Formalization of Clinical Practice Guidelines: Nonalcoholic Steatohepatitis Diagnosis Model-Related Personalized Medicine

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Abstract

Objective: Non-alcoholic fatty liver disease (NAFLD) is a recently recognized entity related to modern lifestyle and with expanded clinical importance because of the rising incidence of obesity and diabetes.

Methods: We have developed a framework for interacting with patient’s heterogeneous data (omics, clinical and biological information) and formalizing medical knowledge.

Results: In this paper we present new diagnosis model to predicate NASH. We extracted 18 clinical concepts and these concepts are annotated with SNOMED CT concepts. We tested our diagnostic model with database of 36 patients. We have a performance of 91%.

Conclusion: This work represents a preliminary step in developing a CDSS and we’ll use a clinical database to test this system and to compare it with others statistic reasoning methods.

Keywords

Non-alcoholic fatty liver disease, Liver Disease, clinical decision support system, knowledge representation, artificial intelligence, fuzzy logics

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1 Introduction

Non-alcoholic fatty liver disease (NAFLD) is one of the most common causes of chronic liver disease in the world [1]. NAFLD is a clinical syndrome and is pathologically characterized by diffuse macrovesicular fatty change in the hepatocytes. NAFLD includes simple nonalcoholic fatty liver disease, nonalcoholic steatohepatitis (NASH) and hepatic cirrhosis [2]. NAFLD is a recently recognized entity related to modern lifestyle and with expanded clinical importance because of the rising incidence of obesity and diabetes. NAFLD is an increasingly recognized cause of liver-related morbidity and mortality and it is frequently associated with insulin resistance. While insulin resistance and hyperinsulinemia, are, in large part, metabolic consequences of obesity, the basis of diversity in severity and progression of inflammation and fibrosis is not known [3].

The presence of fat in the liver means the accumulation of triglycerides. This accumulation determines the evolution of the disease. Infiltration of 30% of hepatocytes is an incipient form, the moderate form means that 60% of hepatocytes were infiltrated and severe form induces over 60% of infiltration hepatocytes [4].

Figure 1: Diagram representing the CBFCM method.
NASH is a disease evolving under the influence of various stimuli still poorly understood. However in this disease, it is well known that insulin resistance is largely implied [5]. Risk factors for NASH/Fibrosis are: Old over 45 years, Obesity, Diabetes/Insulin resistance, low platelets, low albumin, AST > ALT and imaging signs of hyper portal hypertension.

Several biological Nash prediction tests are developed [6, 7]. The evolution of NAFLD and NASH is variant for each patient and it is important to use all relevant information to diagnose the disease: clinical information, biological test, genomic information and imaging. In this paper we describe a new diagnosis support system based on validated knowledge from scientific literature and clinical practice guidelines (CPG) to diagnose NASH. We tested our diagnostic model with database of 36 patients generated randomly.

2 Methods

We have developed a framework for interacting with patient’s heterogeneous data (omics, clinical and biological information) and formalizing medical knowledge.

![Diagram of CPG fuzzy formalization method](http://www.worldgastroenterology.org/assets/export/userfiles/2012_NASH%20and%20NAFLD_Final_long.pdf)

**Figure 2: CPG fuzzy formalization method.**
Table 1: Clinical concepts of NASH diagnosis model.

<table>
<thead>
<tr>
<th>Clinical concepts</th>
<th>Label Description</th>
<th>SNOMED CT Concepts ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Hyperglycemia</td>
<td>80394007</td>
</tr>
<tr>
<td>C2</td>
<td>Hypertriglyceridemia</td>
<td>302870006</td>
</tr>
<tr>
<td>C3</td>
<td>HDL</td>
<td>9422000</td>
</tr>
<tr>
<td>C4</td>
<td>Hypertension</td>
<td>38341003</td>
</tr>
<tr>
<td>C5</td>
<td>BMI</td>
<td>60621009</td>
</tr>
<tr>
<td>C6</td>
<td>Waist circumference</td>
<td>276361009</td>
</tr>
<tr>
<td>C7</td>
<td>Fasting insulin</td>
<td>252251004</td>
</tr>
<tr>
<td>C8</td>
<td>Index HOMA-IR</td>
<td>237650006</td>
</tr>
<tr>
<td>C9</td>
<td>Alcohol consumption</td>
<td>160580001</td>
</tr>
<tr>
<td>C10</td>
<td>ALT</td>
<td>250637003</td>
</tr>
<tr>
<td>C11</td>
<td>AST</td>
<td>250641004</td>
</tr>
<tr>
<td>C12</td>
<td>Apolipoprotein</td>
<td>259599001</td>
</tr>
<tr>
<td>C13</td>
<td>GGT</td>
<td>60153001</td>
</tr>
<tr>
<td>C14</td>
<td>Haptoglobin</td>
<td>85294008</td>
</tr>
<tr>
<td>C15</td>
<td>α-fetoprotein</td>
<td>16236008</td>
</tr>
<tr>
<td>C16</td>
<td>Adiponutrine gene profil</td>
<td>413451007</td>
</tr>
<tr>
<td>C17</td>
<td>Old-Age</td>
<td>70753007</td>
</tr>
<tr>
<td>C18</td>
<td>Sexe</td>
<td>263495000</td>
</tr>
<tr>
<td>D1</td>
<td>NASH</td>
<td>197321007</td>
</tr>
</tbody>
</table>

2.3 Case Based Fuzzy Cognitive Map Reasoning Mechanism

The CBFCM reasoning process follows a number of steps till the system’s equilibrium point. These steps can be found in [10, 12] and we briefly present them here. At first step, the initial state of the concepts is given either from experts or from the existing medical database. During reasoning the CBFCM iteratively calculates its state until convergence. The state is represented by a state vector $C^{(k)}$, which consists of real node values $C^{(k)}_i \in [0,1], i = 1, 2, \ldots N$ at an iteration $k$. The value of each node is calculated by the following equation:

$$C^{(k+1)}_i = f\left(C^{(k)}_i + \sum_{j=1, j\neq i}^{N} C^{(k)}_j \cdot W_{ji}\right)$$ (1)

Where $f$ is a threshold (activation) function:

$$f(x) = \frac{1}{1 + e^{-m(x)}}$$ (2)

Where $m$ is a constant parameter [13]. The parameter $m$ determines how quickly the $f(x)$ approaches the limiting values of 0 and 1. The transformation function is used to reduce unbounded weighted sum to a certain range, which hinders quantitative analysis, but allows for qualitative comparisons between concepts.

In order to remove the spurious influence of inactive concepts (concepts with zero values) on other concepts, and to avoid the conflicts emerge in cases where the initial values of concepts are 0.5, as well as the missing data, a modified CBFCM reasoning formalism can be used. Based on this assumption, we reformulated eq. (1) as:

$$C^{(k+1)}_i = f\left(2C^{(k)}_i - 1 + \sum_{j=1, j\neq i}^{N} (2C^{(k)}_j - 1) \cdot W_{ji}\right)$$ (3)

For example, in Figure 1 the value of a concept “DiagnosisN” is obtained by multiplying the value of each of its input concepts, $C_i$, by their respective weights, $W_{ij}$, giving values in [0..1]. These values are then summed as in eq. (1) and eq. (3) and the nonlinear function $f$ is used.

Figure 3: Example of decision rules.
to limit the range of possible output values. The inference follows an iteration process till the system convergence in a steady state (means a state where all the concepts do not change any more their values).

The simulation stops when a limit vector is reached, i.e., when $C^k_i - C^{k-1}_i \leq \varepsilon$; where $\varepsilon$ is a residual, whose value depends on the application type (and in most applications is equal to 0.001) [13]. The conclusions based on CBFCM should be viewed together with existing scientific knowledge [14].

The construction of CBFCM [9] is consisting of three parts: (a) to determine concepts and (b) to determine the strength of cognitive relationships between concepts (c) to explicit fuzzy control rules (see Figure 2).

In the semantic web N3 formalism, the weights $W_{ij}$ are in the range $[0, 1]$, each weight (concepts’ influences) presents a degree of influence from 0 to 1 [8].

2.4 Information model

The Semantic Web framework based on CBFCM integrate heterogeneous data: clinical data (signs, symptoms...), Biological data (lab test...), Imaging and Omics data. To create a patient clinical profile we need to use all these types of data. These data are annotated with SNOMED CT concepts. We extracted a related part of SNOMED CT using UMLS.

3 Results

We extracted 18 clinical concepts and these concepts are annotated with SNOMED CT concepts (Table 1). We tested our diagnostic model with database of 36 patients. We have a performance of 91%.

Figure 3 is an example of result rules. This output is N3 triples: PatienIdxxx is the ID of our patients, snomedct:266468003 is a decision concept (NASH) and fl:pi is the confidence degree of the decision (the range value is (0-1))

4 Discussion and Conclusion

The CBFCM approach allowed us to integrate heterogeneous clinical data to perform a personalized patient profile. This method can identify causal relationships between clinical, biological, genetic concepts and decision concept (Diagnosis of NASH). The use of CBFCM enables to incorporate several sources of knowledge (several CPGs, knowledge from literature), which is of great advantage since all knowledge is rarely embedded in a unique CPG. Indeed, knowledge of a medical field is usually broad, complex and closely related to other areas so that several knowledge sources are needed to cover and modeled the medical domain in question.

We have implemented the knowledge bases, rules and databases in the same environment (RDF, N3, Euler...) without compatibility constraints; this is one of the advantages of using Semantic Web tools. The success rate of 91% shows the functionality of the model and its future usefulness in clinical practice.

The conducted study allowed us to test cognitive approaches reasoning to enable personalized medicine. The advantage of this approach is to enable the sharing and reuse of knowledge and simplify maintenance. This work represents a preliminary step in developing a CDSS and we’ll use a clinical database to test this system and to compare it with others statistic reasoning methods.

References


