Automatic Summary System for Patients Hematological Examination Result in Textual Representation Form

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Keywords: Natural Language Generation, Narrative Science, Textual Representation, Hematological Examination, Summary Text.

Abstract: Results of hematological examination from a laboratory are presented in the form of medical abbreviations and numbers alongside their units, which are represented in tabular form. The result of laboratory examination is not provided with explanation text on whether the blood components of the hematologic examination results are normal, abnormal or critical. In order to analyze the blood components of a hematological examination, a physician should manually compare each blood component value with the known normal range of values available. In this research Natural Language Generation (NLG) with a template-based method is employed to interpret the results of the patient's hematology laboratory examination. The result of interpretation is written into a summary text in Bahasa Indonesia. Evaluation of the naturalness of the summary text obtained from the system performed by general practitioners and young doctors reported higher percentage interval of 93.1% to 97.5%.

1 INTRODUCTION

Results of hematological examinations obtained from a laboratory are given in medical terms and abbreviations. Those results are in the form of numbers alongside their units (e.g. MCV: 70.4 fL; MCH: 24.3 pg) represented in tabular form with no explanation on whether the blood components of the hematological examination results are within normal, abnormal or critical values. To find out a normal, abnormal or critical blood component, a physician should manually compare each blood component of the hematological examination with a normal range of values available, one after another individually. This manual procedure will consume much time not to mention it is an error-prone task.

Research works that focus on developing a system to interpret data (such as numeric data) into informa-tion in the form of textual representations (such as re-ports or summary text) had been performed by many researchers. Reiter and Dale (2000) developed a system of textual representation to make data (numbers) easy to read and understandable by non-expert users or users who have no time in reading the whole data.

Eugenio et al. (2014) used Natural Language Generation (NLG) or narrative science approach whereby they examined the making of a system that can generate a summary text from a brief record of data written by a physician and a nurse's structural documentation (patient care plan) for a patient with a heart condition who has undergone hospitalization. Generating this summary text is useful for helping patients to take care of themselves after their hospitalization and as an approach to educate patients about what treatments are being performed to patients during the in-patient process. The preparation of the summary text begins with a process of building a graph to see the relationship between two input data (short note data written by the doctor and nurse structural documentation data). Then selected information extracted from the graph obtained was written into the summary text. The last process undertaken was the application of SimpleNLG system.

In addition, research work by Archarya et al. (2016) generated a summary text of hospital patient by linking two heterogeneous sources of doctors and nurses documentation, while considering the complexities of medical terms. The summary text generated was still based on inpatient medical data

Sitompul, O., Nababan, E., Arisandi, D. and Aulia, I.
Automatic Summary System for Patients Hematological Examination Result in Textual Representation Form.
DOI: 10.5220/0010093719241928
In *Proceedings of the International Conference of Science, Technology, Engineering, Environmental and Ramification Researches (ICOSTEERR 2018) - Research in Industry 4.0*, pages 1924-1928
ISBN: 978-989-758-449-7

and did not cover laboratory examination data (e.g. hematol-ogy).

The aim of this research is to develop a system that could help interpreting data resulted from laboratory examination on hematology patient and putting the interpretation into a summary text that would provide information whether the blood components are in normal condition or the values obtained indicate ab-normal or critical condition. In this research, we used Natural Language Generation approach to report the results of patients hematological examination in the form of summary text using template-based methods.

2 NLG FOR TEXTUAL REPRESENTATION OF HEMATOLOGY EXAMINATION RESULT

Natural language generation is the natural language processing task of generating natural language from a machine representation system such as a knowledge base or a logical form. It is like a translator that converts data into a natural language representation. NLG is one of the areas of research that deals with the automation of producing human-readable text suit-able for certain applications (Biran, 2016). Exam-ple of NLG applications that commonly applied is in medical field to improve service and patients safety for hospital pre-treatment (Schneider et al., 2013).

2.1 Haematology Laboratory Examination

The results of laboratory tests can be expressed in three forms of numbers: quantitative numbers (e.g. normal haemoglobin values of women are 12 - 16 g / dl), qualitative (results expressed as positive or neg-ative values without mentioning positive or negative) and semiquantitative (qualitative results which men-tion the positive or negative degree without specifying the exact number of examples: 1+, 2+, etc.).

Hematologic examination (hemogram) con-sists of examination of leukocytes, erythrocytes, haemoglobin, hematocrit, erythrocytes and platelets. Complete blood count checks consist of hemogram along with differential leukocyte checks consisting of neutrophils, basophils, eosinophils, lymphocytes and monocytes (Herawati & Andrajati, 2011).

Interpretation guidelines of the clinical data pub-lished by the Ministry of Health, Indonesia (Herawati & Andrajati, 2011) showing the normal hematological range of values based on sex is shown in Table 1, which describe: Hematocrit (Hct) shows the percentage of red blood cells to total blood volume.

Table 1: The Full Range of Normal Hematological Values.

(Source: Herawati and Andrajati (2011)

Examination	Unit	Sex	
		Male	emale
Hematrokit (Hct)	%	40-50	5-45
Haemoglobin (Hb)	g/dL	13-18	2-16
Eritrosit (RBC)	10^{12}/L	4.4-5.6	.8-5
Blood Sediment Rate (LED)	mm/1 hour	<15	20
MCV	fL	80-	0 0
MCH	Pg	28-34	
MCHC	g/dL	32-36	
Leukosit	10^9/L	3.2-10	
Neotrofil (Segment)	%	36-73	
Eosinofil	%	- 6	
Basofil	%	- 2	
Limfosit	%	15-45	
Monosit	%	0-10	
Trombosit	10^9/L	170-380	

Haemoglobin (Hb) is a component of blood that serves as a means of transport of oxygen (O_2) and carbon dioxide (CO_2).

Red blood cells or Erythrocytes have a primary function that is to transport oxygen from lungs to the body tissues and transport CO_2 from body tis-sues to the lungs by Hb.

Blood Sediment Rate (LED) is a measure of erythrocyte sedimentary velocity describing plasma composition as well as erythrocyte and plasma comparisons. LEDs are affected by the weight of blood cells and cell surface area and the earth's gravity.

Platelets are the smallest element in the blood vessels. Platelets are activated after contact with the surface of the endothelial wall.

3 PREVIOUS RESEARCH

Eugenio et al. (2014) performed a research on the creation of a system that could produce summary text from physician doctors' briefed notes and nurse structural documentation (containing patient care plans) for patients with inpatient heart disease. This summary text is useful for helping patients to take care of themselves after their hospitalization and as an ap-proach to educate patients about what treatments are being performed to patients during the inpatient process.

Archarya et al. (2016) create a system for gener ating summary text of patient hospital data by combining information from two heterogeneous sources of doctors and nurses documentation. Their study focuses on producing summary text taking into consideration the complexities of medical terms. The first step is to extract written content of the medical document from the mix of both sources, and then the content is identified to determine if there are any terms that belong to simple (unexplainable) terms or complex (terms that need explanation) using metrics created.

Another research by Mahamood and Reiter (2011) focused on the effective approach of creating a system that generates a text of medical information reports for parents of premature babies. They analyze the signal and interpret EMR data to identify the important events and the relationship between the events occur-ring in the EMR data. Then use the NLG method to convert the EMR data into a narrative text. Their research focused on the text produced by the system that could be understood by people who are not professionals in the medical field and the resulting report text only gives positive information about infant development.

The difference of this research with the previous research works is that in this study we implement Natural Language Generation to interpret the results of hematological examination of patients into the form of summary text using Template Generation System (TGen-System). TGen System generates the template candidates (i.e sentences with related slots) automatically which has been classified by considering the content sentences.

4 METHODOLOGY

In this research we implement NLG template-based to interpret the data of Complete Blood Count (CBC) into the Indonesian textual representation. The system, called Complete Blood Count Interpreter System (CBCI-System), employs Natural Language Generation (NLG) concept in generating Indonesian textual representation. The textual representation is deployed by filling related data into the appropriate template slots. Furthermore to handle the limitation of traditional template-based approach in term of text diversity and maintainability, we propose Template Generation System (TGen System). TGen System generates template candidates that has been classified based on content of the sentences. This system helps CBCI System to produce the textual report of CBC result which is not only varied but also easier to understand. The proposed architecture of TGen System is presented in Figure 1.

As shown in Figure 1, TGen System generates the list of sentence templates based on the related corpus (i.e. corpus existing text interpretation of CBC) through Text Segmentation, Slot Generation, Simi lar Template Removing, and Template Classification. During the process of TGen system, it requires linguistics knowledge, which is obtained from the hematology experts.

Since the related corpus is the textual report examples of CBC result, the first process of TGen System is Text Segmentation. Conceptually, Text Segmentation works on the sentence level, then it is used to split every sentence contained in corpus based on the newline and end of character. After sentences are segmented by Text Segmentation, the system will decide words or phrases, which are the related slot candidates. The output of Slot Generation can be called as the template candidates. Since Slot Generation may generate the same templates, Similar template Removing is responsible to collect one template called as unique sentence template. Furthermore unique sentence template is classified into three content sentences (such as the opening sentence, general description sentence, and detail description sentence) by using linguistics knowledge. Finally, Output of Template Classification will be template in the interpretation of generated CBC result.

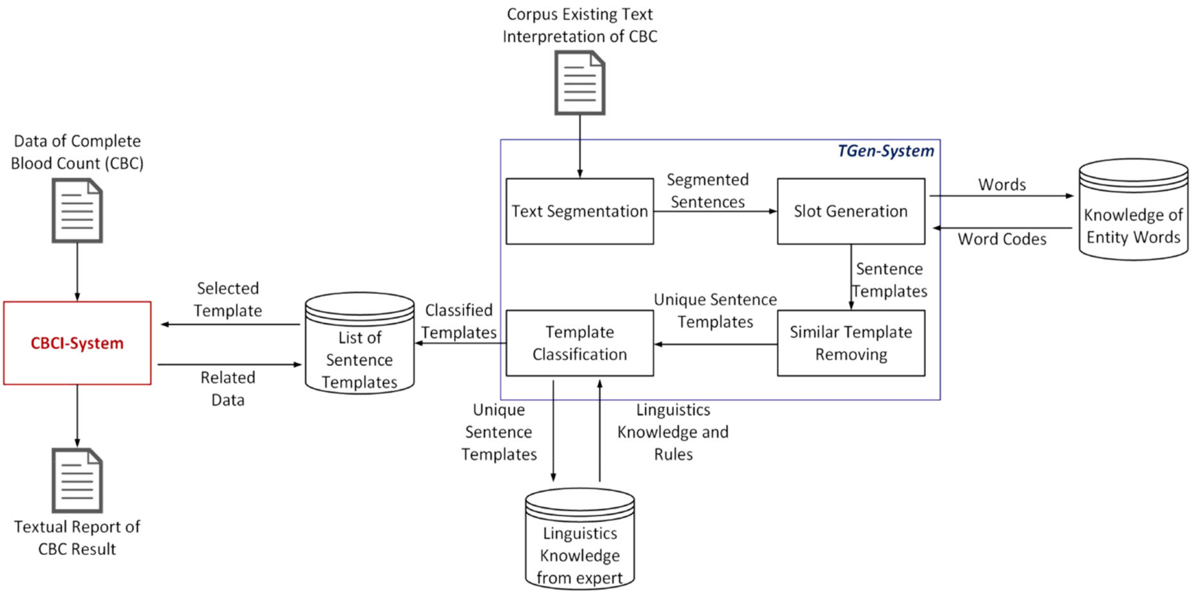


Figure 1: Architecture of the proposed method.

5 RESULT AND DISCUSSION

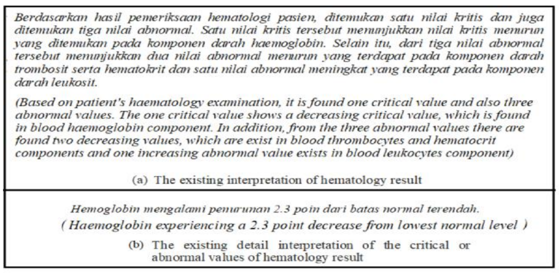
Data used as an input to T-Gen system is the corpus of existing interpretation of hematology results (see for example Figure 2a) and corpus examination of the details critical or abnormal values of hematologic examination results as seen in Figure 2b. In the cor-pus of the results of hematology examination there are 20 examples of text description consisting of 10 examples of description text which have 3 sentences in each paragraph and 10 examples of description text which have 2 sentences in each paragraph totaling in 50 sentences. In addition, within the corpus there are 20 detail example sentences about the critical or abnormal values of the hematologic examination result to be analyzed.

After the corpus of the result of hematology and corpus of the details of the critical or abnormal value of the hematology examination results are analyzed by a series TGen system process, a set of sentence template is obtained. The number of sentence templates obtained from the T-Gen system analysis consists of 10 double-opening sentence templates, 10 sin-gle opening sentence templates, 4 multiple description sentence templates, 7 single expression sentence templates, and 5 detail sentence templates. The Example of sentence template result from TGen system analysis can be seen in Figure 3.

TGen-System can support the CBCI System per formance in generating the interpretation of CBC Result in the medical report. One example of the CBC result from a medical report is shown in Figure 4. Meanwhile, text diversity and maintainability of template can be achieved by TGen-System.

Finally, an evaluation of the system was performed using questionnaires through the appraisal conducted by young doctors as the primary user of the summary text produced by the system and then assessment were performed by general practitioners as a measure of the accuracy of the summary text generated. Three aspects are considered in this evaluation: readability (understandable), clarity and general apropriateness (Belz & Reiter, 2006), (Aulia, 2015).

The result shown that the system has 96.5% readability, 97.0% in clarity and 98.9% in general appropri-ateness.


Berdasarkan hasil pemeriksaan hematologi pasien, ditemukan satu nilai kritis dan juga ditemukan tiga nilai abnormal. Satu nilai kritis tersebut menunjukkan nilai kritis menurun yang ditemukan pada komponen darah haemoglobin. Selain itu, dari tiga nilai abnormal tersebut menunjukkan dua nilai abnormal menurun yang terdapat pada komponen darah trombosit serta hematokrit dan satu nilai abnormal meningkat yang terdapat pada komponen darah leukosit.

(Based on patient's haematology examination, it is found one critical value and also three abnormal values. The one critical value shows a decreasing critical value, which is found in blood haemoglobin component. In addition, from the three abnormal values there are found two decreasing values, which are exist in blood thrombocytes and hematocrit components and one increasing abnormal value exists in blood leukocytes component)

(a) The existing interpretation of hematology result

Hemoglobin mengalami penurunan 2.3 poin dari batas normal terendah.
(Haemoglobin experiencing a 2.3 point decrease from lowest normal level)

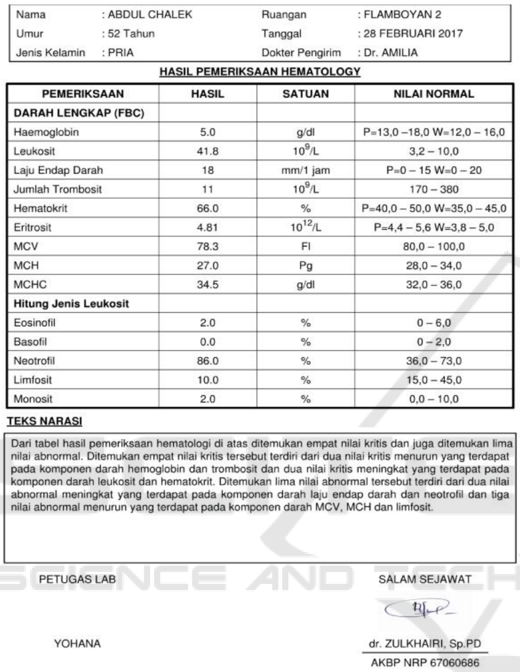
(b) The existing detail interpretation of the critical or abnormal values of hematology result

Figure 2: Example of corpus.

*Dari **SATUAN1** nilai **STATUSKELAINAN** tersebut menunjukkan **SATUAN2** nilai **STATUSKELAINAN TINGKATAN1** yang terdapat pada komponen darah **KOMPONENDARAH1** dan **SATUAN3** nilai **STATUSKELAINAN TINGKATAN2** yang terdapat pada komponen darah **KOMPONENDARAH2**.*

*From SATUAN1 value of the **STATUSKELAINAN** shows **SATUAN2** value of **STATUSKELAINAN TINGKATAN1** existed in blood component **KOMPONENDARAH1** and **SATUAN3** value of **STATUSKELAINAN TINGKATAN2** which is existed in blood component **KOMPONENDARAH2**.*

Figure 3: Example of sentence template generated by T-Gen system.



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Umur	: 52 Tahun	Tanggal	: 28 FEBRUARI 2017
Jenis Kelamin	: PRIA	Dokter Pengirim	: Dr. AMILIA

HASIL PEMERIKSAAN HEMATOLOGY

PEMERIKSAAN	HASIL	SATUAN	NILAI NORMAL
DARAH LENGKAP (FBC)			
Haemoglobin	5.0	g/dl	P=13,0 –18,0 W=12,0 – 16,0
Leukosit	41.8	10^9/L	3,2 – 10,0
Laju Endap Darah	18	mm/1 jam	P=0 – 15 W=0 – 20
Jumlah Trombosit	11	10^9/L	170 – 380
Hematokrit	66.0	%	P=40,0 – 50,0 W=35,0 – 45,0
Eritrosit	4.81	10^{12}/L	P=4,4 – 5,6 W=3,8 – 5,0
MCV	78.3	Fl	80,0 – 100,0
MCH	27.0	Pg	28,0 – 34,0
MCHC	34.5	g/dl	32,0 – 36,0
Hitung Jenis Leukosit			
Eosinofil	2.0	%	0 – 6,0
Basofil	0.0	%	0 – 2,0
Neotrofil	86.0	%	36,0 – 73,0
Limfosit	10.0	%	15,0 – 45,0
Monosit	2.0	%	0,0 – 10,0

TEKS NARASI

Dari tabel hasil pemeriksaan hematologi di atas ditemukan empat nilai kritis dan juga ditemukan lima nilai abnormal. Ditemukan empat nilai kritis tersebut terdiri dari dua nilai kritis menurun yang terdapat pada komponen darah hemoglobin dan trombosit dan dua nilai kritis meningkat yang terdapat pada komponen darah leukosit dan hematokrit. Ditemukan lima nilai abnormal tersebut terdiri dari dua nilai abnormal meningkat yang terdapat pada komponen darah laju endap darah dan neotrofil dan tiga nilai abnormal menurun yang terdapat pada komponen darah MCV, MCH dan limfosit.

PETUGAS LAB — SALAM SEJAWAT

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Figure 4: Summary of the patient's hematology laboratory examination in Bahasa Indonesia.

6 CONCLUSIONS

Based on our experiment, this paper concluded that the proposed system (TGen-System) is able to generate the template candidates automatically by utilizing the linguistic knowledge of related expert. This condition proved that the limitation of traditional template-based approach can be minimized, so that the hematologic report is not only varied but also easier to understand. This paper plans to further improve the reliability of TGen-System in term of determining slots in the complex sentence.

ACKNOWLEDGEMENTS

We gratefully acknowledge that this research is funded by Kemenristekdikti Republik Indonesia through Lembaga Penelitian Universitas Sumatera Utara. The support is under the research grant DRPM Kemenristekdikti of Year 2018 Contract Number: 253/UN5.2.3.1/PPM/KP-DRPM/2018.

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