TẠP CHÍ KHOA HỌC VÀ CÔNG NGHỆ NĂNG LƯỢNG - TRƯỜNG ĐẠI HỌC ĐIỆN LỰC
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NON-DETERMINISTIC FINITE AUTOMATA FOR THE NON-CONTACT MEDICAL EXAMINATION SYSTEM ACCORDING TO CLINICAL SYMPTOMS

ỨNG DỤNG OTOMAT HỮU HẠN CHO HỆ THỐNG Y TẾ KHÁM BỆNH KHÔNG TIẾP XÚC DỰA TRÊN TRIỆU CHỨNG LÂM SÀNG

Nguyen Huy Cong[1], Vu Xuan Manh[1*], Nguyen Hai Binh[2*], Nguyen Thi Thuy[3], Nguyen Huy Khan[1], Tran Van Hiep[1], Vu Minh Thoai[1], Le Hong Minh[1], Doan Hong Quang[1], Vu Ban[1]

[1]Center for Technological Progress, Ministry of Science and Technology
[2]Institute of Materials Science, Vietnam Academy of Science and Technology
[3]Electric Power University

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Abstract:

An engine was developed based on the mathematical model of Non-Deterministic Finite Automata (NFA) to classify non-contact medical examinations according to patients' clinical symptoms. The input data used to build the engine consists of a collection of patients' clinical symptoms, hospital examination streams, and a set of rules for classifying medical examinations based on clinical symptoms. The engine was trained using a dataset collected from the medical records of patients with different clinical symptoms from a central hospital, a district general hospital, and a provincial medical center, totaling approximately 50,000 registrations. This engine has been integrated into the "Contactless Patient Streaming and Examination Registration System" to streamline medical examinations during the Covid-19 pandemic in central and local hospitals. The system enables patients to register, queue online, and be automatically streamed based on the clinical symptoms declared by the patients. The mathematical model used to build the engine was studied, tested, analyzed, evaluated, and compared with other mathematical models. Comprehensive analysis results demonstrate that NFA is the most suitable model for engine development. After integrating the engine into the system, it was tested on a dataset that randomly selected values 100 times from the set of symptoms in the patient medical record database. The result yielded an accuracy of approximately 80.5%.

Keywords:

Machine learning, engine training, patient classification, Non-deterministic finite automata (NFA), clinical symptoms.

Tóm tắt:

Một engine được xây dựng dựa trên mô hình toán học của otomat hữu hạn không đơn định (NFA) để phân luồng khám bệnh không tiếp xúc theo triệu chứng lâm sàng (sau đây gọi là "triệu chứng"). Trong đó, dữ liệu đầu vào để xây dựng engine là tập hợp các triệu chứng lâm sàng của người bệnh; tập hợp các luồng khám bệnh của bệnh viện và bộ quy tắc phân luồng khám bệnh theo triệu chứng lâm sàng. Engine được huấn luyện bằng bộ dữ liệu thu thập được từ hồ sơ đăng ký khám bệnh của bệnh nhân với các triệu chứng lâm sàng khác nhau từ một bệnh viện tuyến trung ương, một bệnh viện đa khoa cấp tỉnh và một trung tâm y tế cấp huyện với tổng số lượt đăng ký khám xấp xỉ 50.000 lượt. Engine này đã được tích hợp vào "Hệ thống đăng ký khám và phân luồng bệnh nhân không tiếp xúc" để phân luồng khám bệnh trong mùa dịch Covid-19 tại một số bệnh viện tuyến trung ương và địa phương. Hệ thống này cho phép bệnh nhân đăng ký, xếp hàng trực tuyến (online) và được tự động phân luồng khám thông qua các triệu chứng lâm sàng mà bệnh nhân khai báo. Mô hình toán học để xây dựng engine cũng được nghiên cứu, thử nghiệm, phân tích và đánh giá với một số các mô hình toán học khác. Kết quả phân tích toàn diện cho thấy NFA là mô hình hợp lý nhất cho việc phát triển engine. Hệ thống sau khi tích hợp với engine được thử nghiệm với bộ dữ liệu lấy ngẫu nhiên 100 lần từ tập hợp các triệu chứng trong kho hồ sơ bệnh nhân. Kết quả cho ra trùng khớp 80,5%.

Từ khóa:

Học máy, huấn luyện máy, phân luồng bệnh nhân, NFA, triệu chứng lâm sàng.

1. INTRODUCTION

The bottle-neck effect occurring while there is a long line of queueing patients waiting to register for hospital admission has been one of toughest challenges to recipient departments on the daily operations especially in the hospitals in central and district level [1]. Lining in a long queue is stressful, time wasting and exhausting for both patients and their family members [2]. Moreover, Vietnam with tropical climate is the perfect environment for seasonal diseases which are easy to spread through the air or direct contact; thus, gathering a large number of people in a small space could lead to cross-contamination. As we have witnessed, during the pandemic COVID-19, the cross-contamination incidents happened in Bach Mai Hospital, K Tan Trieu Hospital, Da Nang Hospital and some other Hospital have created the greatest consequences for Vietnam nationality in general and put a deep scar on the Vietnam Healthcare System in particular [3]. On the other hand, the costly in human resources department and hospital facilities to receive patients puts financial pressure on lower-level hospitals. The overload that puts pressure on the reception department and also causes many inadequacies for them, which making the quality of patient services not high. According to the research team's survey, the overload and local congestion occurred at the place of receiving and classifying patients. Several scientific methods to predict and classify patients have been studied and published. In Hospital Admission, Neural Network has been applied in predicting triage of patients for the Emergency Department (ED) [4-6]. Multiple predict models created by authors using the data from the National Ambulatory Medical Care Survey (NHAMCS) from 2012-2013 emphasized on patient outcomes: being admission, transfer versus discharge home. Receiver operating curves (AUC) have been calculated to examine the accuracy of construct logistic regression (LR) and multiple layer neural network model (MLNN). The value of AUC is 0.824 (95% CI 0.818-0.830) for LR and is 0.823(95% CI 0.817-0.829) [4]. The back-propagation algorithm and algorithm optimization with computer-based model used to make accurate prediction based on the effect of atmospheric changes included pollutants. The result showed that on 7 days before the ED visit, the model was able to predict the test set with average errors of 12% [5]. LR, Deep neural network (DNN) applied in prediction models in medical seek, a total of 560,480 patient visits were recorded by authors. The value of AUC is 0.87 for LR (95% CI 0.86-0.87) and DNN is 0.87 (95% CI 0.87-0.88) [6].

Patient classification is considered as complex and requires flexibility [10, 11] because there is diversity in patient's health problems. Patients required to fill a survey or set of questionnaires is the approach that authors implemented to examine the accuracy of the designed models [7, 12].

By applying the advance of Neural Networks, some acute diseases could be detected such as lymphoblastic leukemia, hypertension, neurologic events from an early stage which is contributing in expanding the lifespan of patients [10-13]. Several health indexes, images could be analyzed to prevent diseases from occurring and give doctors better understanding about a patient's problem [14-16].

Privacy–preserving Medical Treatment System (P-Med) was designed using Nondeterministic Finite Automata (NFA) for remote medical environments with expert knowledge about treatment methods referred to different states in NFA [17].

In the scope of this research, an online medical registration system was integrated with an automatic patient classification engine based on the patient's symptoms. The engine was developed based on our collected data including patient medical records, expert knowledge and machine learning techniques. The system is designed with the main purpose of supporting the medical staffs and the patients at district and provincial level hospitals (where expert knowledge is limited) in the process of medical examination registration and patient classification.

2. THEORETICAL BASIC AND DESIGN PRINCIPLE

The scientific element of the problem is an engine that automatically classifies patients according to the patient's clinical symptoms. This engine requires to be designed to accommodate the ability to acquire expert knowledge through machine learning from medical records or independent experts (data structure issues) and the output patient classification results in the fastest and most accurate way (algorithm problem). In this study, three mathematical models (Binary Search, Hashing Table and Non deterministic finite automata) on data structures and algorithms are studied, tested, analyzed and evaluated to choose the most compatible model for the data structure which is the goal of the given problem. The data structure should be designed to store the patient's set of clinical symptoms, the set of hospital examination streams (specialist clinic), and the set of Classification Rule that map a set of clinical symptoms to one or multiple examination streams.

The first two mathematical models studied and designed, Binary Search and Hashing Table, are described below:

Binary Search is one of the most notable search algorithm that finds the target value in the sorted array [18]. Binary Search has other names as logarithmic search, half interval search [19]. Binary Search stores all the data into one array and compares the target value to the middle value of the array. The algorithm divides into two equal parts and checks the part that target value belongs to and then eliminates the part that does not contain the target value; with the selected part algorithm continuing to perform taking the middle value of part and comparing it to the target value until the position of the target value in the array is found. But the drawback of this method is that there is a probability that the target value is not in the array.

A hashing table is a data structure that stores data in a connective manner. Inside a hash table, data is stored in an array and each data value has its own identical index value [20]. Hash technique or Hashing is a technique to create an index which indicates the location that element is going to be inserted or is to be originated from [21]. Hashing could be defined as a technique or process that uses the hash function to map the keys and values into a Hashing table.

Each symptom denoted by one unique Boolean value (yes or no) is the strict rule to apply Hashing table and Binary Search models. Classification rule is mapping one collection of symptoms to one patient’s stream (hospital departments). Based on one collection of symptoms (patient’s data collected from symptom declaration), Hashing table or Binary Search models map that to the suitable hospital departments. According to those rules, each symptom denoted by positive integer and is the power of 2. The main idea of this rule is to assure that the sum of collections of the same symptoms is unique and not repeatable. Example for this algorithm is demonstrated in Figure 1.

The next model studied and designed was called Non deterministic finite automata (NFA). In automata principles, a finite-state machine is known as deterministic finite automata (DFA); it states that all transitions are unique and defined by its own source states, input symbols; the step of reading input symbols is mandatory for each state of transitions. On the other hand, an NFA or nondeterministic finite-state machine does not need to comply with these restrictions. In particular, NFA can be translated to DFA but every NFA is Non DFA. The NFA was first announced by Micheal et. al. in 1959 [22]. NFAs are used in the implementation of regular expressions and easy to construct compared to DFA.

There are 5 tuples in NFA (M = (Q, Σ, δ, q0, F)) where as,

Q: Finite set of states

Σ: Finite set of the input symbols

q0: Initial state

F: Final state

δ: Transition function: Q X Σ -> 2^Q

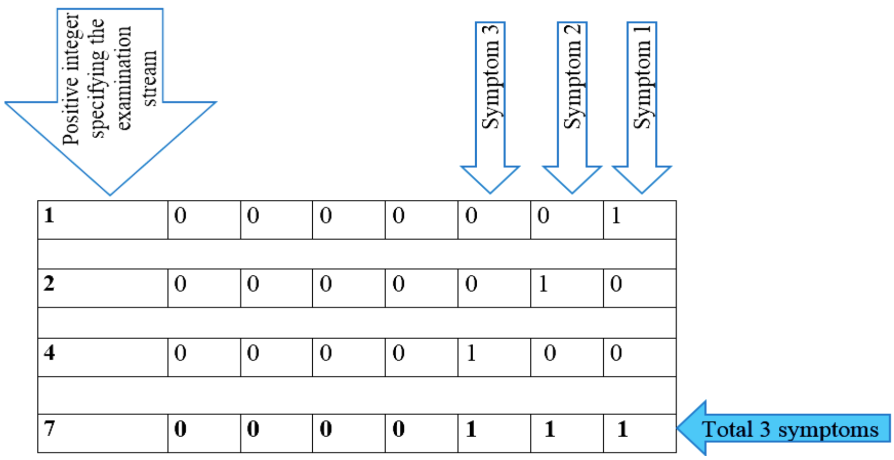

Figure 1. Example for 3 clinical symptoms with positive integers corresponding is 1, 2 and 4

Note:

- Yes symptoms - 1

- No symptoms - 0

An NFA can be represented by digraphs called state diagrams. While creating NFA graphically the following factors are considered:

- The state is represented by vertices;
- The transitions are represented by arc and labeled on top the input character;
- The initial state is tagged with an arrow symbol;
- The final state is represented by the double circle.

Figure 2 is an example of an NFA represented as a state graph.

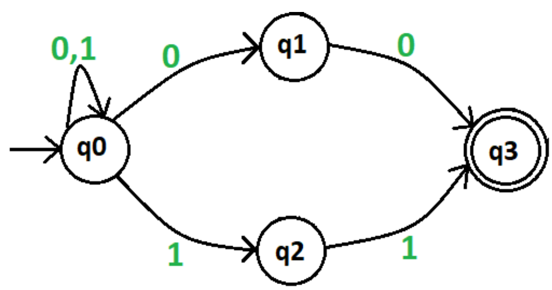

Figure 2. A Non-Deterministic Finite Automata has 4 states and a set of input values of {0,1}

In the diagram of Figure 2, the input state set includes symbols 0 and 1. From state q0 can lead to states q2 and q1 so this is a non-deterministic Automat.

In this study, an NFA model is designed with the clinical symptoms denoted by the finite set of the input symbols (Σ), the hospital departments or clinics is the final state and Classification Rule is the transition function of NFA (δ). Considering one collection of symptoms, it could lead to more than one disease which means the value of hospital departments or clinics is non-deterministic. This situation is challenging while applying the Hashing table and Binary Search Model but it is completely handled by using NFA Model. The clinical symptoms of the NFA Model are more flexible compared to the Hashing table and Binary Search Model, it could accept arbitrary values of symptoms. When one Automata receives one collection of clinical symptoms and finishes in one or several states of finish, patients will be classified to corresponding departments/ clinics related to that final state. Automata are designed based on moving states which allow the system more flexibility and compatibility. In the NFA Model, the initial state is the collection of states and the final state is the hospital departments/clinics. The collection states have a connection with each other and represented by one arc, label of arc is one symptom. The Transaction function is the Classification Rule based on clinical symptoms. Here, clinical symptoms and examination streams are specified as a positive integer. The state transition function is designed in the form of a graph.

3. EXPERIMENTAL

3.1. System model design

For automatic threading using the proposed Engine, a medical examination registration system is designed as Figure 3.

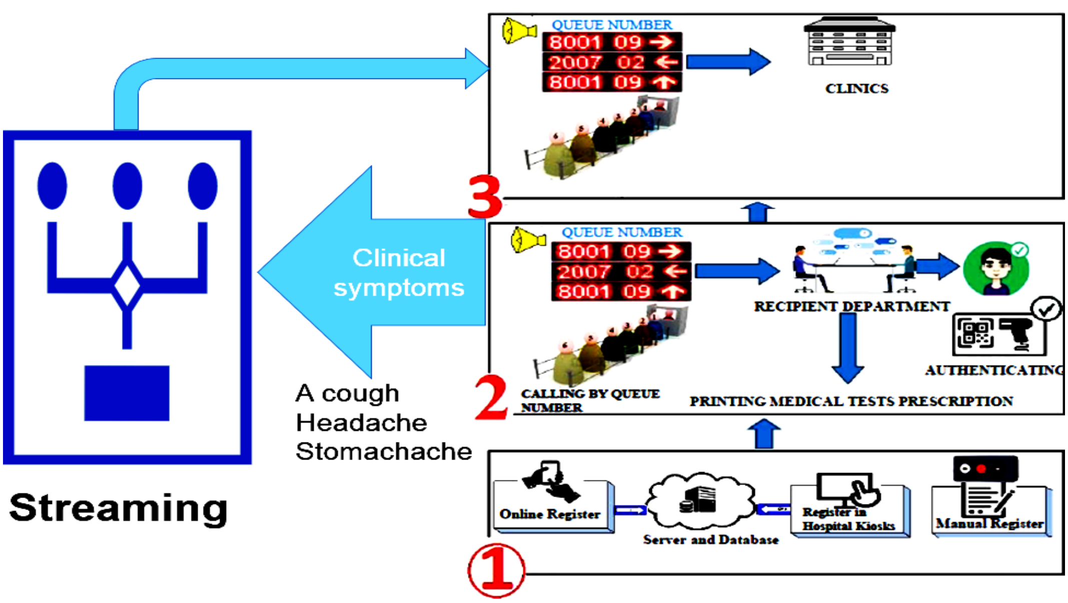

Figure 3. Diagram of non contact register and classify medical examination design

The diagram of system model design in Figure 1 marked 1 to 3 in order for the procedures and separated the entire system into three unique functional blocks:

- Registering medical examination for patients Block;
- Identifying, classifying medical examination to make hospital admission (automatic or through hospital's recipients) Block;
- Managing medical examination for hospital departments/ rooms sorted Block.

Principles of operation:

First of all, patients are required to register for medical examination by one of the following methods: offline or online. With an online method, patients could easily register anytime anywhere by using web browsers or any devices that connected to the Internet. Offline method is the way that patients register for medical examinations in the kiosks placed inside hospitals. Regardless of the method that patients choose, the given form requires the patient's basic information, symptoms. After completing the symptom declaration, patients are going to receive one identifier QR code or one unique ID involved their queue number and required medical examination. Patients could observe the queue number of corresponding departments or clinics and reserved time to change their time schedule to visit the hospital. Paying the registration payment fees are mandatory for patients before they go to the required department to do medical examinations. In recipient counters, the information of patients has been stored in the hospital database by our Automatic Classifying Engine and this Engine collects data from symptom declaration declared by patients and puts it in the hospital database and patients already assigned to corresponding departments/clinics to complete required medical examinations.

At last, all the information of a patient's admission is stored in the system's database and sorted by the registration time. Doctors are going to call patients depending on their registration time through the speakers placed outside of medical examination rooms. Moreover, our system allows multiple high priority patient's stream for special cases but it is dependent on hospital's regulation.

3.2. Implementation

Data structure and logic algorithm, Binary Search, Hashing table and Automata were installed and set up using C++ Language in Microsoft Studio.Net platform version 2019. Data structure was built for testing using multiple algorithms and an application designed to analyze and validate performance and choose the best algorithm for building a Classification Engine. The Classification Engine was built based on suitable data structure and algorithms which have been chosen by us. Finally, we integrated the Classification Engine into the non-contact hospital's admission system.

A collection data was classified by its

attributes and diseases to training for Automatic Classifying Engine to classify based on clinical symptoms. In Figure 4 is the User Interface (UI) of Application to training Engine by two methods: manual and automatic.

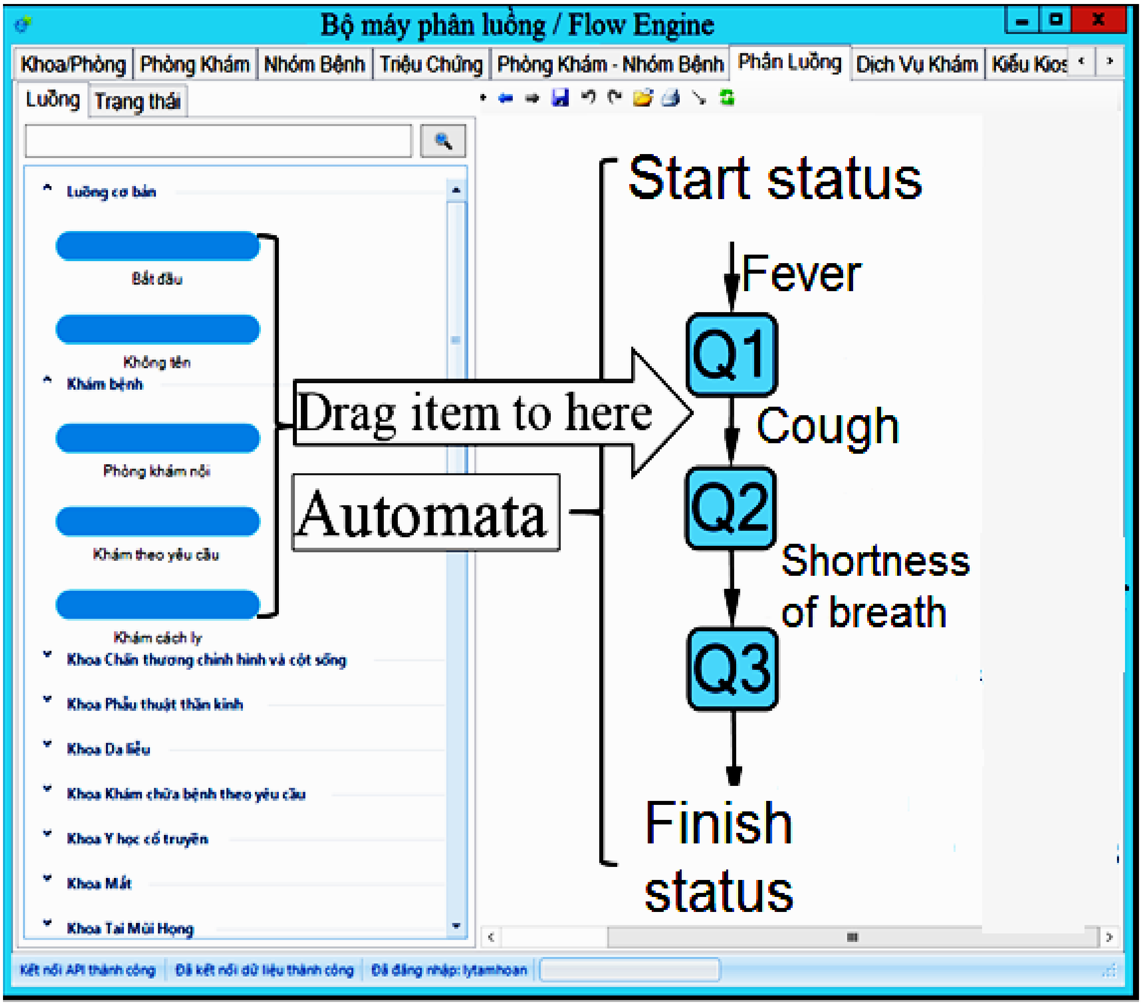

Figure 4. Manual registration data to training Engine

Application to training Engine allows training Engine using the knowledge of experts here are specialist doctors. After training Automatic Classifying Engine, integrate it into the automatic queuing and classifying system to support Hospital recipients in classifying medical examinations and clinics. For manual registration data to training Engine, it starts by creating an initial state which presents the process of patients entering the recipient department to register and then each symptom like fever, cough, and hoarse voice are transition functions leading to different states like Q2, Q3. The final state is the hospital departments where they are required to do medical examinations.

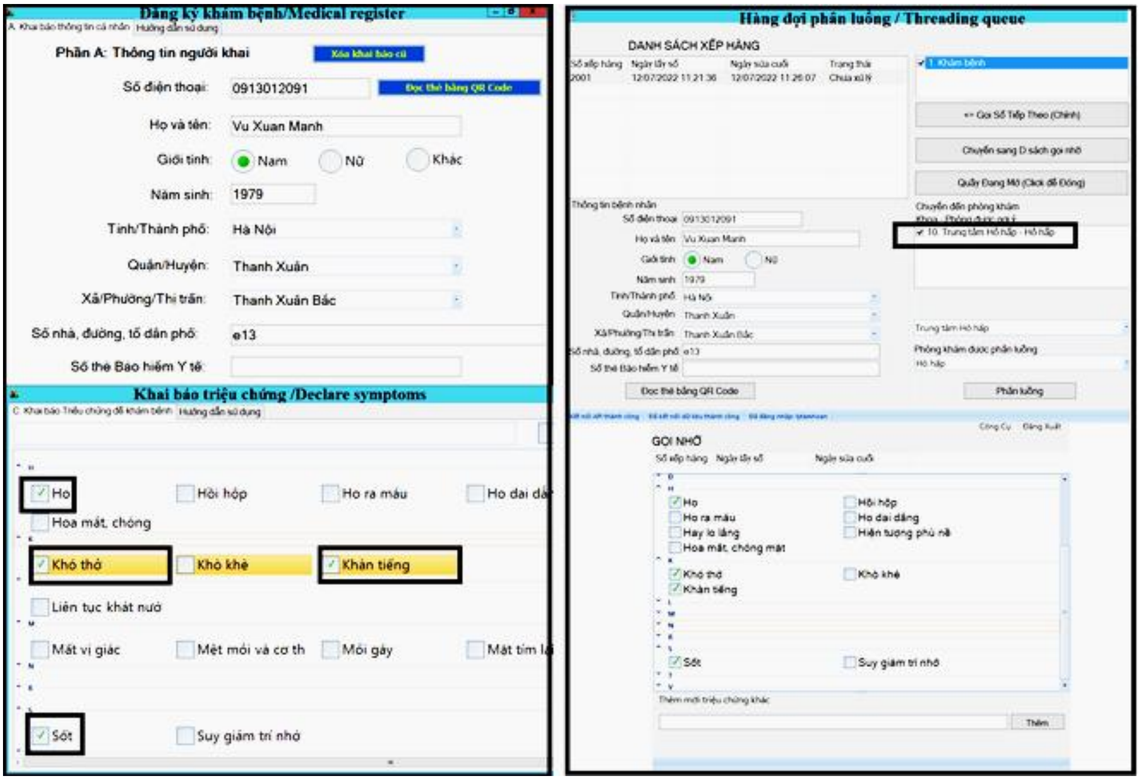

Figure 5. Integrated ACE in online medical examinations and non-contact automatic classifying: a) Application for online registration medical examinations; b) Application for queuing and automatic classifying

In Figure 5, the application for online medical examinations included a Medical register where patients are going to register their information to the system, this information involved the phone number working as ID, full name, gender, year of birth, address, health insurance ID; Declare symptoms by tick on the symptom boxes to declare their clinical symptoms which are input symbol for our ACE. After finishing the online registration medical examination, patients are required to register for queuing and automatic classifying.

4. RESULTS AND DISCUSSION

A collection of data represented 64 clinical symptoms was built based on exponential of 2 showed in the following Table.

Table 1. A collection data represented 64 clinical symptoms

2^1	2^2	2^3	2^4	2^5	2^6	…	2^{63}	2^{64}

Other collections of data were created by grouping arbitrary values from 64 data collections in Table 1, each collection data having minimum is 3 values and maximum is 64 values; the sum of all values is unique and non-repeatable. After grouping arbitrary values, the sum of values in each collection of data adding up is one positive integer and then store that sum in one list arranged in ascending order.

For example: A group of arbitrary values is: 21, 22 and 24, the sum of the group is 2 + 4 + 16 = 22. The number 22 is one value in the list which involves 63 values arranged in ascending order. This list is the patient streams corresponding to clinics. Nevertheless, the number of patient streams may be greater than clinics because there are multiple collections of patient streams doing medical examinations in the same clinic.

To monitor the performance of the data structures and algorithms, a collection of 64 patient streams are going to run through our application to monitor the performance of each and every data structures and algorithms. The result shows in Figure 3.

Figủe 6 represent the relationship between the number of accesses and the execution time. Considering in range from 100 to 100 millions times of concurrent-access shown in Fig 6, we have observed that the execution time of the Binary Search model is the fastest (approximate 7 seconds for 100 million concurrent-access). The NFA model is the slowest and its execution time rapidly increases while the number of concurrent-access increases compared to other models.

At the 100 concurrent-access mark, the execution time of NFA model is 86 µs, Hashing table model is 93 µs, Search Binary model is around 20 µs. At the 100 million concurrent-access mark, the execution time of NFA model is 68 ms which is 10 times greater than Search Binary model with 7 ms. In the aspect of time, the highest value of NFA execution time is approximately one-tenth of seconds for 100 million concurrent-access (equivalent to the population of Vietnam). Nonetheless, the NFA model is more flexible compared to other models. More specifically, each symptom in the NFA model is one label in one arc in the graph. This label may present any types of values, while in other models the label is only received with Yes/No Boolean values. On the other hand, the number of input symptoms for the NFA model is unlimited but the other model's input symptom based on the value of bit presented one integer to store the symptoms. Hence, the NFA model is the most suitable model for building an Automatic Classifying Engine.

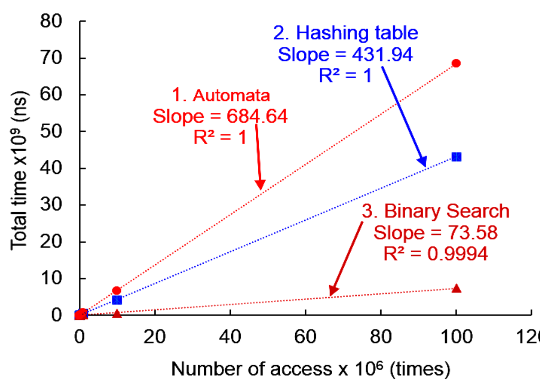

Figure 6. The relationship between the number of concurrent-access mapping from the collections of symptoms to one patient stream and the execution time corresponded to 3 mathematical models: 1) Mappings used NFA model; 2) Mappings used hashing table model; 3) Mappings used Binary Search model

An Automata finite non-deterministic was built based on a collection of data involving 47,900 medical visits of patients in Central Level Hospital (31.0292 %); Province Level General Hospital (61.3925 %); District Level Medical Center (7.5783 %); The data collection consists of clinical symptoms that patients registered through online health questionnaires, patient streams (or examination results) in hospitals. The data analyzation was categorized by gender, age and diseases (patient streams) represented in the following graphs:

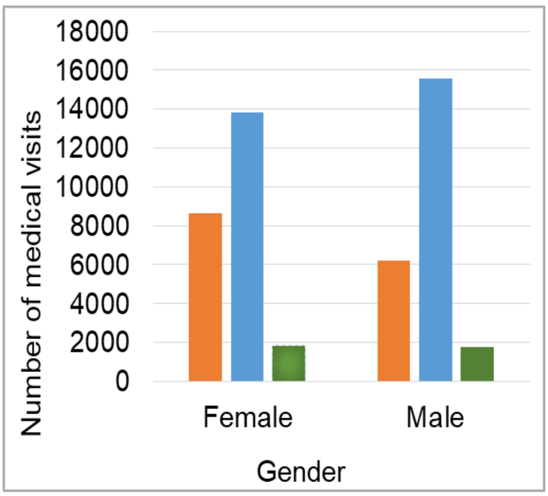

Figure 7. The gender comparison based on number of medical visits in 3 hospitals at central, provincial and district from left to right

According to the statistics about Age Group we analyzed above, there are some critical points we observed: For the central level hospital, most of the patients are adults and for district and provincial level hospitals, the most of patients are children and seniors. This could be explained by the population distribution in Vietnam, there is a large group of adults staying in the urban areas for work and children and seniors staying in the rural areas which lead to the difference in the need of medical examination based on Age Group between urban and rural areas.

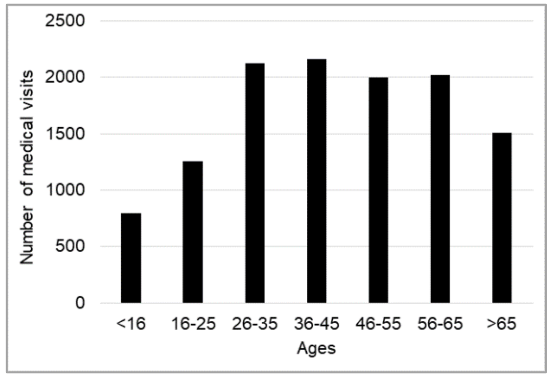

Figure 8. Age Group Comparison based on the number of medical visits in Central Level Hospital

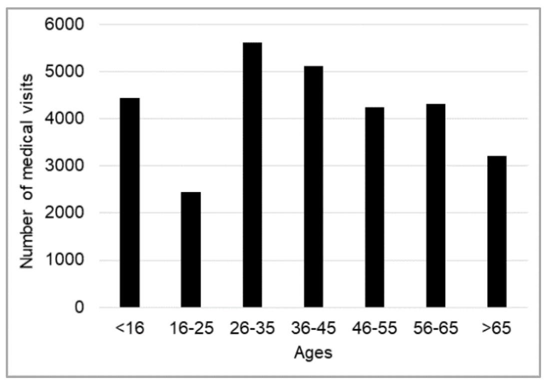

Figure 9. Age Group Comparison based on the number of medical visits in Provincial Level General Hospital

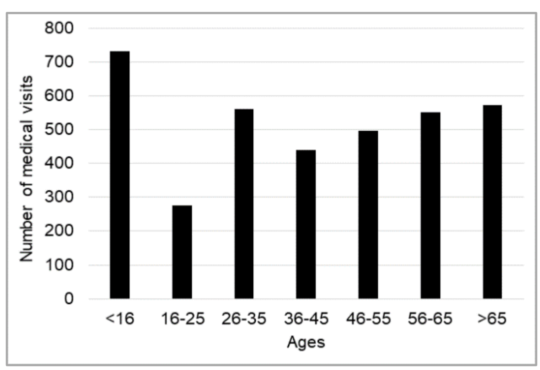

Figure 10. Age Group Comparison based on the number of medical visits in District Level Medical Center

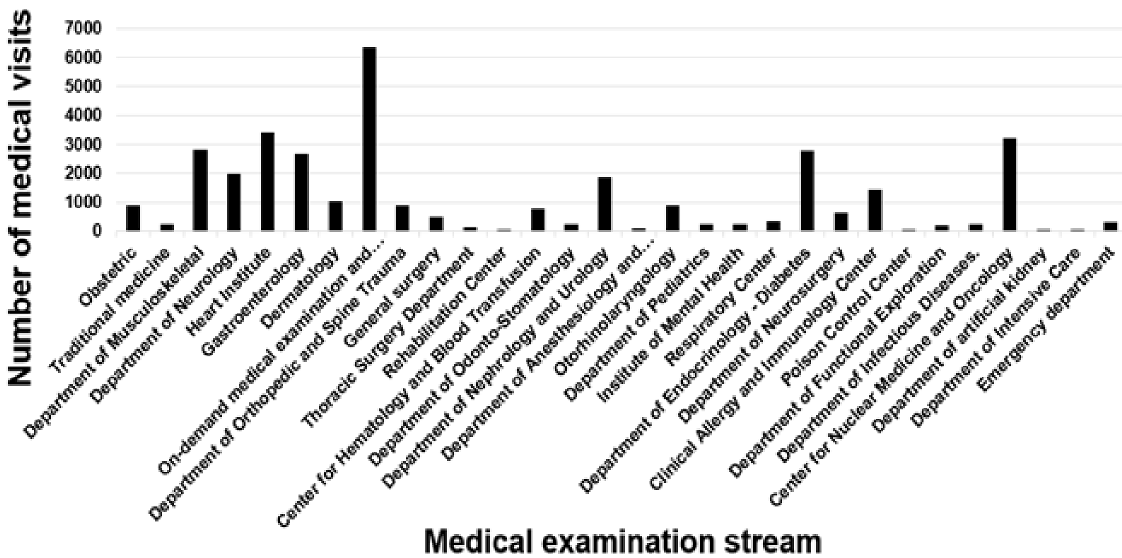

Figure 11. Collection of analyzed data based on medical visits classified in hospital departments in Central, Provincial, District Level Hospital

In Figure 11, the medical examination stream is horizontal axis and the number of medical visits is vertical axis. As shown in the Figure, On-demand medical examination and treatment departments are the most visited of patients in 3 hospitals (6370 medical visits).

After running tests on the ACE integrated system on 100 set of arbitrary collections from clinical symptoms in patient's medical record database, the result approximately 80.5% is single-threaded and the rest is multiple-threaded

5. CONCLUSION

The engine has been successfully developed based on the mathematical model of Non-Deterministic Finite Automata (NFA) to classify non-contact medical examinations according to patients' clinical symptoms. A platform for registration and streaming of contactless medical examinations have has been successfully applied with the records of nearly 50,000 visits at central, provincial and district level hospitals. The ability of machine learning engine has been demonstrated and heavily depends on the volume of training data sets. Therefore, the system collected data from many different specialized hospitals or trained by leading expert's knowledge is going to be more effective for our Engine. After integrating the engine into the system, the obtained results shows that an accuracy of approximately 80.5% based on the dataset that randomly selected values 100 times from the set of symptoms in the patient medical record database. The developed system has been tested at some national hospitals and local medical center. The trained system with a reliable data set is going to be handy and useful for the health care system in areas whereas healthcare service is under-developed.

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Biography:

Nguyen Huy Cong received his MSc degrees from University of Information Technology – VNUHCM. Currently, he is director of Center for Microelectronics and Information Technology, National Center for Technological Progress.

His research interests include artificial intelligence, image processing, simulation technology and data anlysis.

Vu Xuan Manh received his MSc degrees from University of Engineering and Technology – VNU Hanoi in 2011; now, he is the Ph.D student of University of Engineering and Technology – VNU Hanoi (in Electronic Technolgy field). Currently, he is reascher of Center for Microelectronics and Information Technology, National Center for Technological Progress.

His research interests include Embedded systems, software systems, components and analytical systems in biomedical applications.

Nguyen Hai Binh received his Ph.D degree from Vietnam Academy of Science and Technology and MSc and B.Eng. degrees from Hanoi University of Science and Technology, Hanoi, Vietnam, respectively. Currently, he is a researcher at Institute of Materials Science, Vietnam Academy of Science and Technology.

His research interests include microelectronic and micro-electromechanical system fabrication, electronic and optical devices, sensor and analytical system, biomedical devices and system.

Nguyen Thi Thuy received her Ph.D and MSc degrees from Hanoi University of Science and Technology and Bachelor degrees from Hanoi National University of Education, Vietnam in 2014, 2003 and 1998, respectively. Currently, she is a lecturer at Falctulty of Electronics and Communications, Electric Power University.

Her research interests include electronic materials and circuit, sensor and biosensor, biomedical electronics system.