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Naïve Bayesian Learning based Multi Agent Architecture for Telemedicine

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ABSTRACT: Agent-based systems are one of the most vibrant and important areas of the research and development to have emerged in Information Technology in recent years. They are one of the most promising approaches for designing and implementing autonomous, intelligent and social software assistants capable of supporting human decision-making. These kinds of systems are believed to be appropriate in many aspects of the healthcare domain. As a result, there is a growing interest of researchers in the application of agent-based techniques to problems in the healthcare domain. The adoption of agent technologies and multi-agent constitutes an emerging area in bioinformatics. Multi-agent based medical diagnosis systems may improve traditionally developed medical computational systems and may also support medical staff in decision-making. In this paper, we simulate the multi agent system for cancer classification. The proposed architecture consists of service provider agents as upper layer agent, coordinator agent as middle layer agent and initial agent lowest layer agent. Coordinator agent serves as matchmaker agent that uses Naïve Bayesian learning method for obtaining general knowledge and selects the best service provider agent using matchmaking mechanism. Therefore this system can reduce the communication overhead between agents for sending messages and transferring data and can avoid sending the problem to irrelevant agents.

KEYWORDS: agent, autonomous, healthcare, Naive Bayesian, communication.

1 INTRODUCTION

Artificial intelligence and knowledge based system are assuming an increasing important role in medicine for assisting clinical staff in making decision under uncertainty (e.g. Diagnosis decisions, therapy and test selection). Furthermore, many medical procedures involve several individuals, in a number of specialist departments, whose decisions and actions need to be coordinated if the healthcare is to be effective and efficient. For example, a general practitioner may suspect that his patient has cancer. However, as he neither has the knowledge nor the resources to confirm this hypothesis, he must refer the patient to a hospital specialist who can make a firm diagnosis and he needs to consult with specialist. Having confirmed the presence of cancer, the specialist must devise a care program for treating the patient. This typically involves hospital nurses, the patient's general practitioner, and home care organization jointly executing a series of interrelated tasks. To provide the appropriate software support for such coordinated health care management it was decide to adopt an agent-based approach.

In this paper Naïve Bayesian machine learning based multi-agent architecture for telemedicine is proposed and simulates a prototype system for cancer classification. Section [3] presents agent and multi-agent system used for Medical Diagnosis System are presented. Section [4] describes related work with multi-agent system. The section [5] explains proposed Naïve Bayesian learning based multi-agent system. The analysis of the system is described in Section [6]. In section [6] the conclusion of this paper is presented.

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2 MOTIVATION

One of main direction of application of the agents consists in the medical diagnosis. The motivation of the use of agents for different medical problem solving consists in properties of the agents such as: increased autonomy in operation, capability of communication, autonomous learning capability and capability to interact with the environment. These properties allow to the agents to coordinate with other agents and human during different problem solving. System that operates in isolation cannot solve some difficult problem (task). These problem solving require the coordination of more systems with different capabilities and capacities. The capability of a system consists in the specialization detained by the system. The capacity of a system consists in the amount of problem that can be solved by the system using the detained resources. The solving of many difficult problems requires the coordination of more agents with different capabilities and capacities, which motivate the use of multi-agent system versus the use of agents that operate in isolation.

Coordinated medical agent may form medical multi-agent systems. Other motivation consists in the existence of a huge quantity of medical knowledge, individual physician and medical computation system can detain only a limited quantity of knowledge. Multiple agents coordinate with each other in order to speed up computation, complement each other's capabilities, share each other's knowledge and to improve the efficiency of information services. The multi-agent based medical diagnosis system is more popular and researchers are more concentrate on this aspect.

3 AGENT AND MULTI-AGENT SYSTEM

Agent can be considered as a distinct kind of software abstraction, in the same way that methods, functions and objects are software abstractions. More specially, an agent is a high-level software abstraction that provides a convenient and powerful way to describe a complex software entity in terms of its behavior within a contextual computational environment. It differs from an object in the capability to control its own state. The notions of agents are reactive, proactive, and autonomous and interact with other such entities. These properties allow to the agents to coordinate with other agents and human during different problem solving.

In multi-agent system, multiple agents interact in some overarching system architecture. Multi-agent system might be defined as a collection of autonomous agents that can communicate with each other and coordinate their activities in order to solve the problem that could not be tackled by any agent individually [21]. Multiple agents coordinate with each other in order to speed up computation, to complement each other's capabilities, to share each other's knowledge and to improve the efficiency of information services.

There is a growing interest in the application of agent-based techniques to problems in the medical domain. Some of the fields in which they are already being applied are Patient Scheduling, Organ and tissue transplant management, Community care, Information access, Information sharing, Decision support, Training , Internal hospital tasks and so on.

The healthcare industry is now starting to grasp the impact that information technology can have on reshaping its activities. To help eradicate common problems such as, difficult access, rising costs and poor quality of healthcare, telemedicine is on the road to becoming an integral part of medical practice worldwide. There are several definitions of telemedicine. Telemedicine is the practice of medicine without the usual physician-patient physical confrontation, but instead via an interactive audio-video communication system. Industry Canada defines telemedicine as the use of communications and information technology to deliver health and healthcare services and information over large and small distances. With the advent of Internet/Intranet technologies, telemedicine can be perceived as a set of communication modalities that allow for the transmission of medical data, video images and audio between physicians and other healthcare providers. These technologies apply to clinical areas such as radiology, dermatology, pathology, surgery, cardiology, home healthcare and to teaching through teleconferencing. Some of the benefits of telemedicine include the ability of bringing healthcare services to the patient; reducing the time it takes to make diagnosis and treatment decisions and improving the continuity of care [2].

The components of a multi-agent system may be running in different machines, located in many different places. Each of the agents may keep part of the knowledge required to solve the problem; therefore, multi-agent systems offer a natural way of attacking distributed problems. One of the main properties of an intelligent agent is sociability. Agents are able to communicate between themselves, using some kind of agent communication language, in order to exchange any kind of information. In that way they can engage in complex dialogues, in which they can negotiate, coordinate their actions and collaborate in the solution of a problem. Therefore multi agent system can be applied in Telemedicine.

4 RELATED WORKS

John Fox, Jun Huang and N.R. Jennings [15/11] described the design and implementation of a layered architecture for decision support applications in general and for distributed medical care in particular. A prototype system has been developed for other specific application of distributed management of cancer patients among general practitioner, hospitals, home care organizations and pharmacies.

Barna Laszlo Iantovics [5] proposed the development of a medical diagnosis system capable of solving difficult diagnosis problems. The medical diagnosis system is a heterogeneous system with human and artificial agents members specialized in medical diagnosis and assistant agents. The proposed diagnosis system can solve difficult medical diagnosis problems that cannot be solved by doctors or artificial systems specialized in medical diagnoses that operate in isolation. The problem solving by the diagnosis system is partially based on the blackboard-based problem solving.

Barna Iantovice [7] described a novel cooperative hybrid medical diagnosis multi-agent system called CMDS. The cooperative problem solving by the proposed system combines the physicians and artificial agents' advantages in the medical diagnosis elaborations, by using the medical knowledge that are distributed between the members of the system. Medical multi-agent system called MASM [3,4] is proposed by Barna Laszlo Iantovics and that can help physician in their work. This system is complex but increase the accuracy. The system cannot describe the classification method used to classify the diseases. Iantovics Bl also presented ICMA "Intelligent cooperative mobile Agent Architecture" in [6]. The proposed mobile agent architecture allows the creation of mobile agents, which can solve intelligently difficult problem like medical diagnosis problems in insecure network. Advantages of ICMA mobile agents are versus some of the communication capability, protection possibility and intelligence.

The integration of intelligent agents in a multi-agent architecture that supports the provision of telemedicine services for the intelligent management of diabetes mellitus is described by A. Garcia, Enrique J. Gomez, M. Elena Hernando, F. Javier Perdices, Francisco del Pozo and V. Torralba [1]. The combination of different methods to analyze blood glucose monitoring data and insulin data makes possible to extract relevant information about the patient metabolic state under different situations of data completeness. The result of the statistic and the rule-based analysis can be presented to users in a very intuitive way. But it can lead to errors under a situation of missing data.

5 NAÏVE BAYESIAN LEANING BASED MULTI-AGENT SYSTEM

The power of the agent technology comes from the coordination and cooperation among the agents. The solutions fall into one of the two broad categories: the broadcasting based solutions and the middle agent based solutions. The Contract Net protocol (Reid G. Smith (1980)) [10] is an example of the broadcasting based solutions. The middle agent based approach is very flexible and is suitable for small and large agent systems alike. Three types of middle agents are identified [24], namely the matchmakers, the brokers, and the mediators. A matchmaker serves the role similar to that of the yellow page. A broker agent works in a different way. When it receives a request from the service consumer agent, it finds a (ideally the best) service provider to execute the task(s), and then returns the results of the execution back to the service consumer agent. A mediator works in a way similar to the broker but it does more. Most of today's middle agents perform service matching only based on service descriptions. As a result, the agents that are most appropriate for the given request may be discovered and selected. There is actually a third type of solutions, the blackboard-based solutions Xiaocheng Luan [8].

The proposed system for Naïve Bayesian learning based multi-agent (NBMS) is shown in figure1. It is built by using Vertical architecture. This system also built on middle agent architecture. There are some steps to develop the multi-agent based medical diagnosis system. First, need to identify the agent's roles. Secondly, need to identify the responsibilities and services for each role. Thirdly, need to determine the goal and plan to achieve the goals.

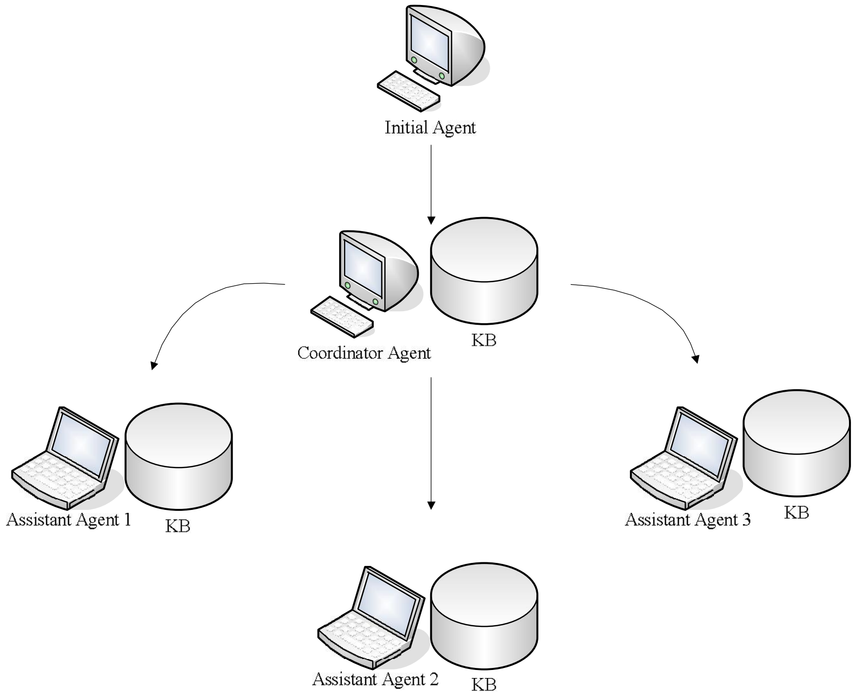

Fig. 1. Naïve Bayesian learning based multi-agent system (NBMS)

5.1 COMPONENTS OF NBMS

5.1.1 INITIAL AGENT

Initial Agent is an agent to interact with user of the system. It accepts the problem and sends the problem to organizer agent for processing. The user only needs to interact with initial agent which is a member of the system. The initial agent hides the complexity of the medical diagnosis problem to the physicians, making easier the fulfilling of some medical tasks by assistant agents and increasing the accuracy of the problem solving.

5.1.2 COORDINATOR AGENT

Coordinator Agent is like a broker agent or middle agent. It sends the problem to desired assistant agent based on its own knowledge. It also performs some interactions between the lower level agents and top agent. It applies Naive Bayesian learning mechanism for building the agent's knowledge. Coordinator Agent matches its own knowledge with service or capabilities of the assistant agents in the system and sends the problem to one of the appropriate assistant agents. The capability of the coordinator agent is the essential part of the proposed system.

5.1.3 ASSISTANT AGENTS

They actually process the problem. They have own knowledge to process the certain problem. They use Naive Bayesian classification and are trained with training datasets. If one of the assistant agents can solve the problem, processes by itself and sends the result to the middle agent.

Three types of assistant agents are lung cancer classification agent, liver cancer classification agent and breast cancer classification agent. Lung cancer classification agent uses data set from UCI which include 32 instances, 58 attributes and 3 classes. Liver cancer classification agent uses data set from UCI which include 345 instances, 7 attributes and 3 classes. Breast cancer classification agent uses data set from UCI which include 699 instances, 11 attributes and 2 classes.

5.2 CONCURRENT METATEM FOR PROPOSED SYSTEM

Concurrent METATEM is a language based upon the direct execution of temporal formulae. It consists of two distinct aspects: an execution mechanism for temporal formulae in a particular form; and an operational model that treats single executable temporal logic programs as asynchronously executing objects in a concurrent object-based system. Based upon executable logic, the language can be used as part of the specification and prototyping of reactive systems. Also, as it uses temporal, rather than classical, logic the language provides a high-level programming notation in which the dynamic attributes of individual components can be concisely represented. Finally, it incorporates a novel model of concurrent computation which has a range of applications in distributed systems [26]. Figure 2 shows a system containing four agents: CO, AGlu, AGli and AGb.

CO (askcheck) [give1,give2,give3]:

$\bigcirc$ askcheck $\Rightarrow \Diamond$ (give1 $\vee$ give2 $\vee$ give3)

Start $\Rightarrow$ askcheck

AG_{lu}(give1)[finish1]:

$\bigcirc$give1 $\Rightarrow \Diamond$finish1

AG_{li}(give2)[finish2]:

$\bigcirc$give2 $\Rightarrow \Diamond$finish2

AG_{b}(give3)[finish3]:

$\bigcirc$give3 $\Rightarrow \Diamond$finish3

Fig. 2. Concurrent METATEM for the proposed system

The agent CO is a 'Coordinator Agent': it can give to only one agent at a time, and will commit to eventually give to any agent that satisfies the askcheck. Agent CO will only accept message askcheck and can send give1, give2 and give3 messages. The lung cancer agent AGlu states that it will only accept give1 message and can only give back finish1 message. As for the liver cancer agent AGli, it will accept give2 message and can only resend finish2 message. The breast cancer agent AGb can accept give3 message and will send finish3 message when the service is completed.

5.3 NAÏVE BAYESIAN LEARNING

Classification of a collection consists of dividing the items that make up the collection into categories or classes [23]. The goal of predictive classification is to accurately predict the target class for each record in new data, that is, data that is not in the historical data. A classification task begins with build data (also known as training data) for which the target values (or class assignments) are known. Different classification algorithms use different techniques for finding relations between the predictor attributes' values and the target attribute's values in the built data. The Bayesian Classifier uses probabilistic methods for classification. Bayesian classifier is known to be optimal when attributes are independent [12, 16]. Bayesian Classifiers are statistical classifier. It is based on Bayes Theorem. They can predict the probability that a particular sample is a member of a particular class. Perhaps the simplest Bayesian Classifier is known as the Naïve Bayesian Classifier. It usually based on a (usually incorrect) independence assumption. Assume that the effect of an attribute value on a given class is independent of the values of other attributes. This assumption is known as class conditional independence. This makes the calculations involved easier, but makes a simplistic assumption - hence the term "naïve".

$$V_{NB} = \arg\max_{v_j \in V} P(v_j \setminus a_1, a_2, ...a_n)$$

$$V_{NB} = \arg\max_{v_j \in V} P(a_1, a_2, ...a_n \setminus v_j)P(v_j)$$

$$V_{NB} = \arg\max_{v_j \in V} P(v_j)\prod P(a_i \setminus v_j)$$

V is the finite set of class

$(a_1, a_2, \ldots. a_n)$ is the new instance

P(vj\ai) conditional probability of V given A: posterior probability

P(vj) independent probability of V: prior probability

P(ai) independent probability of A

P(ai\vj) conditional probability of A given V: likelihood

Moreover Naive Bayesian learning is the optimal method of supervised learning if the values of the attributes of an example are independent given the class of the example. It is embedded within the Coordinator Agent as learning mechanism for obtaining the knowledge and selecting the best service provider agent or Assistant Agent. Assistant Agents also apply Naive Bayesian learning mechanism to distinguish between Cancerous and Normal Cells.

6 ANALYSIS OF THE PROPOSED SYSTEM AND HYBRID SYSTEM

6.1 PROPOSED SYSTEM ARCHITECTURE

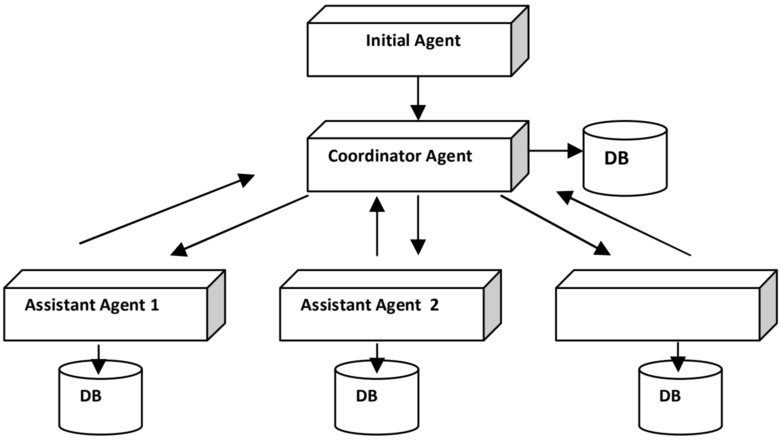

Fig. 3. Proposed System Architecture

The proposed system architecture is shown in Figure 3. In this system, each agent has different knowledge. It is built on matchmaker based coordination mechanism Assistant Agents do not need to keep the information of other same level agents. The agents know nothing about their environment initially and learn to coordinate gradually. In this way, we are able to observe the adaptability of the learning algorithm. Middle agent or coordinator agent keeps the information about the problem and agents' capabilities in the system. Agents must learn to coordinate and to compete in multi-agent domains. Depending on the learning algorithm, the Coordinator Agent may learn to coordinate in a more effective and/or efficient way. By incorporating learning technique, Coordinator Agent would be able to obtain more accurate capability information and can achieve more effective coordination among agents. Therefore, the learning algorithm (i.e. Naïve Bayesian Learning) is employed in Coordinator Agent for obtaining the general knowledge and selecting the best service provider agent. Coordinator Agent sends the problem to a certain subordinate assistant agent (AG) based on its learned knowledge. In this system, number of messages sent is not as high as in the CHA system. In addition, communication time is saved.

6.2 Chain Rule Based System Architecture (CHA)

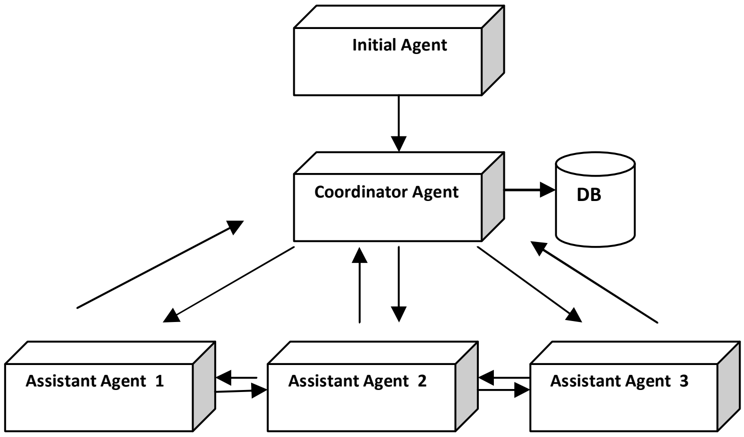

Fig. 4. Hybrid System Architecture

The chain rule based architecture is built on ring based architecture. Each agent has different knowledge. Assistant Agents need to keep the information of other same level agents. Middle agent or coordinator agent keeps the information about the problem and agents' capabilities in the system. Coordinator Agent sends the problem to one of assistant agents (AG). If that agent cannot solve the problem, it will ask another agent for help by sending the problem to the remote agent. If the remote agent does not succeed in classification, it will ask another agent for help and so forth. Thus communication time and number of messages can be increased.

6.3 Performance Related Attributes for Multi-agent Architectures

To evaluate the proposed architectural model and chain rule based architectural model, a set of performance could be used such as performance predictability and adaptability. The performance predictability can be measured by complexity of the system. Adaptability is measured by extendibility of the system.

6.3.1 Complexity

Complexity measures the number of links among agents or middle agents in organizational structure [9]. The more the number of interactions between agents is, the more complex agent-based system is. Complexity (C) is defined as following.

C = Number of links among agents

Cp = m*n

CCHA = n*(n-1) + (m*n)

CP means the complexity of proposed system

CCHA means the complexity of CHA system

n is the number of agents under the ith middle agent (m) and m is the number of middle agents

6.3.2 Extendibility

Extendibility is to evaluate the adaptability of agent-based system. When a new type of service request is introduced into the system, it is necessary to reconfigure the existing system. Reconfiguration includes change, replacement, deletion and addition of agent or middle agent [9]. Extendibility (EL) measures the resources that need to add an agent or middle agent to the existing system. It is defined as following.

E = Number of links that need to add agent or middle agent

For new middle agent

EP = n*mnew

ECHA= n*mnew

For new agent

EP = nnew * m

ECHA = nnew * ((2n + m + (nnew-1))

Ep means the extendibility of the proposed system

ECHA means the extendibility of the CHA system

m is the number of middle agents, n is the number of agents, mnew is the number of new middle agents and nnew is the number of new agents.

6.3.3 Messages

Number of messages means the number of messages sent form one agent to another for completing the goal. It can be the same as the efficiency of the system.

M = Number of messages

MP = 2n+3

MCHA $= 2n + \sum_{i=1}^{n-1} (n-i) + 2$

MP is the number of messages in the proposed system

MCHA is the number of messages in the CHA system and n is the number of agents in the system

The result is shown in Figure 5 and there is a linear increase in total number of messages when number of agents in both systems is increased. According to the result shown, the proposed system uses less number of messages than the chain rule based system in all levels of agents used.

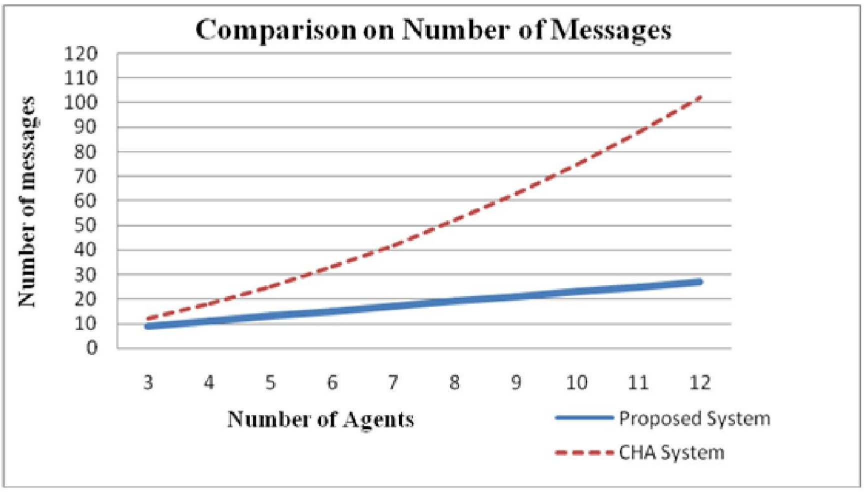

Fig. 5. Comparison on number of messages

6.4 PROCESSING TIME ON FOUR SERVICE PROVIDERS

As mentioned in previous section, the proposed architecture and chain rule based architecture are simulated on three types of cancer classification. In the proposed system simulation, 4 agents are generated one for certain cancer classification agent that the coordinator agent finds and the other three for other cancer classification agents. In the proposed architecture, the time for processing time have no significant difference whatever the arrangement of service provider agents is made. But for chain rule based architecture, the processing time is not stable. Moreover, the appropriate agent is not immediately found. Sometime it is possible to reach the other cancer classification agents first and then they search the other same service provider agent and then the request is sent to one of the available same service provider agent. This procedure is performed in loop until it finds the required agent met or no service provider agent is left. The processing time for proposed system architecture and chain rule based architecture is shown in Figure 6.

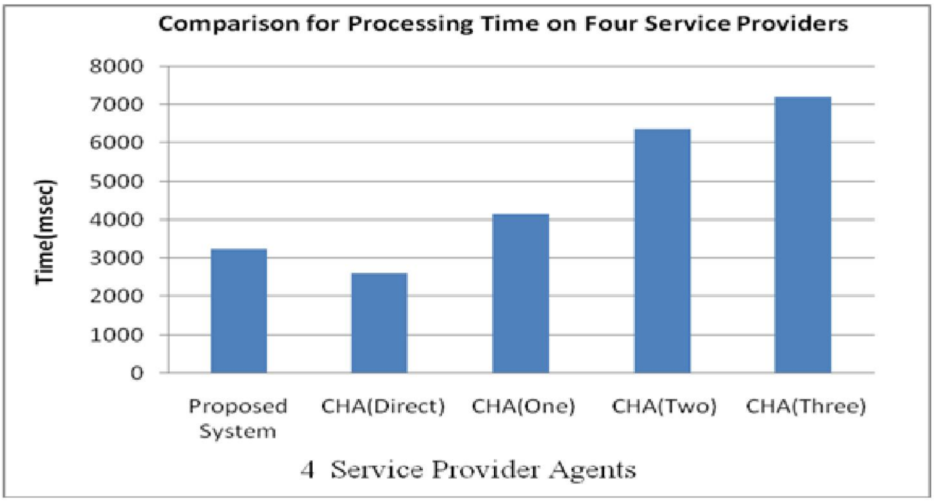

Fig. 6. Comparison for processing time based on four service providers

6.5 AVERAGE PROCESSING TIME ON FOUR SERVICE PROVIDERS

The average processing time is also evaluated on 4 agents, one for certain cancer classification agent that the coordinator agent finds and three for other cancer classification agents as mentioned in previous section 6.5. According to the results of Figure 7, the average processing time taken proposed architecture is less than chain rule based architecture.

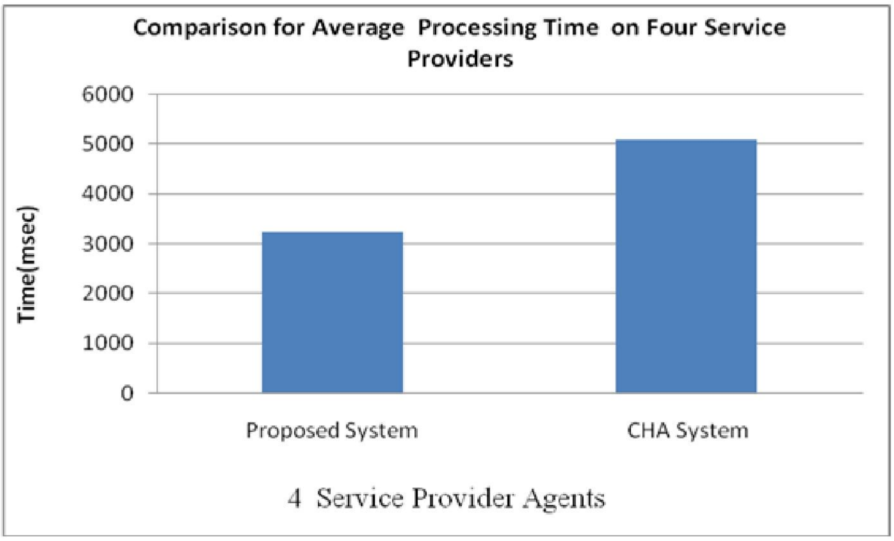

Fig. 7. Comparison for average processing time based on four service providers

6.6 Processing Time for Different Number of Service Providers

The processing time for proposed system architecture and chain rule based architecture on same number of agent for different services is also measured. When the number of agents increases in both systems, the processing time also increases. The processing time for our proposed system is not significantly different even though the number of service provider agent is increased. On the other hand, the processing time for CHA system is not stable. The evaluation tests are based on 3, 6, 9 and 12 agents. The first 3 agents are used for lung cancer classification, liver cancer classification and breast cancer classification respectively. The second 6 agents are 2 lung cancer classification agents, 2 liver cancer classification agents and 2 breast cancer classification agents. The third 9 agents are also separated for 3 lung cancer classification agents, 3 liver cancer classification agents and 3 breast cancer classification agents. The last 12 agents are 4 lung cancer classification agents, 4 liver cancer classification agents and 4 breast cancer classification agents. The processing time on proposed system architecture and chain rule based architecture is tested and shown in Figure 8.

Fig. 8. Comparison for processing time based on different service providers

Experiments are also conducted to compare the proposed system architecture with CHA system architecture on complexity, extendibility, efficiency, number of messages and processing time. Therefore, according to the different evaluation results, it can be clearly seen that our proposed system architecture is better than the CHA system architecture over some performance matrics.

7 Conclusion

In this Information Age, telemedicine and computer driven treatment methods are being used in the field of treatment of disease including cancer in different ways. Telemedicine is the use of communications and information technology to deliver health and healthcare services and information over large and small distances. Some of the benefits of telemedicine include the ability of bringing healthcare services to the patient, reducing the time to make diagnosis and treatment decisions and improving the continuity of care. The components of a multi-agent system may be running in different machines, located in many different places. Each of the agents may keep part of the knowledge required to solve the problem. Multi-agent systems offer a natural way of attacking distributed problems. Agents are able to communicate between themselves, using some kind of agent communication language, in order to exchange any kind of information. They can engage in complex dialogues, in which they can negotiate, coordinate their actions and collaborate in the solution of a problem. Therefore multi agent system can be applied in Telemedicine.

Using the agents in medical field for cancer classification also increases the autonomy. Sending the messages from one agent to another to perform the processing capable the communication. And agent can interact with the environment In this thesis, a multi-agent architecture for telemedicine is proposed. Proposed multi-agent architecture is simulated for three types of cancer classification using UCI cancer dataset. The proposed architecture is able to assign the task directly to the correct agent that can perform the task, without extra routing to other agents and reduce message passing time.

Comparison of the proposed system with Chain Rule based system architecture has been performed. The comparison are shown on the number of messages, complexity, extendibility, efficiency and processing time. According to these the proposed system architecture is more suitable. CHA based system is better than the proposed system when the service provider agent is found immediately. However, immediately found mechanism is not always occurring. Besides the processing time for CHA system is unstable. Therefore, the results for the proposed system are better than the CHA

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