Recommendation Statements Identification in Clinical Practice Guidelines Using Heuristic Patterns

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***Abstract*—Clinical Practice Guidelines (CPGs) are considered as an effective tool to improve and standardize healthcare. A number of organizations are developing and maintaining clinical guidelines to provide state of the art healthcare services. However, the guidelines contain background information along with disease specific information which tends to create difficulties in using it during actual practice as well as in transforming it into a machine interpretable format. The most relevant information needs to be isolated from irrelevant information. In this study, we proposed a methodology that separates relevant information known as recommendation statements from irrelevant information by using heuristic patterns. We have extracted 10 patterns in a semi-automatic manner from hypertension guideline and evaluated the extracted patterns for identifying recommendation statements in the guideline and achieved 85.54% accuracy. These extracted patterns facilitate domain expert to get disease specific information in real time during the clinical workflow. Moreover, it can also work as a preprocessing step during the transformation of guideline to computer interpretable models.**

Keywords*—Heuristic patterns, Recommendation Statements Identification, Clinical Practice Guidelines, Information Extraction (IE)

I. Introduction

The Clinical Practice Guidelines (CPGs) are defined as "systematically developed statements to assist practitioners and patient decisions about appropriate healthcare for specific circumstances" [1]. The emergence and ease of access to internet increase the influence of CPGs. CPG is an essential medium for standardizing and disseminating medical knowledge. The primary ambition of CPGs is to restrict practice variations and provide evidence based treatment [2]. The services CPG can offer includes, specific decision relevant information retrieval, patient data summarization, context specific intimation generation, and patient relevant clinical option selection [3]. CPG services can improve the healthcare quality employed in clinical workflows [4]. The CPGs along with other information consists of recommendation statements that specify process flow based on patients' condition and provide details of "what to do" with the patient [5]. For example, the statement "the evidence statements supporting the recommendations are in the online supplement" is an informative sentence while, "in the general population aged = 60 years, initiate pharmacologic treatment to lower blood pressure -LRB- BP -RRB- at systolic blood pressure -LRB- SBP -RRB- = 150 mm Hg or diastolic blood pressure -LRB- DBP -RRB- = 90 mm Hg and treat to a goal SBP < 150 mm Hg and goal DBP < 90 mm Hg" is a recommendation statements that described the detail actions needed to be taken for the target users. Both statements are taken from hypertension guideline [6] which is used for this study.

The goal of CPGs can be accomplished by integrating it into clinical workflows. Publishing CPGs in medical journals is facing issues in dissemination and is ineffective for changing clinical practice behaviors [7]. Most of the healthcare practitioners are unaware of the existence of CPGs, and even they experience difficulties in understanding when directed them toward concern CPG [8]. Those who knows about CPGs usually do not utilize it during real practices. One primary reason may be the structure and format of the CPGs. They are written in natural language and consist of other related information along with disease specific information. Identifying disease specific and scenario based information in real time seems inconceivable. This deficiency can be overcome by automatically identifying recommendation statements in CPGs.

CPGs can either be used by human experts during healthcare flow or can be transformed to machine understandable format to be part of the recommendation systems. Both these cases need CPG understanding and relevant information identification. Identifying and extracting recommendation statements from other information is a time consuming and erroneous task. CPGs contains disease specific information, therefore, it requires domain knowledge. The human burden needs to be reduced by automating this process.

The complete automation of the recommendation statements identification process faces many issues. The major hurdle is due to the variation in linguistic expression. All recommendation statements do not follow "if condition then action" format. The CPGs are written by different

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organizations and most of the organizations have different guidelines writing formats. However, in all formats, the recommendation statements consist of some hidden patterns and specifier phrases. Those patterns need to be identified that can be used later on for automatic identification of recommendation statements.

The objective of this study is to identify heuristic patterns used in recommendation statements of CPGs. These patterns can be used later for extracting recommendation statements in the CPGs. This kind of study provides twofold advantages. It can be used as preprocessing step for transforming CPGs to computer interpretable format. Also, it can facilitate healthcare provider to find disease specific information in CPGs during clinical workflow in real time. We used hypertension guideline [6] for heuristic pattern identification and evaluation. We extracted a total 10 patterns for recommendation statements' identification which outperforms and achieved 85.54% accuracy.

The rest of the paper is organized as follows. Section II presents the related work of the study. Section III describes our proposed recommendation statement identification methodology. Section IV presents result achieved and section V concludes the paper and presents the future direction of the study.

II. Related Work

The historical backdrop of CPGs begins in the late 1970s by the Nation Institute of Health Consensus Development Program with the emanation of consensus statements for improving healthcare quality through identification and adaption of the best practices [9]. The ease of accessibility to CPGs attract researchers to facilitate healthcare providers by integrating the best practice and up to date research in clinical workflows. The CPGs can easily be incorporated in clinical workflow by transforming it into a machine understandable format.

R. Servan et al. [10] developed a methodology to facilitate human modelers for CPGs formalization and reduce manual effort by using linguistic patterns. The authors used templates and examine the role of knowledge templates in formalization and modularization of CPGs. The methodology used medical domain ontology for generating linguistic templates. The activity needs to encompass includes, extract patterns, select core patterns, apply patterns, generate executable model, and evaluate the executable model. This methodology produced reusable guidelines block/template for authoring and formalizing CPGs. However, this approach needs a customized domain ontology for mapping the concept while generating template. The authors used classes from Unified Medical Language System (UMLS) with customized classes for generalization. Generating customized ontology and generalizing the UMLS classes is a tedious task and erroneous class generalization may lead to the incorrect template and incorrect guideline modeling.

K. Kaiser et al. [11] proposed a system to analyze activities formulations in CPGs. The authors used UMLS classes to identified patterns which employed for activities representation and the semantic relations among them. The study consists of four steps. In the first step, they analyze CPG regarding actions and procedures. In the second step, they explore the relationship between actions and procedures. In the third step, they expand the semantic type of the identified relation for generalization. Finally, theyK. Kaiser et al. [11] proposed a system to analyze activities formulations in CPGs. The authors used UMLS classes to identified patterns which employed for activities representation and the semantic relations among them. The study consists of four steps. In the first step, they analyze CPG regarding actions and procedures. In the second step, they explore the relationship between actions and procedures. In the third step, they expand the semantic type of the identified relation for generalization. Finally, they generate a dictionary of the identified actions, procedures, and their relations. They used "Induction in labour" [12] guideline which consists of 48 actions statements among 120 statements for the pattern and their relation extraction. The experiment was performed on "Management of labor" guideline and achieved a recall of 67% and precision of 97%. Despite high precision and recall, this system has limited capability of identifying only actions and procedures. The other dimensions of information for instance intentions, effects or parameters get ignored and the system has no capability to detect them.

R Wenzina et al. [5] proposed a rule-based method using a combination of linguistic and semantic information of UMLS semantic type. The authors hypothesized that each guideline statement had its owns domain dependent linguistic and semantic patterns. They also induce weighting coefficient called relevance rate that shows statements relevancy for modeling. The relevance rate enables the authors to identify the condition-action combination. Relevance rate show either the statement is crucial for clinical pathway. Ashtma guideline was used for pattern extraction. The pattern extracted from the guideline was consisted of 12 "if" and 4 "should" statements. The analysis showed that rules of type "if" has a better result than the one of type "should".

H. Hematialam et al. [13] proposed an automatic technique of finding and extracting recommendation statements in CPGs. The authors used a supervised machine learning model (Naïve Bayes, J48, and Random Forest) that classify guideline statements into three categories: NC (no condition), CA (condition-action), and CC (condition consequence). The domain expert annotated three types of guidelines (hypertension, chapter 4 of asthma, and rhinosinusitis) and the authors used these guidelines as a training set for training machine learning model. The authors used Part of Speech (POS) tags as features for the model to make the model more domain independent. Each action-condition statement has a modifier, and the most used modifiers in the guidelines used by authors in their study were "if", "in", "for", "to", "which", and "when". The statements were parsed by using CoreNLP Shift-Reduce Constituency parser and the candidate statements were find by using regular expressions. The identified candidate statements were transformed/paraphrased to "if condition, then consequences" format to be used for rule generations. The authors used models are one shot models and required retraining each time if a change occurs in the training dataset.

W. Gad El-Rab et al. [14] proposed a framework for CPGs active dissemination and automatic knowledge extraction for

Clinical Decision Support System (CDSS). The framework automates some of the manual activities to facilitate and reduce manual efforts of human modelers. The framework follows multi-step approach and used Unstructured Information Management Architecture (UIMA) for identifying medical concepts. The task performed in the pipeline includes XML parsing, text cleansing, medical concept tagging, medical tags disambiguation, clinical context pattern detection, clinical context filtering, and clinical context mapping. The framework achieved good outcomes, however, the primary obstruct of the framework is, it required clinical context type. Due to the lack of pre-annotated test data set the framework was tested on only two clinical context types.

The clinician can exploit CPGs by integrating and utilizing it in real practices. However, existing CPGs are published in unstructured format and machine cannot directly understand it, which diminishes CPGs and most of the latest research resides and use for academic purpose only. CPGs need to be transformed to a machine interpretable format so that it can be used in real clinical workflows as well as can be utilized by CDSS systems for up to date recommendation generation.

III. PROPOSED METHODOLOGY

The CPGs can be transformed to machine interpretable model in three steps: recommendation statements identification, recommendation statements understanding, and rule generations as depicted in the Fig. 1. Recommendation statements identification mainly focuses on extracting the statements representing recommendations in CPGs from the other statements. Recommendation statements' understanding mainly concerns about the analysis of identified statements to find key feature (conditions and actions). While, in rule generation, the identify key features are transform into a machine interpretable model (in our case if-then rules). In this work, our main focus is on the first step i.e. recommendation statements identification.

In the CPG conversion process, the recommendation statements identification being the first step has a pivotal role and all subsequent steps depend on the result of this step. Erroneous statements identification or missing any relevant information ultimately leads to incorrect model/rule generations. To accurately identify these statements, we thoroughly analyze the recommendation statements of hypertension [6] guideline annotated by a domain expert.

This analysis leads us to the conclusion that each recommendation statement contains some clue word(s) also known as a heuristic pattern through which the recommendation statements can be differentiated from non-recommendation statements.

The functional flow of the proposed methodology is depicted in Fig. 2. The proposed research identifies and filters out recommendation statements using two steps process: preprocessing and recommendation identification. Preprocessing deals with the reading guideline and appropriately formatting it for successive steps.

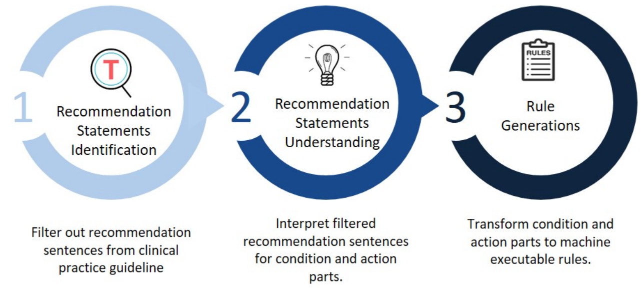

Fig. 1. Steps required for CPGs conversion

While recommendation statements identification identifies the intended recommendation statements. The details of these two steps are as follows.

A. Preprocessing

The early research has proven that nearly 50% to 80% time of the entire process is spent on preprocessing which shows the importance of the process [15]. The purpose of preprocessing phase is to convert the original data/input in to data mining ready structure. Therefore, preprocessing was devised in the proposed workflow which comprises of three sub steps. First, the document reader reads the guideline documents. Secondly, the word documents are transformed into document format (Dom object). Finally, the document is then split into sentences by the Sentence Extractor. These sentences are then passed to Recommendation Identification component for filtering required statements.

B. Recommendation Identification

The recommendation statements identification task is formulated into a classification task which classifies the guideline statements into two possible categories Recommendation Sentences (RS) and Non-Recommendation Sentences (NRS). The aforementioned classification is performed based on extracted heuristic patterns. The dictionary based tagger maps the input statements with patterns stored in heuristic pattern base.

The statements are tagged with RS if any pattern matched, otherwise, it is tagged as NRS. The output of the dictionary based tagger is guideline statements with the corresponding tag. The tag Filter component then filters out the intended statements tagged as RS and discard NRS tagged sentences.

The proposed approach can benefit in two ways. It can conciliate and assist healthcare professionals in identifying patient specific information in the guideline during real clinical scenarios. Also, it can work as the preprocessing step for the transformation of CPGs to machine interpretable format and can also work for other knowledge extraction systems, that extracts knowledge from CPGs and store in machine interpretable format.

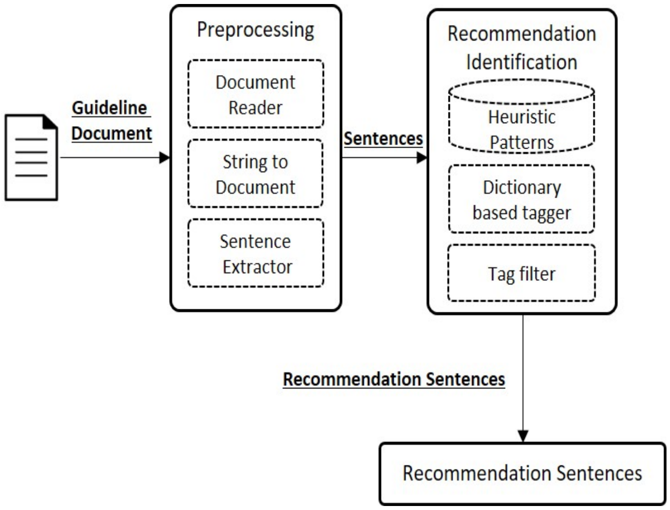

Fig. 2. Proposed system architecture

IV. RESULT AND DISCUSSION

We analyzed published hypertension guideline [6] that contains total 278 statements including 78 recommendation statements annotated by a domain expert. The same guideline was used and annotated by H. Hematialam et al. [13] in their study as discussed earlier. They have trained and evaluated Naïve Bayes, J48, and Random Forest algorithms and achieved accuracy of 74%, 74%, and 81% respectively. In our study, we considered all CA (Condition-Action), CC (Condition Consequences), and A (Action) statements as recommendation statements. We divided the guideline into approximately 70% (195 including 58 recommendation statements), 30% (83 including 20 recommendation statements) for training and testing data set respectively. We analyze the training set for identifying patterns. We identified 10 heuristics patterns from the training set. The extracted patterns are given in table I.

TABLE I. EXTRACTED HEURISTICS PATTERNS

No	*Patterns*
1	.*treatment (should|with|to).*
2	.*(recommend(ed)?) treatment.*
3	.*should (include|continue).*
4	.*(increase|decrease) .*dose.*
5	.*(add|remove) (.*) drug.*
6	.*Recommendation \d+\s+:.*
7	.*(dis)?continu(e|ed|ing|ation).*
8	.*to improve.*
9	.*(patient(s)?)?with (disease).*
10	.*regardless of.*

We examine the remaining statements (83) of the guideline with the extracted patterns and achieved accuracy of 85.54%. We compare the proposed system with the H. Hematialam et al. [13] because both used the same hypertension guideline. The comparison is depicted in Fig. 3. The proposed system achieved higher accuracy as compared with H. Hematilams' models. The confusion matrix and detail measure of the proposed approach is given in table II and table III respectively.

TABLE II. CONFUSION MATERIX OF PROPOSED APPROACH

	TP	*TN*
RS	14	6
NRS	6	57

TABLE III. DETAIL MEASURES OF THE PROPSED APPRAOCH

Measure	*Value (%)*	*Derivations*
Sensitivity	0.7000	TPR = TP / (TP + FN)
Specificity	0.9048	SPC = TN / (FP + TN)
Precisoin	0.7000	PPV = TP / (TP + FP)
Nagative Predictive Value	0.9048	NPV = TN / (TN + FN)
Fale Positive Rate	0.0952	FPR = FP / (FP + TN)
False Discovery Rate	0.3000	FDR = FN / (FP + TP)
Fasle Negative Rate	0.3000	FNR = FN / (FN + TP)
Accuracy	0.8554	ACC = (TP + TN) / (P + N)

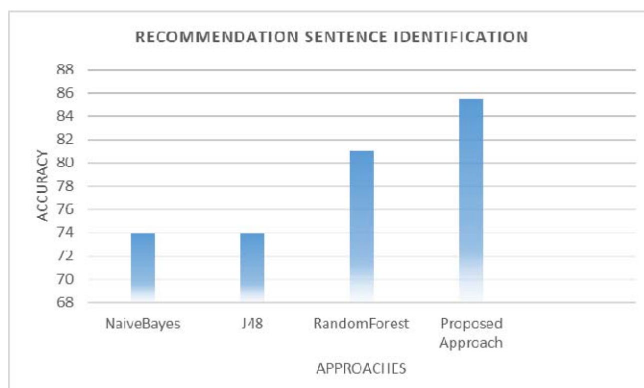

Fig. 3. Comparison of proposed vs existing approaches

V. CONCLUSION AND FUTURE WORK

In this paper, we developed a methodology that classifies the guideline statements into recommendation and non-recommendation statements using heuristic patterns. Using our approach, we achieved a higher level of accuracy as compared to the existing work. The proposed work of filtering recommendation statements can reduce the burden and assist healthcare practitioner at the time of real practice for identifying scenario based and disease specific evidence. Also, it can facilitate guideline based machine learning model generation. In future, we want to generalize this work by POS tags and UMLS semantic network for the extracted patterns to reduce the domain dependency.

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REFERENCES

[1] [1] K. N. Lohr and M. J. Field, Clinical practice guidelines: directions for a new program, vol. 90. National Academies Press, 1990.

[2] [2] D. A. Davis and A. Taylor-Vaisey, "Translating guidelines into practice: a systematic review of theoretic concepts, practical experience and research evidence in the adoption of clinical practice guidelines," Can. Med. Assoc. J., vol. 157, no. 4, pp. 408–416, 1997.

[3] [3] J. Fox, V. Patkar, I. Chronakis, and R. Begent, "From practice guidelines to clinical decision support: closing the loop," J. R. Soc. Med., vol. 102, no. 11, pp. 464–473, 2009.

[4] [4] K. Kaiser, S. Miksch, and S. W. Tu, Computer-based support for clinical guidelines and protocols: proceedings of the symposium on computerized guidelines and protocols (CGP 2004). 2004.

[5] [5] R. Wenzina and K. Kaiser, "Identifying condition-action sentences using a heuristic-based information extraction method," in Process Support and Knowledge Representation in Health Care, Springer, 2013, pp. 26–38.

[6] [6] P. A. James et al., "2014 evidence-based guideline for the management of high blood pressure in adults: report from the panel members appointed to the Eighth Joint National Committee (JNC 8)," Jama, vol. 311, no. 5, pp. 507–520, 2014.

[7] [7] D. A. Davis, M. A. Thomson, A. D. Oxman, and R. B. Haynes, "Evidence for the effectiveness of CME," Jama, vol. 268, no. 9, pp. 1111–7, 1992.

[8] [8] E. Kilsdonk, L. W. Peute, R. J. Riezebos, L. C. Kremer, and M. W. Jaspers, "From an expert-driven paper guideline to a user-centred decision support system: A usability comparison study," Artif. Intell. Med., vol. 59, no. 1, pp. 5–13, 2013.

[9] [9] P. B. Jacobsen, "Clinical practice guidelines for the psychosocial care of cancer survivors," Cancer, vol. 115, no. S18, pp. 4419–4429, 2009.

[10] [10] R. Serban, A. ten Teije, F. van Harmelen, M. Marcos, and C. Polo-Conde, "Extraction and use of linguistic patterns for modelling medical guidelines," Artif. Intell. Med., vol. 39, no. 2, pp. 137–149, 2007.

[11] [11] K. Kaiser, A. Seyfang, and S. Miksch, "Identifying actions described in clinical practice guidelines using semantic relations," in KR4HC 2010-2nd International Workshop on Knowledge Representation for Health Care, 2010, pp. 99–108.

[12] [12] National Collaborating Centre for Women's and Children's Health (UK), Induction of Labour. London: RCOG Press, 2008.

[13] [13] H. Hematialam and W. Zadrozny, "Identifying Condition-Action Statements in Medical Guidelines Using Domain-Independent Features," ArXiv Prepr. ArXiv170604206, 2017.

[14] [14] W. Gad El-Rab, O. R. Zaïane, and M. El-Hajj, "Formalizing clinical practice guideline for clinical decision support systems," Health Informatics J., vol. 23, no. 2, pp. 146–156, 2017.

[15] [15] V. Srividhya and R. Anitha, "Evaluating preprocessing techniques in text categorization," Int. J. Comput. Sci. Appl., vol. 47, no. 11, pp. 49–51, 2010.