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Electronic Health Record Error Prevention Approach Using Ontology in Big Data

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***Abstract*—*Electronic Health Record* (EHR) systems have been playing a dramatically important role in tele-health domains. One of the major benefits of using EHR systems is assisting physicians to gain patients' healthcare information and shorten the process of the medical decision making. However, physicians' inputs still have a great impact on making decisions that cannot be checked by EHR systems. This consequence can be influenced by human behaviors or physicians' knowledge structures. An efficient approach of alerting to the unusual decisions is an urgent requirement for current EHR systems. This paper proposes a schema using ontology in big data to generate an alerting mechanism to assist physicians to make a proper medical diagnosis. The proposed model is *Ontology-based EHR Error Prevention Model* (OEHR-EPM), which is implemented by a proposed algorithm, *Error Prevention Adjustment Algorithm* (EPAA). The ontological approach uses Protege to represent the knowledge-based ontology. The proposed schema has been examined by our experiments and the experimental results show that our schema has a higher-level accuracy rate and acceptable operating time performance.**

***Index Terms*—Electronic health records, ontology, big data, error prevention, cloud computing**

I. Introduction

Currently, *Electronic Health Record* (EHR) systems have been broadly used in tele-health fields with the development of the Web-based technologies [1]. There are a variety of advantages with implementing EHR systems, such as improving the efficiency of the diagnosis processes, achieving master data management, and real-time information management. From a perspective of physicians, adopting EHR can enable them to obtain patients' medical records that can be used as a reference for diagnoses. The medical information stored in the database is expected to play a positive role in medical decision making.

However, the final determination is still made by physicians who are supposed to make medical notes for formularizing the prescriptions or solutions [2]. The accuracy of the decisions are usually related to physicians' knowledge backgrounds, professional level, and personal behaviors. These external elements may result in unstable or inaccurate medical diagnoses even though it might not be a common situation [3]. Each diagnosis error has a great potential for causing a serious consequence for a patient. Therefore, it is significant for EHR systems to provision an error prevention approach that can alert those unusual or uncertain medical notes.

This paper focuses on this issue and proposes an error prevention approach with using ontology in big data. The proposed schema is named *Ontology-based EHR Error Prevention Model* (OEHR-EPM) that is designed to generate an alert when the system detects any unexpected or rare decisions. The approach is based on an adjustment that can identify whether a structured medical note is associated with the final medical note or diagnosis.

The crucial algorithm used in the proposed schema is *Error Pre-vention Adjustment Algorithm* (EPAA), which can estimate if the examined medical notes are within the acceptable determination scope in the big data context. The estimation depends on the interrelationships between terms within the specific domain, which are represented by adopting ontology. We use *Web Ontology Language* (OWL) to represent the knowledge-based ontology.

The significance of addressing the proposed research is that error prevention functionality is an urgent demand for increasing healthcare diagnosis efficiency and executing smart tele-health. The major motivation of the research is generating a sharable and reusable domain knowledge-based ontology that can be understood by machines. The main contributions of this paper include:

1) This paper proposes a new approach for improving the accuracy level of EHR systems.
2) We explore a schema for using ontology in tele-health in detecting unusual diagnosis.

The remainder of the paper is organized as the following order. Section II represents a motivational example explaining an example of implementing the proposed schema. Related works are summarized in Section III. Next, crucial concepts and the proposed model are described in Section IV. Our algorithms are given in Section V. Our experiment

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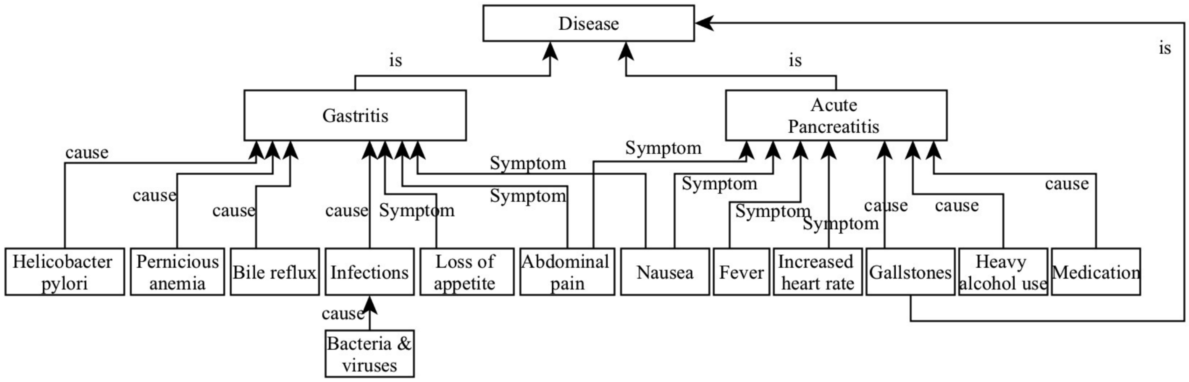

Fig. 1: Example of ontological structure for gastritis and acute pancreatitis

and the results are represented in Section VI. Finally, conclusions are drawn in Section VII.

II. Motivational Example

This section provides a description of implementing the proposed schema via a motivational example. The example states a scenario that the proposed paradigm can assist physicians to avoid misdiagnose by distinguishing the gastritis from pancreatitis. These two illnesses have a few similarities to symptoms that has a great chance causing a misdiagnose. A misdiagnose of pancreatitis can result in a serious consequence, such as surgery and death. Our approach uses an ontological approach for the error checking operations, in which the reminders or error corrections will be produced.

Fig. 1 exhibits an example of ontological structure for gastritis and acute pancreatitis. The figure illustrates a partial structure that shows three types of interrelationships, including *is*, *symptom*, and *cause*. One entity can be a subclass of multiple classes. For example, according to Fig. 1, *Nausea* has two parent classes with the same type of interrelationship, namely *Acute Pancreatitis* and *Gastritis*. Another situation is that *Gallstones* has two parent classes with different types of interrelationships, including *cause* and *is* relations.

Align with Fig. 1, we use Protege to generate an ontological graph. Fig. 2 exhibits a partial component of the OWL ontology that demonstrates a few classic relation types between classes. As shown in the graph, nausea is a symptom of both diseases, namely acute pancreatitis and gastritis. Meanwhile, compare with loos of appetite that is a cause of gastritis, gallstones is a cause of acute pancreatitis as well as a disease. Both acute pancreatitis and gastritis are diseases. In this case, misdiagnoses might be happened when physicians make a medical note based on the symptom of nausea that is also shared by two classes.

For solving this problem, we extract the problem from the ontology and convert it into the set selection problem. Fig. 3 represents two basic ontology-based disease diagnosis set relations, which is used by our proposed schema

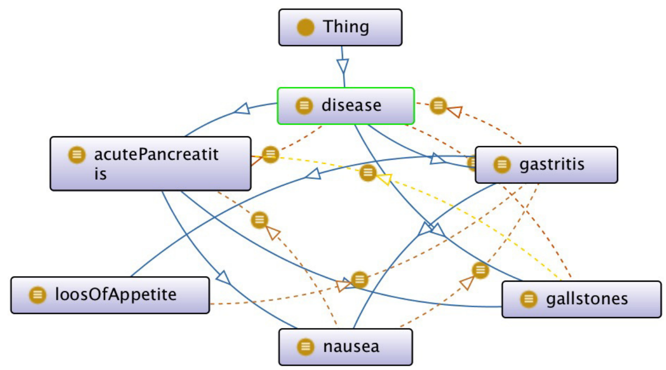

Fig. 2: A partial component of OWL ontology generated by Protege, which is associated with Fig. 1

for matching the selected sets. Assume that a physician makes a medical note based on the symptoms of $\{A, B\}$, and $\{A', B'\}$. Each circle with a letter represents either a pathogeny or a symptom that is used by doctors to make a diagnoses, which implies that both $\{A, B\}$ and $\{A', B'\}$ are the proofs used for producing medical notes. Four sets in Fig. 3 show four combinations referring to the medical decisions, including *Sets 1, 2, 3,* and *4*. Each combination set points at one unique disease.

Fig. 3 (a) represents that the set $\{A, B\}$ is an intersection of two sets, including *Set 1* and *Set 2*. Our goal is that an alert will be created when physicians make medical notes according to the set $\{A, B\}$. The output label will be a reminder of checking more medical conditions deriving from *Set 1* and *2*, which include $\{C, E, A, B\}$ and $\{A, B, D, F\}$. Similarly, in Fig. 3 (b), *Set 3*, $\{A', B'\}$, is an inclusion of *Set 4* that points at another disease. The output label will be a reminder of re-checking the condition for another potential sickness, which is connected with *Set 4*, $\{A', B', C', D', E'\}$.

In a practical perspective, the set relations are complicated and nested. An ontological approach can formulate the com-

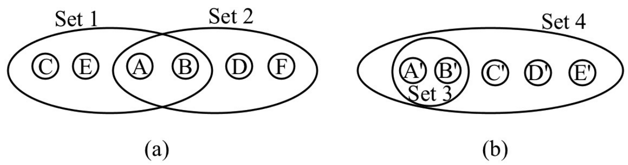

Fig. 3: Basic ontology-based disease diagnosis set relations

plex relations between sets and enable efficient matching operations. Details of the model are given in Section IV.

III. Related Works

Recent research has explored the field of EHR systems in various dimensions. One of the major concerns of implementing EHR systems is to protect patients' personal information from abusing and all unexpected operations [4]. Previous research has studied this issue and proposed a number of security-aware algorithms [5] or solutions [6]. For instance, a security-aware optimization for ubiquitous computing systems was developed with using SEAT graph approach [5]. However, ontology-based secure solutions were rarely explored by recent research.

Next, the rapid growth of implementing big data in telehealth has a great impact on the applications of EHR systems [7], which enabled context-based EHRs [8]. The size of data volume is treated as an essential aspect for the EHR analytic systems [9]. Achieving a higher-level performance is considered a critical issue that has been explored in both software [10] and hardware [11], [12] fields. For example, an advanced task scheduling approach has been proposed to realize high performance within the timing constraints [13]. Another achievement addressed data allocation for hybrid memory with genetic algorithm [14]. Nonetheless, ontology-based big data solutions still need more research work in tele-health fields.

Moreover, *Extensible Markup Language* (XML) syntax and semantic validations are two significant aspects for achieving error-free service transactions and performing service integrations that are implemented on the employed heterogenous computing services. Recent research has proved that *Extensible Stylesheet Language Transformations* (XSLT)-based Schematron validation has a chance to generate invalid results [15]. Addressing this issue, one solution was using the *Document Object Model* (DOM) validating parser to validate the XML or Schematron documents [16]. However, novel techniques have brought new challenges in data validation as well as new interrelationships.

Furthermore, cloud computing techniques have also been influencing the implementations of EHR systems [17], [18]. Multiple aspects have been considered in this field, such as performance [19], [20], security [21], wireless communications [22], and Web services. For instance, an online optimization for scheduling preemptable tasks on *Infrastructure-as-a-Service* (IaaS) cloud systems has been developed and proved by the recent research [23]. Considering the data security issue, an *Attributed-based Encryption* (ABE) has been proposed for sharing personal health records in a secure manner [24]. However, few research works have been focused on cloud-based error prevention for EHR systems to detect potential errors in medical diagnosis.

In addition, some EHR systems are adopted on embedded systems, which have been explored in multiple aspects by recent research [14]. Minimizing the costs is a main challenge when adopting heterogeneous embedded systems in tele-health [25]. Prior research had developed an efficient solution that can greatly lower down the costs along with the timing constraints with using dynamic programming [26]. Nevertheless, the research on embedded systems hardly concerned the interrelationships in EHR systems.

In summary, this paper concentrates on using ontological approach in big data to achieve error preventions in EHR systems. The following section describes the main concepts and our proposed model.

IV. Concepts and the Model

A. Proposed ontological approach

The term *Ontology* refers to a paradigm describing interrelationships between entities with identifying various characteristics in the systems [27]. In OEHR-EPM, an ontological approach is implemented to formulate the relationships between medical entities, such as medical records.

There are three crucial entities in the model, including patients' medical records, physician medical notes, and diagnosis analytics and references. Define the dataset *Diagnosis Analytics and References* (DAR) as γ, in which γ=$\{\gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_n\}$ and the γ_i with $i \in N$ refers to the taxonomy of the symptomatology.

Define *Patients' Medical Records* (PMR) as δ, in which δ=$\{\delta_1, \delta_2, \delta_3, \ldots, \delta_n\}$ and the δ_i with $i \in N$ refers to the sub-datasets of patients' medical records representing the detailed information for each medical record. All medical records need to be formulated to structured data. For each medical record, we use datasets $\{\delta_{ij}\}$ with $i \in N, j \in N$ to identify sub-entities in PMR. Further sub-datasets will be generated depending on the practical requirements.

In addition, define *Physicians' Medical Notes* (PMN) as λ, which need to be formularized to structured data. The dataset $\{\lambda\}$ is used to represent the medical diagnosis results or notes made by physicians. Considering the variance and diversity of PMN, the dataset $\{\lambda\} = \{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n\}$ in which λ_i with $i \in N$ represents the taxonomy of the medical notes. For each λ, it may has a few layers representations according to the ontology.

B. Ontology-based Electronic Health Record Error Prevention Model (OEHR-EPM)

Our solution is based on implementing the proposed model, OEHR-EPM, which consists of three defined entities. Fig. 4 represents the structure of OEHR-EPM that illustrates the interrelationships between the entities. The model only considers the process of generating medical

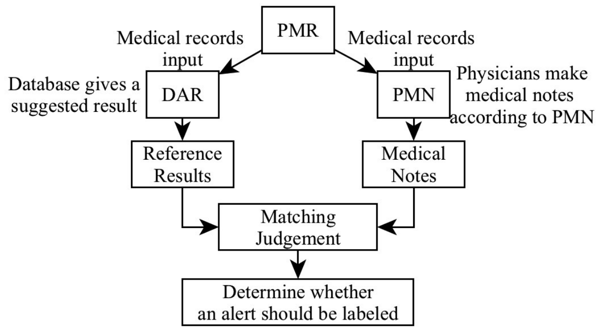

Fig. 4: Structure of Ontology-based Electronic Health Record Error Prevention Model (OEHR-EPM)

notes checked by the system. Other interrelationships maybe existed among entities, such as medical notes input by physicians, which are not covered in this model.

As described in Fig. 3, the crucial process of error prevention is finding out the sets involving the subsets that are used by physicians to make final decisions. Definition of the target sets having potential diseases and the smaller sized sets used by doctors are defined in Definition IV.1.

Definition IV.1. *Let* $\mathbb{P} = \{\mathbb{P}_1, \mathbb{P}_2, \ldots, \mathbb{P}_i\}, i \in N$ *be the set referring to Medical Alert, represented as* $\mathbb{P} \Leftarrow$ *Medical Alert. Let* $\mathbb{M} = \{\mathbb{M}_1, \mathbb{M}_2, \ldots, \mathbb{M}_i\}, i \in N$ *be the set referring to Medical Note Decision, represented as* $\mathbb{M} \Leftarrow$ *Medical Note Decision. Define* $Label_a \leftarrow \mathbb{P}$, $\mathbb{P}_i \neq \mathbb{M}$, $\mathbb{P}_i \supset \mathbb{M}$.

The lemma used for identifying the sets containing the potential diseases except the medical notes is given in Lemma IV.1 as well as the proof.

Lemma IV.1. *Let* $\mathbb{P} = \{\mathbb{P}_1, \mathbb{P}_2, \ldots, \mathbb{P}_i\}, i \in N$ *be a set consisting of a few subsets,* $\mathbb{P}_i$*, targeting various diseases, which are used to create alert(s). Assume* $\exists$ *set* $\mathbb{M} = \{\mathbb{M}_1, \mathbb{M}_2, \ldots, \mathbb{M}_i\}, i \in N$*, which is used by physicians to create medical notes.* $\exists$ *set* $\mathbb{Q} = \{\mathbb{Q}_1, \mathbb{Q}_2, \ldots, \mathbb{Q}_i\}, i \in N$*, for any subsets* $\mathbb{Q}_i \subseteq \mathbb{Q}$*, suppose* $\mathbb{M} \subset \mathbb{Q}_i$ *&* $\mathbb{Q} \neq \emptyset$*, then* $\mathbb{P} = \mathbb{Q}$.

Proof. Let z element be in $\mathbb{M}$ as $z \in \mathbb{M}$. Assume $\exists\, \mathbb{P} \neq \mathbb{Q}$, if $z \in \mathbb{P}_i$, then $z \notin \mathbb{Q}_i$. Suppose $\mathbb{M} \subset \mathbb{P}_i$, $\mathbb{M} \subset \mathbb{Q}_i$, if $z \notin \mathbb{Q}_i$, then $z \notin \mathbb{M}$. Therefore, element z must in both $\mathbb{P}_i$ and $\mathbb{Q}_i$, and $\mathbb{P}_i$=$\mathbb{Q}_i$, as required. □

As shown in Fig. 4, on one side, physicians make medical notes according to patients' medical records. The medical notes should be structured data that are coded by the defined medical taxonomy. At the same time, on the other side, the database also generates a reference result deriving from the analysis of the symptoms. The reference result is created by the pathology knowledge base and big data analysis.

Furthermore, the coded outputs from two sides are compared and judged. An alert reminding physicians of re-checking patients' medical conditions will be created when the matching result shows medical notes have potentials of less considerations on possible diseases. This process is defined as an *Adjustment Checking Process* (ACP). Otherwise, the system will keep on without creating an alert.

TABLE I: Main notations used in this paper

Notations	Definition
γ	Diagnosis analytics and reference (dataset)
δ	Patients' medical records
λ	Physicians' medical notes
μ	Disease diagnosis set generated by the system
Record	Dataset in dataset γ describing disease feature sets
Feature	Data in set *Record* describing disease features
Flag	Temporary variable used for judgement
$Label_a$	Generate an *Alert* output label
$Label_p$	Generate an *Approved* output label

V. ALGORITHMS

This section represents our main algorithm, EPAA, which is designed to determine whether an alert should be created, which reminds physicians of information re-check. The algorithm is used for ACP in which demonstrates the main process of our proposed model. The main notations used in this paper are given in Table I. The EPAA algorithm is exhibited in Algorithm V.1.

Algorithm V.1 Error Prevention Adjustment Algorithm

Require: Datasets γ, δ, and λ
Ensure: μ

Input datasets γ, δ, and λ
Initialize μ, $\mu \leftarrow \emptyset$
FOR $\forall$ *Record* in γ
    Flag $\leftarrow$ True
    FOR each *Feature* in δ
        IF *Record* do not have *Feature*
            Flag $\leftarrow$ False
            BREAK
        ENDIF
    ENDFOR
    IF *Flag* == True
        Add Record into μ
    ENDIF
ENDFOR
RETURN μ
Compare μ and λ
IF $\forall$ μ is larger than λ
    RETURN $Label_a$
ELSEIF
    RETURN $Label_p$
ENDIF

The crucial goal of Algorithm V.1 is to find out all disease sets of which the medical notes is a subset. Align with the pseudocode, the main phases of Algorithm V.1 include:

1) Input diagnosis analytics dataset γ, patients' medical records δ, and physicians' medical notes λ.

2) Initialize the disease set μ, empty set μ.
3) For all dataset in γ, initialize a *Flag* and assign a *True* value.
4) Enter a for loop, for each *Feature* in dataset δ, assign a *False* value to the *Flag* if the set *Record* do not have *Feature*. Implement break.
5) If the value of *Flag* is true, add *Record* into the disease diagnosis set generated by the system μ. Return the value of μ.
6) For all elements in μ, compare them with λ and then output a comparison result.
7) If the set size of μ is larger than λ, generate an output, *Alert* label ($Label_a$). Otherwise generate a different output, *Approved* label ($Label_p$).

VI. Experiment and the Results

This section describes our experimental configuration and some experimental results for evaluating the performance.

A. Experimental configuration

The experimental configuration is designed for simulating the execution scenario of the cloud-based tele-health systems that use our proposed mechanism. There are two servers being deployed in the experiment, which separately simulate the implementations of the cloud server and dataset server. The server used for the simulation is an HP server with Ubuntu 15.04, Xeon E5 2.4 GHz 6-core CPU, and 16 GB memory. The other server simulating dataset server is an HP server with AMD Opteron 2.4 GHz 8-core CPU, 8 GB memory, and MySQL 5.7.

We have five experimental settings, which use different sized datasets to simulate various usage scenarios in practice. The five experimental settings of datasets include: 100K, 50K, 10K, 5K, and 1K. For each experimental setting, we use one parameter with different values to evaluate the accuracy rates and performances. The selected parameter, H, is the size of patient medical records stored in the datasets. The dataset used in our experiment is a simulation of the real data. We gain real healthcare data from an anonymous medical institution in China. The simulated datasets use the distribution of the real healthcare data to generate a simulated dataset.

For the purpose of the experimental evaluation, we define the accuracy rate $\mathbf{R} = \mathbb{P}/\mathbb{P}_t$. $\mathbb{P}$ is the number of sets that triggers medical re-check alerts, which is generated from real medical notes. $\mathbb{P}_t$ is the number of theoretical sets that can potentially trigger medical re-check alerts, which is generated from medical knowledge ontology. $\mathbf{R}$ can represent the percentage of the alert creations in the entire theoretical knowledge pool. The value of $\mathbf{R}$ has a positive relationship with the preciseness of medical notes and indicates the performance of our algorithm.

This experimental configuration aims to simulate the implementations of the proposed schema under different operating contexts. We target a few evaluation goals, including the relations among accuracy level, the size of datasets, and the number of patients, the relations between calculation time and dataset sizes, and time consumption and the amount of stored medical notes.

B. Experimental results

We represent our experimental results in this section. The selected parameter is the number of patients, which is configured as three levels, namely $H_1 = 100$, $H_2 = 50$, and $H_3 = 30$. Fig. 5 represents an accuracy evaluation under five experimental settings with three parameters.

According to Fig. 5, the accuracy levels are close when the sizes of datasets are large enough. It is an important feature for the proposed model since the datasets are normally large in practice. Moreover, our proposed schema can always gain a higher-level accuracy rate. The highest $\mathbf{R}$ is more than 95%. The lowest rate is gained by the Setting 5 with the parameter H_3. Next, the amount of medical notes is also an influencing element, which has a positive relationship with $\mathbf{R}$.

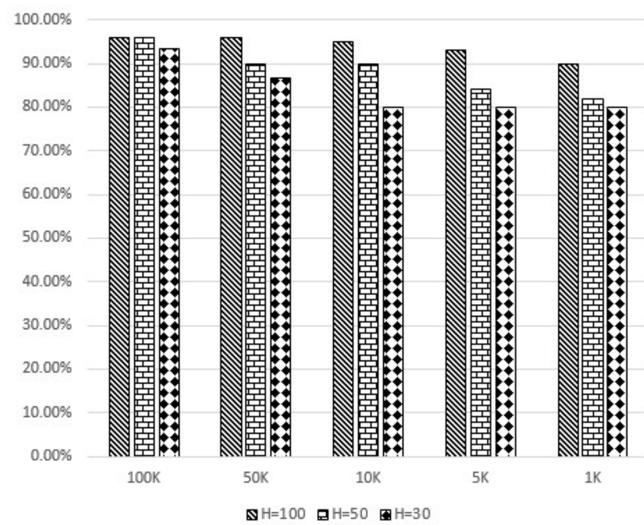

Fig. 5: Accuracy evaluation under five experimental settings with three values of the parameter, $H_1 = 100$, $H_2 = 50$, and $H_3 = 30$

The reasons why the accuracy rates were not 100% was twofold. First, the datasets used in the experiment were not sufficient enough, which simulated the datasets deployed in practice. Second, the medical notes might be out of the scope of matching sets $\mathbb{P}$, which resulted in the noise.

Fig. 6 exhibits the experiment results showing the time consumption comparisons under five experimental settings with different values of the parameters. The bars represent that there is a great impact caused by the size of datasets and the computing time dramatically goes up when the dataset sizes becomes bigger. The highest calculation time is generated by the Setting 1 with parameter H_3, which is longer than 3750 milliseconds. Moreover, the number of patients' medical notes generally has a negative relationship with the calculation time.

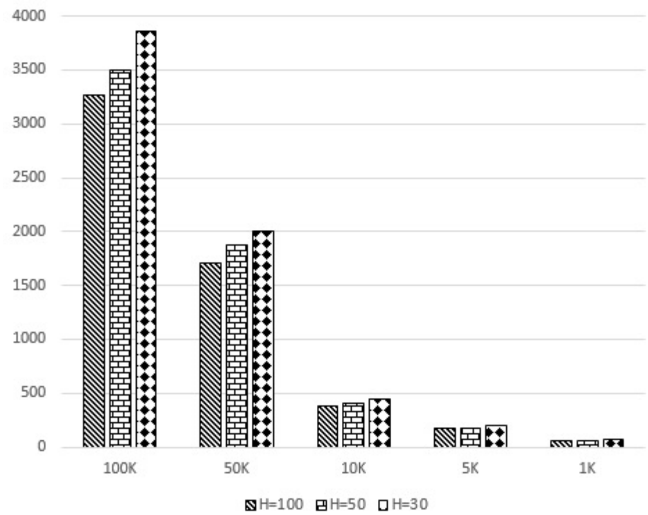

Fig. 6: Time consumption comparison under five experimental settings with three values of the parameter, $H_1 = 100$, $H_2 = 50$, and $H_3 = 30$

In summary, the experimental examination has proved that our proposed mechanism is applicable under various contexts. OEHR-EPM has a high performance in matching accuracy rate due to the implementation of the ontological approach. The calculation time is acceptable when the dataset size is not too large.

VII. Conclusions

This paper focused on the issue of diagnosis error prevention in EHR systems and proposed a solution that can efficiently avoid medical diagnosis errors in big data. The proposed mechanism was OEHR-EPM that was created to achieve the expected prevention aim with using an ontological approach. The main algorithm in the proposed model was EPAA that was a novel schema with using ontology. Our experimental evaluations had proved the efficiency of the proposed model. Future work will address the limitations of the research in this paper, such as potential messy information and calculation optimization.

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