Application of Machine Learning on the Diagnosis of 18 Common Pediatric Disease in Central African Republic

George Wu, Bin Li

Washington Institute of Health Sciences Georgetown University Medical Center

Corresponding author: George Wu, Bin Li, Email: whgeorgewu5@gmail.com, bl444@georgetown.edu

Artificial intelligence (AI) is widely used in the medical field to improve the professional level and efficiency of clinical work. In some developing countries, the shortage of qualified healthcare providers is one of the major causes of the unavailability and low quality of healthcare. Studies have shown that the application of AI improves healthcare in developing countries. This study is inspired to develop a diagnostic promoted system that is instrumental in addressing the problem of the Central African Republic, which, by a report, has the poorest healthcare access in the world. A simulated database containing 18 common pediatric diseases in the Central African Republic was used as training and testing dataset to compare the prompt diagnostic accuracy of three models of AI, including decision tree, random forest, and neural network model. The results indicate that given the dataset with laboratory data, the average accuracy of the decision tree model is 0.971, the random forest model is 0.977, and the neural network model is 0.969. In the dataset without laboratory data, the average accuracy of the decision tree model is 0.971, the random forest model is 0.977, and the neural network model is 0.923. The results indicate that the prompt diagnostic accuracy of the three models is roughly similar, all higher than 0.9, the random forest model has the highest accuracy, and in the absence of laboratory data, a high accuracy rate of 0.977 was achieved. This study suggests that developing AI diagnostic prompt techniques may help improve the diagnostic level of medical workers in developing countries, especially in the absence of laboratory data, and may also achieve a satisfactory diagnostic accuracy.

Keywords:Machine Learning, Diagnostic Prompt, Pediatric Diseases, Central African Republic.

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1 Introduction

Artificial intelligence (AI) is an innovative and rapidly growing technology of computer science that aims to resolve problems that typically require human intelligence. Machine Learning is a popular subject under AI, and neural network, which is used in this project, is a mature, classical, and widely accepted model of Machine Learning. Nowadays, AI is widely used in the medical field to improve the professional level and efficiency of clinical work [1-3]. In developing countries, the shortage of qualified healthcare providers is one of the major causes of the unavailability and low quality of healthcare. Studies have shown that the application of AI improves healthcare in developing countries [4]. According to the findings of a large-scale study, many developing countries, such as the Central African Republic, have poor healthcare access and quality in the world [5]. To explore the possible applications of Machine Learning to improve the quality of healthcare in these countries, the project aims to develop an AI model that provides diagnostic prompts to help local medical workers deal with dozens of common, fatal diseases and disabilities in the Central African Republic, the nation with lowest healthcare and quality in the world [6]. In this project, three models of AI, including decision tree, random forest, and neural network model will be trained with a database for the selected diseases. It is expected that this preliminary study can provide a hint for future clinical research and AI system development.

2 Methods:

For this study, a mock database was obtained from Georgetown University that included approximately 5000 cases for the 18 pediatric diseases (1-14 year-old) that cause the most disability-adjusted life years in the Central African Republic [6]. The 18 common diseases are: Diarrheal diseases, Malaria, Lower respiratory infections, Tuberculosis, Protein-energy malnutrition, Measles, Meningitis, Dietary iron deficiency, HIV/AIDS, Invasive Non-typhoidal Salmonella, Sickle cell disorders, Asthma , Idiopathic epilepsy, Upper respiratory infections, Congenital heart anomalies, Vitamin A deficiency, Leukemia, and Visceral leishmaniasis. There were 118 clinical manifestations and laboratory examinations. The clinical data (symptoms and laboratory data) and diagnosis were labeled in Microsoft Excel. For diagnosis, zero represents a case not being diagnosed as a certain disease, and 1 represents a case being diagnosed as a certain disease. For symptoms and laboratory data were normalized from zero to one except age (years) and duration of illness (days). The Excel documents were saved as CSV files.

VScode (https://code.visualstudio.com/) was used as a code editor. Tensorflow (https://www.tensorflow.org/) provides the neural network model. The same number of neurons as the input attributes (symptoms and laboratory data) was assigned to the first layer and 20-50 neurons in the second layer. The output layer is composed of two neurons, representing whether a case is diagnosed as a certain disease or not. ReLU was used as the activation function, sparse categorical cross-entropy was used as the loss function, and Adam was used as optimization function.

Sklearn (https://scikit-learn.org/stable/) provides decision tree and random forest classification models. A decision tree was constructed with 5-10 nodes as the maximum depth of the tree. A random forest model was constructed with 100-1000 estimators and a maximum depth of 5-10 nodes.

For each disease dataset, the data was shuffled and split into training and test sets. The training set contains 80% of the data in the dataset, and the test set contains 20% of the data in the dataset. Repeat 20 times to create 20 train-test sets. Neural networks, decision trees, and random forest models were applied on the above 20 test sets, and the accuracy of the diagnostic prompt for each disease was recorded for each trial. Calculate the average accuracy for each model. Student t-test was used to compare the significance of the prediction accuracy between the three models. The flow chart is shown in Figure 1.

3 Results

The results show that for the disease datasets without laboratory data, the average diagnostic prompt accuracy of the decision tree is 0.971, random forest is 0.977, and neural network is 0.923. For the disease datasets with laboratory data, the average diagnostic prompt accuracy of the decision tree is 0.971, random forest is 0.976, and neural network is 0.969 (Figure 2.).
Statistical analysis shows that the average accuracy of decision tree and random forest model is significantly higher than that of neural network for the disease datasets without laboratory data ($p<0.01$), and the random forest model is significantly better than decision tree ($p<0.01$). For the disease datasets with laboratory data, the accuracy of the random forest model is significantly higher than that of decision tree and neural network ($p<0.01$), and there is no significant difference between decision tree and neural network. Statistically comparing the differences with and without laboratory data, only the neural network has significant differences ($p<0.01$).

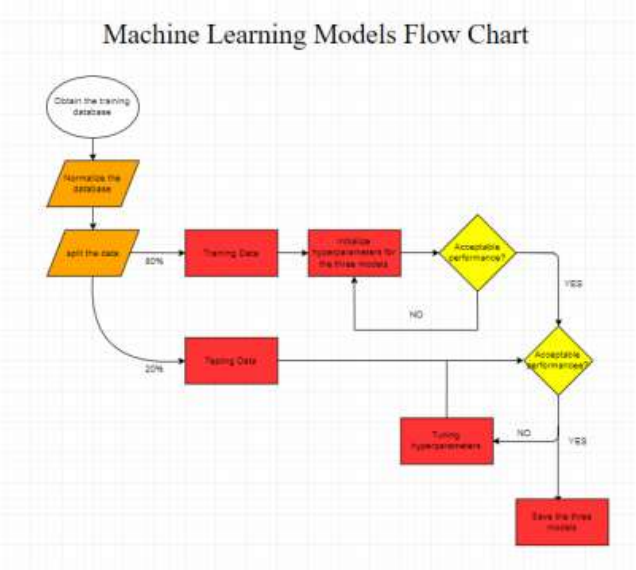

Figure 1. Machine learning models flow chart.

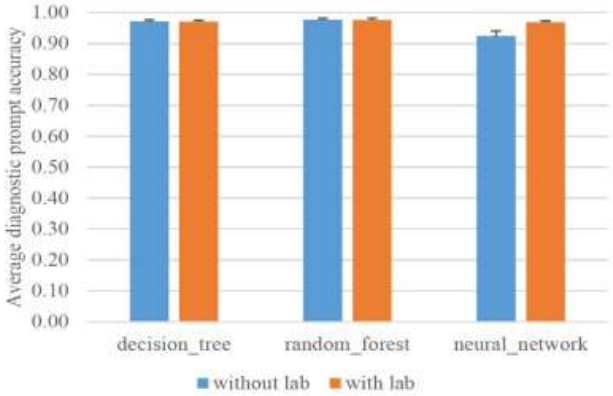

Figure 2. Comparison of the average diagnostic prompt accuracy of three machine learning models based on the simulated datasets (with or without laboratory data) of 18 common pediatric diseases in the Central African Republic.

4 Discussion

The infrastructure of information technology is gradually spreading in many low- and middle-income countries. AI has already begun to be implemented in addressing health problems in these countries. There are four major health problems currently using machine learning techniques: (1) diagnosis, (2) patient morbidity or mortality risk assessment, (3) disease outbreak prediction and monitoring, and (4) health policy and planning. There is a general consensus in the industry that, although the field is still in its infancy, AI-driven medical developments may improve health outcomes in low- and middle-income countries [7]. Another study suggests that AI research for primary care is also in the early stages and requires more research investment [8].

Based on the training and testing results of the three AI models on a simulation clinical data set of 18 common diseases in the Central African Republic, although the prompt diagnostic accuracy of the three models is roughly similar, all higher than 0.9, the random forest model has the highest accuracy, and in the absence of laboratory data, a high accuracy rate of 0.977 was achieved. This study suggests that developing AI diagnostic prompt techniques may help improve the diagnostic level of medical workers in developing countries, especially in the absence of laboratory data, and may also achieve a satisfactory diagnostic accuracy.

This study provides a clue for the development of an artificial intelligence diagnostic prompt system dedicated to areas with limited medical resources. For further research of this project, the World Health Organization, local governments or other medical institutions need to collect clinical data in these areas with poor medical resources, train a diagnostic model that is more in line with the actual situation, and develop suitable applications.

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