

Artificial General Intelligence Approach for Reasoning in Clinical Decision Support

Aleksandar Kaplar*, Miloš Smić*, Aleksandar Kovačević*

* Faculty of Technical Sciences, University of Novi Sad, Novi Sad, Serbia

{aleksandar.kaplar, milos.simic, kocha78}@uns.ac.rs

Abstract—Clinical decision support systems (CDSS) are designed to assist physicians and other health professionals with numerous clinical tasks, such as establishing a diagnosis or determining the appropriate course of therapy. While much research has been conducted in the field, with various degrees of success, little emphasis has been placed on unified knowledge representation with uncertainty and learning capabilities of a diagnostic system. Non-axiomatic logic (NAL), an Artificial General Intelligence project designed to realize general-purpose logic, provides consistent format for representing and reasoning-learning with knowledge that has diverse degrees of uncertainty. This paper reviews the methods used in design of CDSS, and proposes a CDSS framework based on NAL.

I. INTRODUCTION

Clinical decision support systems (CDSS) are systems designed to influence clinical decision-making tasks, done by physicians and other health professionals, in order to improve the quality of health care [1].

An important and non-trivial problem of CDSS is the diagnostic process – helping the physicians in determining which questions to ask, or deciding which tests to order and procedures to perform. To model such a complex tasks the system would need to be able to resolve inconsistencies, to conclude new evidence based on its current knowledge, and to ask questions and generate hypotheses in order to explain its reasoning. In other words, a CDSS needs to have human-like reasoning capabilities.

Current research in the field of clinical systems is largely focused on the application of artificial neural networks (ANNs), due to their proven high accuracy [7, 8, 9]. Research has shown that ANNs diagnostic predictions are usually as good as, or better than, those of the physicians. However, the knowledge stored in ANNs is very hard to interpret for medical professionals and the reasoning behind the computed diagnostic solutions is hard to explain, that is, they don't provide support for the complete diagnostic process [1].

Another approach to diagnostic support are knowledge-based expert systems [10, 11, 12]. Knowledge-based expert systems have an intrinsic quality of being able to provide decision explanations. One of the first and widely known knowledge-based expert system was MYCIN, developed at Stanford University in the 1970s. MYCIN's knowledge base consisted of if-then rules with certainty factors attached to consequent diagnoses. For inference a backward chaining reasoning strategy was employed. In a test conducted at Stanford, MYCIN outperformed members of the Stanford medical school faculty. However, MYCIN was never actually used in practice and after 1979, due to lack of maintenance, its knowledge base became out of date [13].

Disadvantage of rule-based systems¹, such as MYCIN, is that they become increasingly unmanageable when the number of rules increases, and they often contain several thousand rules or more. Furthermore, “if-then” rule systems usually have difficulty dealing with uncertainty, due to the fact that they don't employ logic with sound theoretical support for representation of different kinds of uncertainty.

It is our belief that aforementioned issues can be solved with the use of techniques of Artificial General Intelligence (AGI). AGI is a field of artificial intelligence whose research is focused on the goal of creating a general purpose intelligent system. In contrast to traditional knowledge-based systems, AGI systems are designed to with general-purpose logic that is able to reason across multiple domains and deal with various kinds of uncertainty. A well suited AGI project for reasoning in medicine is Non-Axiomatic Reasoning System (NARS) [5, 6]. Among other things, NARS is scalable, supports learning, and provides support for the complete problem-solving process. A case-study in medical diagnosis of NARS and its core logic, the Non-axiomatic Logic (NAL), was conducted in 2011. That case study showed that NAL can be successfully applied in the medical domain [2]. NAL has, also been used for analysis of reasoning applicable to Percutaneous Coronary Interventions [3]. In the domain of decision support, NAL has been used as a core logic for a conceptual framework with reasoning capabilities for crisis response decision-support systems [4]. The framework case study was in the domain of urban firefighting. Results of the study showed that their framework provided a promising approach for intelligent decision-support systems in crisis management.

In this paper we propose a conceptual framework for CDSS, with the support for the complete diagnostic process, based on the use of text mining and AGI techniques. To the best of our knowledge, there haven't been any significant attempts at solving aforementioned issues present in rule or machine learning based CDSS with an AGI approach, that is, with the use of a general-purpose intelligent system with reasoning and learning capabilities.

This paper is organized as follows. Section 2 contains a brief overview of NAL. Our conceptual framework is presented in Section 3. Section 4 presents an example NAL case study in medical diagnosis. Section 5 concludes the paper and provides directions of future work.

II. NON-AXIOMATIC LOGIC

NAL is the core logic of NARS an AGI project. It is designed to be a uniform logical foundation for AGI, as well as an abstract description of the human thought process. It is constructed around the notion of insufficient

¹ When a knowledge-based system is implemented with production rules, then it is called a rule based system [10, 16].

knowledge and resources. That notion defines that the meaning of any term and the truth-value of any statement is determined by the evidence available to the system. By design, NAL can consistently represent and reason with different types of uncertainty.

NAL is organized into 9 levels. Each level extends the previous ones by introducing new concepts, grammar, and/or inference rules. A practical system which uses NAL doesn't need to implement all 9 levels to function, instead it can only use the levels needed for its specific reasoning tasks. Briefly, each level includes the following:

- NAL-1: Inference rules for inheritance.
- NAL-2: Similarity, instance, and property copulas.
- NAL-3: Compound terms.
- NAL-4: Arbitrary relations among terms.
- NAL-5: Higher-order statements.
- NAL-6: Variables.
- NAL-7: The concept of time.
- NAL-8: Support for operations, i.e. procedural statements.

- NAL-9: Self-control and self-monitoring.

NAL is a term logic, its sentences are given in the form of "S r P (*f*, *c*)". Where S is the subject, P is the predicate and r is the copula which represents the relation between the two terms. The most basic relation in NAL is inheritance, symbolized as "→". Statements S→P can be read as S is a type of P, for example *coldPatient*→*patient* a *coldPatient* is a type of *patient*.

The truth-value (*f*, *c*) is a pair of real numbers, in the range [0,1], defined by the evidence available to the system. The letter *f* is called frequency and its value represents the ratio between the positive evidence w^+ and total evidence w . The second number *c* is the confidence of the system which describes how stable the frequency will be in light of the new evidence. Confidence is defined as $w/(w+k)$, where *k* is the constant amount of future evidence (*k* is usually set to the value of 1). For example, in the statement *cold-patient*→[*cough*] <0.79, 0.73> the value of 0.79 (frequency) can be read that there is a 79% chance of cough being a symptom of cold, and the value of 0.73 (confidence) means that the system is 73% confident that the value of frequency won't be changed in the foreseeable future by new evidence.

The system provides various kinds of inference rules such as deduction, induction, and abduction. Those inference rules can derive new knowledge from existing knowledge. Each of the rules has its truth-value function that calculates the truth-value of the conclusion according to the evidential support provided by the premises. NALs knowledge base doesn't need to be consistent at all times, and its revision rule is used to handle inconsistencies. The revision rule is used to unify the same knowledge contained in two beliefs derived from disjoint evidential sets. Also, if the amount of statements becomes too large, the composition rule can be used to combine them and enable more efficient reasoning. Full description of the logic can be found in [5, 6].

In a practical scenario, the truth-value of the knowledge initially given to the system can determined

by the user. Additionally, if the knowledge comes from statistical data source, then the evidence can be extracted from the given data, which in turn determines the truth-values. For example, a physician can, based on his experience, know that a certain disease presents with a certain symptom in 80% of the cases. That expert knowledge can be directly imputed in the system. On the other hand, if the statistical data is available for a disease and its symptoms the frequency and confidence values can be directly calculated by the given formulas.

It is important to note that NAL is not better than mathematical or probabilistic logic in a sense that it will provide more accurate inferences than them, the creator of NAL stated: "Whenever the knowledge/resource demands of a traditional model can be satisfied, it usually works better than NAL. When those demands cannot be satisfied, NAL works better than illegally applying a traditional model" [6].

III. PROPOSED FRAMEWORK

In order for a CDSS to properly support the complete diagnostic process, it needs to be able to gather information, recognize patterns, ask questions, make decision under uncertainty, and such, that is it needs to have human-like reasoning capabilities [16, 17]. A system with human-like reasoning capabilities needs to be constructed around several key concepts, such as [4, 5, 6]:

- its inference engine needs to be constructed around a solid theoretical foundation that supports uncertain and inconsistent knowledge,
- knowledge base must be scalable,
- it should provide real-time response,
- system should support learning, and
- it should provide support for external processes (e.g. it should be able to pass the relevant data from its knowledgebase to a ANN and use the results that ANN generates in its own reasoning).

Aforementioned concepts are usually attributed to AGI systems, and they can be used as a foundation for the construction of a CDSS. Use of AGI systems could decrease the cost and improve the reusability of the system in different domains. Therefore we propose a framework that uses text mining techniques for knowledge-base maintenance/creation and a general-purpose logic for its reasoning with learning capabilities.

Our proposed framework is given in figure 1. The framework was designed with NAL as the core logic of the reasoning engine. The framework consists of three main components: the text mining subsystem, the knowledge base, and the reasoning engine.

Text mining in medicine is not a new concept. It has thus far been applied for named entity recognition, de-identification, etc. [14, 15]. In the aspect of CDSS text mining can be applied to medical textbooks and electronic health records. Medical textbooks are thoroughly vetted sources of medical knowledge written by medical experts. With the use of text mining, the knowledge in medical textbooks can be translated into a knowledge base of a CDSS, which in turn can decrease

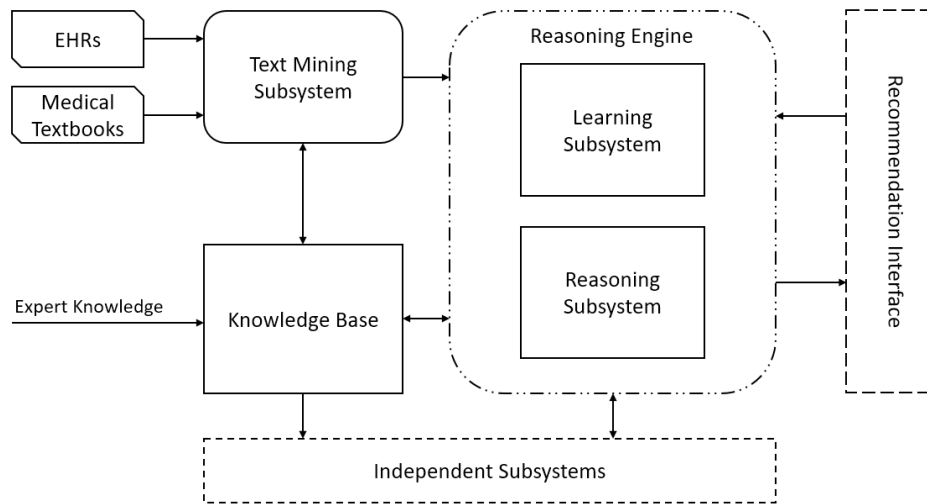


Figure 1. Proposed Framework

the knowledge base maintenance cost. Text mining can also be applied to electronic health records (EHRs). EHRs contain a wealth of data in the form of unstructured text. Data such as the complete disease history of a patient, the decisions physicians made in different scenarios, as well as the diagnostic process and treatment process done by the patients physicians, can be extracted from EHRs. The data contained in patients histories can be used to improve the accuracy of the CDSS or even to help the system to learn new and previously unknown relations. On the other hand, the data about the behavior of physicians in different scenarios can help model and improve the decision making task of the system without the need of explicit input from the experts.

The knowledge base in the proposed framework can be updated in three ways: by the experts themselves, by the text mining subsystem, and by the reasoning engine through its learning subsystem. All changes to the existing knowledge in the knowledge base should be validated by the clinicians.

NAL is used as the core logic of the reasoning engine. The reasoning engine consists of two parts: the reasoning subsystem and the learning subsystem. The reasoning subsystem can be seen as the reasoning engine itself. It accepts external input, and uses the knowledge, contained in the knowledge-base, to provide support to the users. The learning subsystem monitors and stores all the reasoning done by the reasoning subsystem. After the systems receives feedback from clinician (e.g. after the proposed treatment the patient still exhibits the same symptoms) it uses that feedback data to update the uncertainty values of the applied inferences. For example, if the system has two competing diagnoses for a set of symptoms, the system will choose one of the diagnoses as primary based on the truth values. If the system receives a negative feedback from the user, for the chosen diagnosis, it will use that feedback to slight modify the truth values of both diagnosis for the set of used symptoms.

Another advantage of the use of AGI systems such as NAL/NARS is their ability to use external process in their own reasoning. For example, if the system reasons that a potential cause of patients symptoms can be a certain

disease, the system with NAL as the core logic can pass the relevant data to an ANN (or any other model) and use its findings for further reasoning. This ability enables the CDSS to be easily extensible without the need for extensive changes in the design of our framework.

IV. CASE STUDY

This section presents a very simple case study of NAL in the domain of medical diagnosis. A more detailed case study, with more complex scenarios, can be found in [2]. The data in the example below was tested on an open source implementation of NARS, the OpenNARS 2².

If we assume that the knowledge-base contains the knowledge given in table 1. Table 1. Contains the

Table 1. Initial knowledge

cold-patient→[cough]	<0.79, 0.90>
cold-patient→[runny-nose]	<0.90, 0.90>
cold-patient→[fever]	<0.65, 0.87>
allergy-patient→[runny-nose]	<0.95, 0.92>

knowledge about two possible diagnoses: cold-patient and allergy-patient. Cold-patient, that is the cold, can present with three symptoms: cough in 79% of the cases, runny nose in 90% of the cases, and fever in 65% of the cases. Allergy-patient, that is allergies, presents with the symptom of runny nose in 95% of the cases. If the system receives the input with partial data, e.g. that a patient exhibits symptoms of a runny nose and of a cough (given in table 2.) the system will derive: {patient1} → cold-patient <0.90, 0.41>, that is, patient1 is a cold patient. On the other hand, if the system gets the complete input

Table 2. Input data for patient1

{patient1}→[runny-nose]	<1.0,0.90>
{patient1}→[cough]	<1.0,0.90>

Note: When inputting data with NAL a default values for frequency and confidence are 1.0 and 0.90 respectively

information about the patient, given in table 3, it can derive a solution, in this case, with a slightly higher frequency value: {patient2}→allergy-patient <1.0,0.39> The low confidence values can be attributed to the low amount of evidence given to the system.

² <https://github.com/opennars/opennars2>

Table 3. Input data for patient2

{patient2}→[runny-nose] <1.0,0.90>
{patient2}→[cough] <0.0,0.90>
{patient2}→[fever] <0.0,0.90>

It is important to note that the relations given in tables above are simple, and that they would be much more complex in a real-world application. Due to simplicity of the test case, the use of text mining is not shown in the example above. In the context of a real-world application, the time consuming and expensive task of forming the knowledge-base, usually done by experts, can be efficiently done by the use of text mining.

V. CONCLUSION

In this paper, we presented a conceptual framework for Clinical Decision Support Systems based on the use of a general-purpose logic for intelligent reasoning and medical text mining.

A framework, for CDSS, with reasoning and learning capabilities, based on NAL, has the potential to solve main disadvantages of traditional knowledge based systems, such as:

- Dealing with uncertainty, which is unavoidable in the diagnostic process, is one of the core concepts around which NAL is constructed. As such, it provides consistent format for representing uncertainty and reasoning with uncertain and inconsistent knowledge.
- Most knowledge based systems are domain specific with their core logic being closely coupled with domain specific knowledge the system works with. Such systems are often too costly to maintain due to the fact that a domain expert is required to update the knowledge base. In contrast, NAL has a general-purpose logic and control mechanism that is separate from domain specific knowledge. This separation allows the system to update its knowledge base via automatized techniques, i.e. text mining from medical books that are already written by domain experts.
- Lastly, NAL is scalable to large amounts of knowledge and complicated problems, because NAL does not exhaustively search all possibilities when solving a problem. Instead, it only considers a “reasonable” amount of them, depending on the amount of available resources [5].

In comparison to other approaches for diagnostic support, an AGI approach provides the system with various kind of reasoning rules (such as comparison, revision, choice, induction, etc.) instead of deduction only.

Another novelty introduced by our framework is the use of text mining as a way of constructing/maintaining the knowledge base. Such use of text mining techniques could, besides decreasing the maintenance cost, potentially decrease the time in which new medical findings (or facts) are confirmed, by analyzing EHRs, and made available to general practitioners.

In our future work we intend to implement the described framework for the comorbidity diagnostic

support, in cooperation with Nephrology clinic at Clinical Center of Serbia in Belgrade.

ACKNOWLEDGMENTS

This work has been partially supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia (project III47003).

REFERENCES

- [1] Berner, E. S., & La Lande, T. J. (2016). Overview of clinical decision support systems. In *Clinical decision support systems* (pp. 1-17). Springer International Publishing.
- [2] Wang, P., & Awan, S. (2011, August). Reasoning in non-axiomatic logic: a case study in medical diagnosis. In *International Conference on Artificial General Intelligence* (pp. 297-302). Springer Berlin Heidelberg.
- [3] Lanzer P, Wang P (2015) On the Logic of Percutaneous Coronary Interventions. *Int J Clin Cardiol* 2:033.
- [4] Slam, N., Wang, W., Xue, G., & Wang, P. (2015). A framework with reasoning capabilities for crisis response decision-support systems. *Engineering Applications of Artificial Intelligence*, 46, 346-353.
- [5] Wang, P. (2006). *Rigid flexibility* (Vol. 55). Springer.
- [6] Wang, P. (2013). *Non-axiomatic logic: A model of intelligent reasoning*. World Scientific.
- [7] Wimmer G., Hegenbart S., Vecsei A., Uhl A. (2017) Convolutional Neural Network Architectures for the Automated Diagnosis of Celiac Disease. In: Peters T. et al. (eds) *Computer-Assisted and Robotic Endoscopy. CARE 2016. Lecture Notes in Computer Science*, vol 10170. Springer, Cham
- [8] Narain R, Saxena S, Goyal AK. Cardiovascular risk prediction: a comparative study of Framingham and quantum neural network based approach. *Patient preference and adherence*. 2016;10:1259-1270.
- [9] Chen, J., Qi, X., Tervonen, O., Silvén, O., Zhao, G., & Pietikäinen, M. (2016, August). Thorax disease diagnosis using deep convolutional neural network. In *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the* (pp. 2287-2290). IEEE.
- [10] Buchanan, B., & Shortliffe, E. (1984). *Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project*.
- [11] Martins, S. B., Lai, S., Tu, S., Shankar, R., Hastings, S. N., Hoffman, B. B., ... & Goldstein, M. K. (2006). Offline testing of the ATHENA Hypertension decision support system knowledge base to improve the accuracy of recommendations. In *AMIA Annual Symposium Proceedings* (Vol. 2006, p. 539). American Medical Informatics Association.
- [12] Kong, G., Xu, D. L., Body, R., Yang, J. B., Mackway-Jones, K., & Carley, S. (2012). A belief rule-based decision support system for clinical risk assessment of cardiac chest pain. *European Journal of Operational Research*, 219(3), 564-573.
- [13] Miller, R. A. (2016). Diagnostic decision support systems. In *Clinical decision support systems* (pp. 181-208). Springer International Publishing.
- [14] Dehghan, A., Kovacevic, A., Karystianis, G., Keane, J. A., & Nenadic, G. (2015). Combining knowledge-and data-driven methods for de-identification of clinical narratives. *Journal of biomedical informatics*, 58, S53-S59.
- [15] Kovačević, A., Dehghan, A., Filannino, M., Keane, J. A., & Nenadic, G. (2013). Combining rules and machine learning for extraction of temporal expressions and events from clinical narratives. *Journal of the American Medical Informatics Association*, 20(5), 859-866.
- [16] Musen, M. A., Middleton, B., & Greenes, R. A. (2014). Clinical decision-support systems. In *Biomedical informatics* (pp. 643-674). Springer London.
- [17] Miller, R. A. (2016). Diagnostic decision support systems. In *Clinical decision support systems* (pp. 181-208). Springer International Publishing.