean proportion of negatives which are correctly identified. These performance metrics are calculated according to the data in the confusion matrix that are mentioned in [12].

III. IMPLEMENTATION, RESULTS AND DISCUSSIONS

A. Mobile Application Architecture

During the implementation of SYMPTOMUS, the Python and scikit-learn machine learning platform, as well as Android Studio, has been used for details refer Section 2. The SYMPTOMUS contains six modules i.e., disease information, symptoms checker, health news and suggestions, a reminder for medicins intake, body mass index (BMI) calculator, and pulse checker. The application's front-end part is developed explicitly in the Russian language, and this is due to the prevalence of the language in this area. The application supports only Russian language with all medical terms along. These functionalities in the application help patient to keep track and get a trusted suggestions on their condition. This is due to the reason that primarily it is going to be used in post-USSR countries. The interaction of modules and data flow is shown in Figure 2.

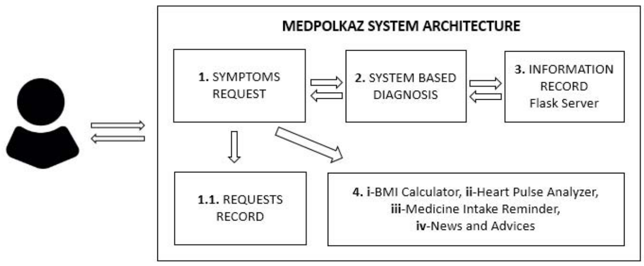


Fig. 2. Application activities diagram.

The main panel dashboard is presented in Figure 3 and symptoms checker is shown in Figure 4. The patient can select an option for diagnosis or look for the information about the condition, which is presented in dashboard main panel.

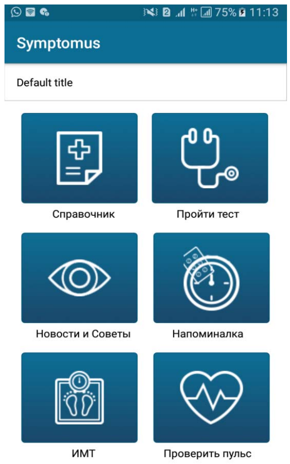


Fig. 3. Main application board

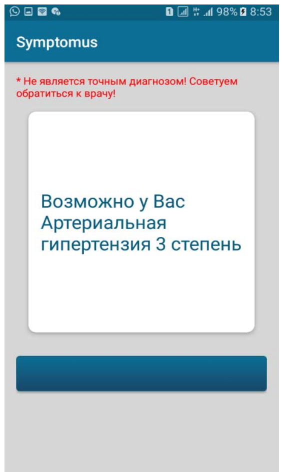


Fig. 4. Diagnosis result of symptoms checker

The diagnosis results that are based on symptoms is a type of system that checks the availability of the flu, hypertension, general heart problems and checks for type 1 diabetes by means of asking the patient various questions, see Figure 4.

The BMI is an important medical factor that checks the obesity condition of the person. This rate determines the ratio of body weight to height and to evaluate how they fit together. The application provides BMI calculator with simple and user-friendly design, where the user enters requested information and gets the particular results shown in Figure 5. Application automatically stores all needed information and uses it for the proper diagnosis and later use.

Fig. 5. Screenshot of BMI checker

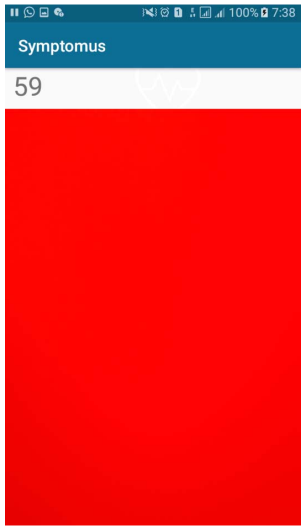
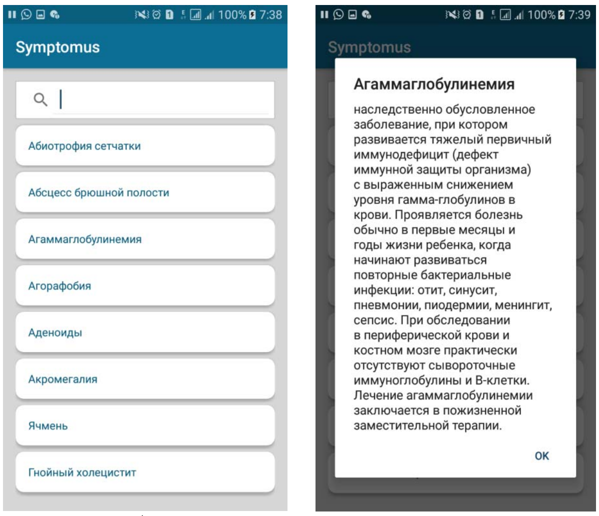


Fig. 6. Heart rate monitor and pulse checker

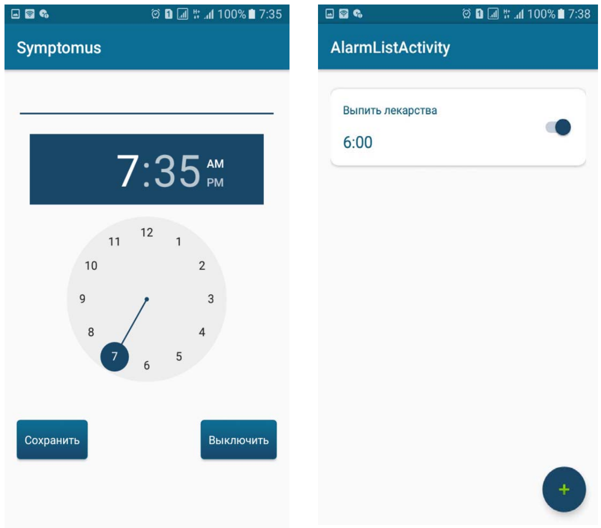
The tool also allows the user to check a heart rate by means of cell phone camera, shown in Figure 6. The detection is performed by using photoplethysmography (PPG) method. PPG is considered as a simple and low-cost optical technique that can be used to detect blood volume changes in the microvascular bed of the tissue. It is often used non-invasively to make measurements at the skin surface. The PPG method takes an image of a blood vessel and by using image processing techniques and computer vision analyzes the flow and color contrast of the blood and produces the result, for details refer [13]. Although the origins of the components of the PPG signal are not fully understood, it is generally accepted that they can provide valuable information about the cardiovascular system [13].

In Figure 7 (A and B), the informational module shows information about several diseases. By using this module patient can read and get latest updates about various diseases because generally medical terms are provided in Latin, which makes them difficult to understand. On more module which we believe will be useful, is medicine intake reminder shown in Figure 8, where patients' can set intake time of their different medicines, and get reminders on time.



A. B.

Fig. 7. Information and news module



A. B.

Fig. 8. Medicine intake reminder

B. Process of training and testing classifiers

Models simulations performed over scikit-learn ml framework for two machine learning algorithms explained in Section 2 over the medical dataset. The after a proper training the classifiers, we stored a trained version of them as an object in a file i.e., a process called pickling. For both methods 10-kfold cross-validation method has been used, and overall percentages are calculated. Such approach was more convenient and efficient because the pickled classifiers can be integrated into the mobile application and sending data in terms of requests-and-responses for classification can be performed over JSON object.

The confusion matrices and performance metrics scores are provided in Table 1 and 2 respectively. We can see that ID3(decision tree) outperforms in all metrics the rule-based method. Rule-based methods are relatively easy to implement but prone to overfitting due to the reason that diagnosis conditions become complex and difficult to maintain. According to the result, the method is good in identifying people without the disease. In overall, the rule-based method has satisfactory results and can be used for diagnosis of non-trivial diseases.

TABLE I. THE CONFUSION MATRICES OF THE CLASSIFIERS

Actual Value	**Expected Value** *Positive*	*Negative*
Positive	TP : (29 - 35)	FN : (17 - 8)
Negative	FP : (12 - 5)	TN : (62 - 72)

Coming to decision tree method, as can be seen from results, it has achieved the average accuracy of the diagnosis process by 90%, and in general, it also can better detect patients without disease. During the preliminary studies, we have used a hold-out method in order to train and test classifiers, because the primary goal of this research study was to develop a working prototype medical tool. In general, the decision trees can be used in the diagnosis of complex diseases if the right parameters for the method are found and set.

TABLE II. PERFORMANCE METRICS OF CLASSIFIERS

Classifiers	Accuracy (%)	Sensitivity (%)	Specificity (%)
Rule-based	75.83	70.73	78.48
Decision tree	89.16	81.39	93.51

IV. CONCLUSIONS

The healthcare system worldwide facing many challenges due to various factors. The goal of this work was to develop a medical tool that tries to solve various issues and help assist patients as well as doctors. The tool is based on two machine learning algorithms for disease diagnosis which is the rule-based method and decision tree algorithm. The tool contains several modules like symptoms checker, disease information, health news and suggestions, a reminder for medicine intake, body mass index (BMI) calculator, and pulse checker that helps patients with their conditions. Over the scikit-learn framework, we were able to develop and integrate algorithms inside the medical tool. During the benchmarking study, the implemented machine learning algorithms achieved the following performance: an accuracy of 75% for the rule-based classifier, and 89% for ID3 decision tree classifier.

REFERENCES

[1] Stuart J. Russell, Peter Norvig. "Artificial Intelligence: A Modern Approach" 2nd ed. New Jersey: Pearson Education, Inc., pp. 733–59, 2003.

[2] Peter Harrington. "Machine learning in action". Vol. 5. Greenwich, CT: Manning, 2012.

[3] Gordon Schiff, Omar Hasan, Seijeoung Kim, Richard Abrams, et al. "Diagnostic error in medicine: analysis of 583 physician-reported errors", Archives of internal medicine. Vol. 169, 20, pp. 1881-1887, 2009.

[4] Mark Graber, Robert Wachter, et al. "Bringing diagnosis into the quality and safety equations", Jama. Vol. 308, 12, pp. 1211-1212, 2012.

[5] Amit Garg, Neill KJ Adhikari, Heather McDonald, M Patricia Rosas-Arellano, et al. "Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: a systematic review", Jama. Vol. 293, 10, pp. 1223-1238, 2005.

[6] Regina Sinsky. "HealthTap's Social Network of 5,000 Doctors Is Ready to Give Free Advice The New York Times." New York, USA, 2011.

[7] Padmanabhan Ramnarayan, Amanda Tomlinson, Gautam Kulkarni, Anupama Rao, and Joseph Britto. "A novel diagnostic aid (ISABEL): development and preliminary evaluation of clinical performance", Medinfo. Vol. 11, 2, pp. 1091-1095, 2004.

[8] Ahmad Al-Hajji. "Rule-Based Expert System for Diagnosis and Symptom of Neurological Disorders - Neurologist Expert System (NES)", Proceedings of the 1st Taibah University International Conference on Computing and Information Technology, Al-Madinah Al-Munawwarah, Saudi Arabia, pp. 12-14, 2012.

[9] Chin-Yuan Fan, et al. "A hybrid model combining case-based reasoning and fuzzy decision tree for medical data classification." Applied Soft Computing 11.1, 632-644, 2011.

[10] Lior Rokach, and Maimon Oded. "Data mining with decision trees: theory and applications." World scientific, 2014.

[11] Belén Cruz Zapata. "Android studio application development." Packt Publishing Inc., 2013.

[12] Kadir Tufan. "Noninvasive diagnosis of atherosclerosis by using empirical mode decom-position, singular spectral analysis, and support vector machines." Biomedical Research, vol. 24, pp. 303-313, 2013.

[13] Denis Laure, and Ilya Paramonov. "Improved algorithm for heart rate measurement using mobile phone camera." In Proceedings of the 13th Conference of Open Innovations Association Fruct, pp. 85-93. 2013.