A Symptom Distribution Method in Global Knowledge to Medical Expert System

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Abstract: Changes to services in the medical field will follow the changing of era, no longer relying on a single expert but can adapt to multiple experts, by offering convenience to help emergency room doctors and specialist doctors. The technology that will be discussed in this research is building a framework of knowledge of large-scale medical experts. Knowledge is obtained by relying on medical record data as the results of that knowledge that are used to distribute the symptoms according to specialist units in the hospital. Therefore, doctors who are in the emergency unit can do first aid to patients as well as to get the appropriate specialist information based on a knowledge-based system with the patient's condition, so that the work of the emergency room doctor and specialist doctors can utilize the knowledge-based system in conducting care in patients and can save observation time in examining other patients.

1 INTRODUCTION

In today's digital era, a lot of research has been done to develop a system towards digitalization. One part of computer science that can help make work easier is artificial intelligence (AI) (Dzierzanowski et al., 1985). An expert system is a part of AI that is built based on expert knowledge and information from books (Gorzalczany and McLeish, 1992). In its application, expert systems are often used to diagnose problems that occur in the community. One of the development of expert systems is to help in the medical field (Dzierzanowski et al., 1985). During its development, many systems were built using AI to improve medical services (Krantz et al., 1988) and (Cota et al., 2017), decision support (Razzouk et al., 2006) – and (Navarra, 2016), to assist in diagnosing diseases (Dzierzanowski et al., 1985), (Adlassnig and Scheithauer, 1989), (Malmir et al., 2017). The software that was successful in applying AI into the medical field to diagnose diseases in the 20th century included MYCIN, SPHINX, LOCALIZE (Brazis et al., 2012), PUFF, INTERNIST, and GAITSPERT (Dzierzanowski et al., 1985), (Chorbev et al., 2009). AI which is a field of science has many branches that can be applied in the medical field. This can be seen in the success of various software that uses different methods(Dzierzanowski et al., 1985). MYCIN has succeeded in becoming a system based on expert systems that is able to help medical staff provide clinical consultations (Van Remoortere, 1979), (Li, 2010), SPHINX uses inference and pattern recognition methods capable of providing consultations related to jaundice (Sampat et al., 2005), to the INTERNIST which is able to provide diagnoses in various diseases (Miller et al., 1982).

In developing AI for medical purepose it is inseparable from the role of medical personnel and doctors directly. The combination of knowledge possessed by experts in the medical field with computing is an expert system. The expert system was developed from a simple display that was still in the form of a command-line interface (CLI) ("Classification and diagnosis of diabetes: Standards of medical care in Diabetesd2018," 2018) until finally a graphical user interface (GUI) version was developed that made it easy for users to interact with the system (Gianni et al., 2019). Even Bao, et al. (Schiller and Mandviwalla, 2007) has been able to develop an expert system that can be used in several hospitals in rural ar-

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eas by using virtual machines that are connected to a network. Further development of the expert system that is connected to the network allows patients to do longdistance consultations with several doctors or experts who are included in a system (Chambers and Conway, 1992).

The use of expert systems in the medical field itself is divided into several types, namely expert systems based on rules or logic and expert systems based on mathematical or statistical computations (Liao, 2005).

2 LITERATURE REVIEW

In improving the accuracy of expert system diagnostics in the health sector, researchers conducted a combination of rule-based and statistical-based. This section will discuss previous studies related to the expert system in its application in the health sector or medical expert system. The expert system was developed using a rule-based method, based on statistics, or a combination of both.

2.1 Rule-based (Logic- based) Expert System

An expert system based on logic leads to a manipulation of objects rather than mathematical computations (Dzierzanowski et al., 1985), ("Foundations of neural networks, fuzzy systems, and knowledge engineering," 1997), (Herry and Frize, 2003). This is more due to understanding between the problem domain and the knowledge held by experts (Dzierzanowski et al., 1985), (Li, 2010), (Albert et al., 2015). Furthermore, the expert system that is built will greatly affect the health of the lives of patients (Hyeon et al., 2016). Knowledge from experts which is applied to a rule-based expert system is capable of representing the relationship between problems and consequences that will occur (Adlassnig and Scheithauer, 1989) in the form of IFTHEN (Gianni et al., 2019). The ability to represent these relationships is obtained based on a logical approach from real-world cases that are transferred from expert knowledge (Aronson et al., 2005). The use of rule-based expert systems in the medical field provides ease in enhancing system capabilities. If one day the expert has a new experience or the expert's knowledge increases in disease, then the rules can be changed according to expert knowledge. For example, there are rules which are deleted or added in the diagnosis of disease to achieve better diagnostic results, but the addition or deletion of rules cannot be done instantly but requires verification and validation so that the expert system that is built remains stable (Schiller and Mandviwalla, 2007).

In addition to making the expert system that is built remain stable, verification and validation are also needed so that every rule and fact stored in the knowledge base is still true and honestly made based on expert knowledge. Poor accuracy and incomplete rules are of great concern in the validation of a rulebased expert system (Lockwood and Chen, 1995), (Eyadat and Alsmadi, 2012). However, rule-based expert systems have drawbacks, one of which is limitations when the system is unable to explain or make a rule against disease diagnosis so that it is combined with several other methods in AI such as fuzzy logic (Sutton et al., 2012) and (Das et al., 2013), data mining (Mihaela-Adina and Gheorghisă, 2015) , (Fefilatyev et al., 2007) and semantics (Sakorn, 2016).

Medical ES	Author(s)
MYCIN	Edward Shortliffe (1976)
SPHINX	Marius Fieschi, Michel Joubert, Dominique Fieschi, dan M. Roux (1982)
LOCALIZE	Michael B. First, Bruce J. Weimer, Sean McLinden, dan Randolph A. Miller (1982)
PUFF	Janice S. Aikins, John C. Kunz, Edward H. Shortliffe, dan Robert J. Fallat (1983)
INTERNIST	R. A. Miller, Harri E. People, dan Jack D. Myers (1982)
GAITSPERT	James M. Dzierzanowski, John R. Bourne, Richard Shiavi, Henrik S. H. Sandell, dan D. Guy (1985)
MAIESTRO	Daniel B. Hier, Frank Rinaldo, Martha W. Evens, et al. (1990)
Neonatal Jaundice ES	C. Dharmar, S. Srinivasan, D. Mital, dan S. Haque (2002)
Medical Prediction ES	Doina Dragulescu dan Adriana Albu (2007)
SA Tabu Miner	Ivan Chorbev, Dragan Mihajlov, dan Ilija Jolevski (2009)
Arithmetic CAP2 in Medical Diagnosis ES	Zhaoxia Li, Yueling Zhang (2010)
Two - Dimensional Fuzzy Repertory Grid (TDFRG) ES	Ming Hseng Tseng dan Hui Ching Wu (2011)
ES for Diabetes Diagnosis	Tawfik Saeed Zeki, Mohammad V. Malakooti, Yousef Ataeipoor, dan Talayeh Tabibi (2012)
EXEMED	Alexandra Pomares Quimbaya, et al (2014)
TARDIS	Michael Albert, Matthias Görs, dan Klaus Schilling (2015)
Medical ES using RDR	Jonghwan Hyeon, et al. (2016)
Fuzzy Conditional Medical ES	Venkata Subba Reddy Poli (2015)
DSS modeled by Fuzzy ES	Behnam Malmir (2017)
Ontology-Based Medical ES	Sakorn Mekruksavanich (2017)
Expert system for nutrition care process of older adults	Tudor Cioara, et al. (2018)

Figure 1: Rule-Based Medical Expert System.

2.2 Quantity Measure based (Statistics based) Expert System

Expert systems that are based on mathematical computations arise because some researchers consider that sometimes the systems are not able to make or explain a rule to achieve the correct diagnosis. The development of expert systems of this type uses mathematical methods such as Bayesian formulas (Sapna and Tamilarasi, 2009), artificial neural networks (Yahia et al., 2000), data mining techniques (Mihaela-Adina and Gheorghisă, 2015), and optimization (Mihaela-Adina and Gheorghisă, 2015). The use of expert systems based on mathematical computations provides a jump in accuracy and a jump in the speed of the diagnostic process. Mathematical computations are not used to replace the rule-based expert system, but rather to accomplish and improve performance to cover the deficiencies that exist. Although the system is capable of providing a good spike in performance, but the use of expert systems based on mathematical computations is limited to human ability to label (Valizadegan et al., 2013). This can trigger debate from other medical personnel who have different views based on knowledge and views held (Sadideen et al., 2013). A simple example is a usage of genes or offspring as a parameter or label in making a diagnosis (Gay et al., 2013) and (Dharmar et al., 2002).

Medical ES	Author(s)
MEANS	Sergiy Fefilatyev, et al (2007)
Classification from multiple experts	Hamed Valizadegan, Quang Nguyen, Milos Hauskrecht (2013)
GA-ELM	S. Aishwarya dan S. Anto (2014)

Figure 2: Statistics-Based Medical Expert systems.

2.3 Medical Expert Systems Category

Technology development in the world of health is important. Starting from the examination process, diagnosis, to the patient care process must be done with extreme care and precision. This becomes a challenge for young doctors and paramedics who are just starting a career in doing so, especially in dealing with problems with a high degree of difficulty. Artificial intelligence is a part of technologies that enables the development of medical tools for junior paramedics and doctors who are experienced in solving problems they faced (Dharmar et al., 2002). One part of artificial intelligence that is often used in the development of these tools is the expert system (Dzierzanowski et al., 1985), (Dharmar et al., 2002), (Tan et al., 2016). The development of expert systems themselves can be divided into several categories including diagnosis, repair, instruction, interpretation, prediction, forecasting, design and planning, monitoring, control, classification/identification, discovery, debugging, and selection (Tan et al., 2016).

2.3.1 Diagnosis

Diagnosis in the world of health requires comprehensive medical knowledge because sometimes the causes of the disease (symptoms) can vary making it difficult for patients to identify their health conditions (Sakorn, 2016). An expert system that is capable of making the right diagnosis is expected to be able to help patients and medical staff in making a diagnosis.

2.3.2 Repair

Repair in the medical expert system is referred to as a system that is capable of providing solutions in treatment for patient recovery.

2.3.3 Instruction

Instruction in the expert system is capable of providing a sequence of handling of disease.

2.3.4 Interpretation

The interpretation referred to in this medical expert system is a system capable of processing input from users both experts, medical personnel, and patients to be able to provide diagnosis results and good treatment recommendations.

2.3.5 Prediction

The ability of the expert system developed is in making predictions about what will happen. Prediction generated by the system can be in the form of disease progression towards positive or negative.

2.3.6 Design and Planning

The system is capable of providing a framework and work plan for handling patients based on the results of the system's diagnosis of disease. Planning and handling generated by the system can be knowledge given by experts at the time of manufacture and the results of learning the system (if the expert system can learn).

2.3.7 Monitoring and Control

The capability of the expert system is in monitoring patient conditions and comparing them with previous conditions. Then the system is capable of providing new treatment solutions to the development of the patient's condition. Such monitoring and control capabilities are very helpful for medical personnel in handling patients who must be monitored closely and in detail.

2.3.8 Classification and Identification

Classification is the ability of an expert system to classify the type of disease to the patient's condition. While identification is the capability of an expert system in recognizing patients from their symptoms.

2.3.9 Discovery

In the development, there is an expert system that is capable of recognizing and/or discovering a new type of disease based on symptoms and the development of the patient's condition.

2.3.10 Discovery

Expert systems with this category are expert systems that are capable of fixing errors both independently and with the help of experts.

Medical ES	Description
MYCIN (Shortliffe, 1976)	Diagnosis of symptoms and provide results based on more than 500 rules. MYCIN was then considered to be close to the competency of specialist doctors' abilities in a blood infection.
SPHINX (Fieschi *et al.*, 1982)	Sphinx has advantages in making a diagnosis (one of which is diabetes). Weighting the rules makes the system able to reduce the error rate.
LOCALIZE (Brazis, Masdeu dan Biller, 2012)	Localize uses neuroanatomic knowledge in detail as a knowledge base. Localize is capable of detecting many injuries, even capable of detecting injuries that have never been explained before. Localize is also able to make an explanation of the wound based on neuroanatomic knowledge.
PUFF (Aikins *et al.*, 1983)	Puff is a system that is capable of processing data and diagnose lung disease. Puff is also capable of diagnosing and monitoring functional lung.
INTERNIST (Miller, Pople dan Myers, 1982)	Internists take a different approach from existing expert systems. This expert system is capable of diagnosing internal diseases based on the knowledge the nurse has. Furthermore, the Internist is also able to create a hierarchy of diseases from the general to specific.
GAITSPERT(Dzierzanowski *et al.*, 1985)	Gaitspert is an expert system that was built to evaluate the human mobilization system of patients who have cerebral vascular accidents. Gaitspert was able to provide recommendations related to what must be done by nurses and therapists.
MAIESTRO (Weissman, Diers dan Bemesderfer, 1974)	Maiestro is an expert system created to assist nurses in dealing with stroke patients. This expert system is capable of carrying out anatomic diagnoses, diagnosis of stroke mechanisms, provide

Figure 3: The Use of Medical Expert System.

	recommendations for test sequences, treatment, and prognosis.
Neonatal Jaundice ES (Dharmar *et al.*, 2002)	This expert system was built to help find the cause of hyperbilirubinemia in newborns. The weakness of this system is the inability of the system to learn on its own.
Medical Prediction ES ("Classification and diagnosis of diabetes: Standards of medical care in Diabetesd2018," 2018)	This system is capable of diagnosing hepatitis. This expert system uses logical inference to diagnose hepatitis suffered by patients, while statistical inference is used to diagnose the type and form of hepatitis suffered by patients. Furthermore, artificial neural networks are used to study the evaluation of biological indicators.
SA Tabu Miner (Chorbev, Mihajlov dan Jolevski, 2009)	The system was built on a web-based using the knowledge of experts in the medical field as additional learning. This expert system uses heuristic optimization algorithms for learning systems in classifying diseases and making rules.
Arithmetic CAP2 in Medical Diagnosis ES (Li dan Zhang, 2010)	This expert system uses CAP2 which is an improvisation of the C4.5 algorithm to diagnose Parkinson's disease. This system still uses experts to make corrections to the rules made by the system.
Two-Dimensional Fuzzy Repertory Grid (TDFRG) ES (Tseng dan Wu, 2011)	This system uses two dimensions of the repertory of the grid to expand the repertory of symptoms and the severity of the disease along with the importance of hepatitis. Knowledge from experts is still used as a benchmark for the accuracy of the system diagnosis results.
ES for Diabetes Diagnosis (Zeki *et al.*, 2012)	The development of an expert system for diagnosing diabetes uses experts as a source of knowledge. Furthermore, this system is capable of providing diabetes indication.
ES for Diabetes Treatment (Tabibi, Zaki dan Ataeepoor, 2013)	This expert system was developed with the main objective to provide recommendations for the treatment of diabetes patients. The system also has the ability to check-up and prevent diabetes side effects.
ES for Blood Cancer (Toloie Ashlaqi dan Mohsen Taheri, 2010)	An expert system that was built to speed up the diagnosis and treatment of blood cancer patients.
TARDIS (Albert, Görs dan Schilling, 2015b)	The system is capable of carrying out a diagnosis of lung disease and provide excellent feedback.

	This system has been tried and applied to patients with chronic conditions.
Medical ES using RDR (Hyeon *et al.*, 2016b)	The usage of ripple-down-rules (RDR) in expert systems is to reduce interventions that occur when building initial knowledge bases. This expert system focuses on classification.
Fuzzy Conditional Medical ES (Poli, 2016)	This expert system was built using fuzzy conditional inference. This technique is to solve problems about medical knowledge that is fuzzy. The knowledge base for this expert system uses a fuzzy knowledge base.
DSS modeled by Fuzzy ES (Malmir, Amini dan Chang, 2017)	The usage of a Fuzzy Expert System (FES) as a generator for the selection of solutions in decision systems (DSS) in the health sector. Case studies using kidney infection data show better accuracy and precision than machine learning methods.
Ontology-Based Medical ES (Mekruksavanich, 2017)	The system is capable of classifying and diagnose diabetic patients. The system uses weighting similarity based on density. Furthermore, the system is also capable of assisting patients in monitoring their health independently.
Expert system for nutrition care process of older adults (Cioara *et al.*, 2018)	This system was built with the aim of monitoring and controlling the supply/intake of nutrients/nutrition in the elderly. Nutritionists become experts who play a role in providing knowledge for this system. The system uses semantics in considering the nutritional intake that will be given to the elderly.
Semantic Fuzzy ES for Diabetes Support Application (Lee dan Wang, 2011)	This expert system aims to support decisions related to diabetes treatment. The system uses five layers of fuzzy ontology in forming Fuzzy Diabetes Ontology (FDO) and as knowledge for the semantic decision support agent (SDSA) in providing descriptions related to decisions taken by medical personnel.
Multilayer rule-based ES for diagnosing uveitis (Mutawa dan Alzuwawi, 2019)	This expert system was built using knowledge obtained from ophthalmologists to diagnose uveal duct disease. The system uses multilayer rules so that it can detect uveitis based on unusual symptoms.
FES for depression diagnosis (Fazel Zarandi *et al.*, 2019)	The Expert system was built using fuzzy logic type-2 to diagnose and monitor the mental health of patients.
NLP approach for breast cancer expert system	The expert system was built to help decision making about the

(Oyelade *et al.*, 2018)	diagnosis of breast cancer. This system uses NLP to recognize the symptoms entered by medical personnel to then be able to provide a proper diagnosis
ES for intestinal parasitosis using image processing (Nkamgang *et al.*, 2019)	This expert system was built to identify diseases related to human intestinal parasites. The system was developed using image processing which functions to recognize parasitic images that exist in the human intestine and then be classified according to classes predetermined by medical experts in the area. The classifier used is the neuro-fuzzy classifier.
ES for peripheral arterial disease detection (Jana *et al.*, 2019)	The system developed with this Android-based system is capable of detecting one form of heart disease, namely peripheral arterial disease. This system has advantages such as being able to detect abnormal blood flow, classification of arterial diseases (normal, stenosis, and occlusion), identification of the location of arterial, proximal, and distal zones.
Glycemia measurement classification to enhance data interpretation in gestational diabetes ES (Caballero-Ruiz *et al.*, 2016)	The system built is part of a gestational diabetes expert system. Development was carried out on the glycemia measurement classifier section which was changed to an automatic classification. With classification automation, the system is capable of providing proper diet and treatment based on the patient's glycemic data.
Fuzzy rule-based EX for diagnosis thyroid disease (Biyouki, Turksen dan Zarandi, 2015)	This expert system was built to diagnose patients with thyroid gland using the neuro-fuzzy classification. The classification uses k-mean to make initial rules and scaled conjugate gradient (scg) algorithm to determine the optimum value of the parameters used. The results of the classification process are then used to create fuzzy rules for modeling and evaluating systems.
ES for vertebral column disease (Acevedo *et al.*, 2017)	This expert system was built using a data bank and assisted with assessments by experts as a source of knowledge. The method used in this study is Morphological Associative Memories (MAM) which uses computational based on lattice algebraic structures. This expert system is capable of diagnosing spinal disease with an accuracy of 99.7%. This is better than some other diagnosis systems.
Expert Clinical Decision Support System to Predict Disease (Hashi, Uz Zaman dan Hasan, 2017)	This system aims to make a diagnosis of diabetic patients. The method used is C4.5 and KNN for classification. Classification results are assisted by knowledge from doctors to provide better accuracy results. The system was also developed to be accessible to other medical personnel via the internet.
MEANS (Fefilatyev *et al.*, 2007b)	This expert system is intended to assist medical personnel in screening tumor patients. This system helps medical personnel to conduct multi-screening, namely the ability of medical personnel to screen patients simultaneously. This is to improve the accuracy of the decisions that will be taken related to the treatment of tumor patients.
Classification ES from multiple experts (Valizadegan, Nguyen dan Hauskrecht, 2013b)	This expert system uses the knowledge of various experts to detect patients with Heparin-Induced Thrombocytopenia (HIT). The experts did the labeling that was mutually agreed upon and then classified by the system using a support vector machine (SVM).
GA-ELM (Aishwarya dan Anto, 2014)	GA-ELM Is an expert system for diagnosing patients with diabetes. This expert system uses genetic algorithms (GA) to sort out features that can be used as a reference. The selected data is then classified using extreme learning machine (ELM).

Source of Figure 3 : (Shortliffe, 2012), (Fieschi et al., 1982), (Brazis et al., 2012), (Aikins et al., 1983), (Miller et al., 1982), (Dzierzanowski et al., 1985), (Weissman et al., 1974), (Dharmar et al., 2002), (Chorbev et al., 2009), (Li, 2010), (Tseng and Wu, 2011), (Zeki et al., 2012), (Tabibi et al., 2013), (Toloie and Mohsen, 2010), (Albert et al., 2015), (Hyeon et al., 2016), (Poli, 2015), (Malmir et al., 2017), (Sakorn, 2016), (Cioara et al., 2018), (Lee and Wang, 2010), (Mutawa, 2019), (Biyouki et al., 2015), (Oyelade et al., 2018), (Nkamgang et al., 2019), (Jana et al., 2019), (Estefania et al., 2016), (Biyouki et al., 2015), (Elena et al., 2016), (Hashi et al., 2017), (Fefilatyev et al., 2007), (Valizadegan et al., 2013), (Aishwarya and Anto, 2014).

3 GROUP EXPERT

This research will propose a group expert system model (GDSS) that can be used in the Emergency Unit (ER). The GDSS is capable of diagnosing patient symptoms, physical examinations, and the anamnesis, and distribute the results of diagnoses to specialist doctors so that they can be followed up faster and better.

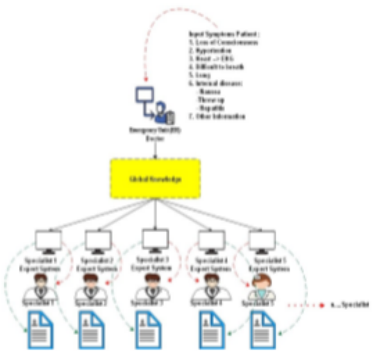

Figure 4: Group Expert System

Figure 4 is an illustration of the application of the system carried out in the ER. The doctor on duty in the ER is responsible for examining the patient's condition: physical examination, anamnesis and symptoms and laboratory results (if previously a laboratory examination has been conducted) that the patient has come to at the ER. Global Knowledge is a gathering place for all knowledge obtained from the patient's medical record, input data: physical symptoms, anamnesis, and laboratory examination results (if a laboratory examination is conducted). Data from global knowledge is distributed to expert systems that are owned by each specialist doctor. The final results of the expert system of each specialist doctor will provide the results of the diagnosis and treatment care of the patient in the ER.

3.1 Knowledge Representation

After the knowledge acquisition process has been completed, the knowledge is transformed into a knowledge base and a rule base which is then collected, coded, organized and illustrated in another design form into a systematic form. The way to represent data into knowledge is in the form of attributes, rules, semantic networks, frames, logic and production rules (Leung and Wong, 1991), ("Proceedings of the 1997 20th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval," 1997). It aims to simplify the data so that it is easy to understand and make the program development process effective. The expert system uses production rules derived from decision trees and decision tables.

3.2 Building a Knowledge Base

In building a knowledge base, two algorithms are needed, namely an algorithm to receive knowledge and an algorithm to fill knowledge.

Algorithm for receiving knowledge. The following algorithm is the algorithm used in the system to receive knowledge from experts. This algorithm is used to fill all specialist medical doctors and symptoms data.

Algorithm 1 Receive Input for Knowledge Base

```
1: procedure InputToKnowledgeBase
2:     inputAvailable ← true
3:     while inputAvailable ≠ false do
4:         INPUT ← code, spCode, symptomps
5:         FillKnowledgeBase(code,spCode,symptoms)    ▷ See Algorithm 2
6:     end while
7: end procedure
```

Figure 5: Algorithm 1 Receive Input for Knowledge Base

Row 1: Procedure definition, without parameter.
Row 2: Fill in the input Available variable with true value. As long as input Available variable value is true, the input is still available to be filled into the knowledge.
Row 3-6: Looping for data input (code, specialist medical doctor code, and symptoms). This part is used to receive input and then fill those input into a knowledge base (available in algorithm 2).

3.3 Algorithm for Filling Knowledge

There are three parameters to carry out this procedure, namely code (code of symptoms), specialist code (code for specialist doctors), and symptoms (knowledge of symptoms).

Algorithm 2 Fill In the Knowledge Base

```
1: procedure FillInKnowledgeBase(Code: VarChar(10), SpecialistCode:
   VarChar(10), Symptoms)
2:     code ← Code
3:     spCode ← SpecialistCode
4:     symptoms ← Symptoms
5:     KnowledgeBase ← code, spCode, symptoms
6: end procedure
```

Figure 6: Algorithm 2 Fill in the Knowledge Base

Row 1: Procedure definition. This procedure needs 3 parameters: Code (for symptoms code), Specialist Code (for specialist medical doctor who has the knowledge about this symptoms), and then Symptoms (for symptoms knowledge).
Row 2-4: Fill all three parameters into local variabel for later processing.
Row 5: Persistently write code, spCode, and symptoms into knowledge base.

3.4 Inference Algorithm

The inference algorithm of the system is divided into two, namely the input distribution algorithm according to the patient's symptoms and the algorithm to find the appropriate specialist to deal with these symptoms.

Input distribution algorithm for patient symptoms
Row 1: Procedure definition. It does not need any parameter and is used for all patient symptoms' input. Output of this procedure is an array which consists of all symptoms' code for the patient and all specialist codes who are able to handle the symptoms.

```
Algorithm 3 Input All Symptoms
1: procedure InputPatientSymptoms
2:     specialistArray[][] ← empty
3:     symptomsAvailable ← true
4:     while symptomsAvailable ≠ false do
5:         INPUT ← symptompCode
6:         code ← symptomCode
7:         specialistArray[code][] ← FindSpecialist(code)   ▷ See Algorithm 4
8:     end while
9: end procedure
Output: specialistArray[codes][allSpecialistCodes]
```

Figure 7: Algorithm 3 Input Symptoms

Row 2: specialist Array initialization. This array is a 2 dimensions array which consists of [symptom code] [list of specialist medical doctor]. At the of the procedure, this array will be filled.
Row3: symptoms Available initialization. This variable is used to mark the symptoms whether they are still available or not.
Row 4-8: Looping as long as the data still available for input. For every loop, symptom Code will become the input and will be filled into local variable (code). The code variable will become the parameter to find the specialist in algorithm 4. Upon finishing, this procedure will return two dimensions array which consists of all symptoms (codes) and all specialist codes for every symptom (all Specialist Code).

Seeking algorithm for an appropriate specialist
This step, the step where the symptoms of the patient will be related to the specialist's knowledge based on the knowledge of each specialist.

```
Algorithm 4 Find Specialist Medical Doctors
1: function FindSpecialistMedicalDoctors(Code: VarChar(10))
2:     arraySp[] ← empty
3:     code ← Code
4:     for Allrecordsinknowledgebase do
5:         symptomCodeKb ← readSymptomCode
6:         if code = symptomCodeKb then
7:             specialistCode ← syptomCodeKb
8:             arraySp[] ← specialistCode
9:         end if
10:    end for
11:    return arraySp[AppSpecialistMedicalDoctorForSymptom]
12: end function
Output: arraySp[AppSpecialistMedicalDoctorForSymptom]
```

Figure 8: Algorithm 4 Input Symptoms

Row 1: Function definition. This function needs one parameter: code (code of symptom for which the specialist doctors are about to find. This function returns array value which consists of all specialist medical doctors for the symptom.
Row 2: array Sp initialization, begins with empty value.
Row 3: Fill in Code into local variable code.
Row 4-10: Looping to read all records in knowledge base. In every loop, symptom code in knowledge base is read and become an input for symptom CodeKb (row 5). If the code is the same as symptom CodeKb then specialist medical doctor in knowledge base will be put into arraySp (row 6-8).
Row 11: Return arraySp value which has already filled with all specialist medical doctors for the symptoms.

4 CONCLUSIONS

The results of this study are an algorithm that will be implemented in the next journal, which is an algorithm that is implemented in real conditions in the emergency unit and the distribution of symptoms to patients received by each Specialist unit based on the knowledge possessed by specialists in the unit emergency. Knowledge data is extracted from medical record data obtained at the hospital. The results of this algorithm are a knowledge base that can produce a conclusion of the type of disease so that it will help the work of doctors in the ward of the emergency unit and specialist units in making further observations and treatments on these patients.

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