Artificial Intelligence in Medicine
A literature study on probabilistic networks in use as medical support in Healthcare
Summary:

The following work focuses on the support of medical decision making by systems based on the research field artificial intelligence. It will summarize the most important aspects of Artificial Intelligence in Medicine (AIM) in a brief abstract and then present a case study of a support system based on a Bayesian network.
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1. **Introduction**

1.1 **Background**

There have been big chances in the field of medical treatment and healthcare in general through the last decades. Through rapid growth of detailed medical knowledge and through higher expectation to the healthcare system the need of the physician of effective support tools have arisen. It is nearly impossible for a physician to keep up with the developments in medical research. Because of this computers are necessary as new tools in the field of healthcare. The computers are supposed to fulfill two important functions, on one hand they should be a system for organizing, storing and retrieving medical knowledge, on the other hand they should be able to suggest appropriate diagnostic, prognostic and therapeutic decisions and decision making techniques.

1.2 **Purpose of this work**

The purpose of this work is to give a brief overview on Artificial Intelligence in Medicine (AIM) and its involvement in healthcare nowadays. Furthermore, for a deeper understanding of how useful the application of artificial intelligence can be I will concentrate on the Bayesian network and its use in healthcare research.

1.3 **About this work**

This work is a literature study based on different articles from different magazines and from the internet concerning research in the field of artificial intelligence. I will summarize the main ideas as well as comment on them from my own point of view. The work is split into two main parts, Artificial Intelligence in Medicine and The Bayesian network as model for artificial intelligence in medicine. In the first part I will try to give a brief overview on how AIM has developed and what are the main ideas of this research. The second part of this work will describe the Bayesian network and its characteristics, its way of construction and its function in medicine. Further, an example of a research project with a Bayesian network is give to illustrate the problems that can appear when a network for use in real-life situations is constructed.

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2. Artificial Intelligence in Medicine (AIM)

2.1 What is AIM?

Artificial Intelligence in Medicine (AIM) is a field of research that slightly started to be developed in the late 1950ies and early 1960. Already in 1959 Ledley and Lusted saw the enormous potential of that artificial intelligence and its technologies could have in medical care. Intelligent computers could store and process information of knowledge to be able to assist physicians with tasks like diagnostic.  

In the early AIM research the new computers were seen as the tool to reshape the healthcare system. They were supposed to help the physicians to keep up to the rapid development in the medical sector. The idea behind this perspective was that there was a lack of time that did not allow deeper literature studies and a lack of human memory capacity resulted in problems for the physicians to memorized important and even small facts on different illnesses, treatments etc. This is why computers, in that stage of AIM development, were seen as tools for organizing, storing and retrieving medical knowledge as well as tools for suggesting appropriate diagnostic, prognostic and therapeutic decisions and decision making techniques.  

Through the years the perspective on AIM has slightly shifted. If diagnostics was the core concern of this field of research in the beginning, it has shifted to a more complex view nowadays. There is less emphasis on diagnostics as task requiring a computer. Nowadays AIM systems are described has CDSS, clinical decision support systems. They are intelligent systems that are used different sectors of the medicine, e.g. as help in supporting medication prescribing, in laboratories and in educational settings, for clinical surveillance etc. Even the focus of the researchers on new techniques has changed. One of the most important tasks is not longer just the development but also to find an accurate purpose in which a certain system fits in best.  

2.2 The use of AIM in clinical environments

Nowadays CDSS are built in line with a weak approach on AI. This means that the focus of the development of AI systems that are not intended to be independent and somehow human like. These systems are meant to be more like a “helping hand” that support human beings in all different kind of tasks in daily clinical environments. The most common type of CDSS in use is knowledge-based systems. These systems are also known as expert system. They contain clinical knowledge, normally represented in form of sets of rules, on a distinct task and are able to make conclusions based on individual medical records of a patient.  

There are all kinds of different tasks in clinical environments which an expert system can be applied upon. Examples for such tasks and the use of an expert system can be seen below in three different examples.

- Diagnostic assistance:
  An expert system can help the physician to formulate a diagnosis based on the patient’s medical record and the understanding the system has of an illness

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2 http://www.coiera.com/aimd.htm (2006-09-29)  
4 http://www.coiera.com/aimd.htm (2006-09-29)  
5 http://www.coiera.com/aimd.htm (2006-09-29)
- **Image recognition and interpretation:**
  The system is able to recognize and interpret different clinical images, e.g. MRI

- **Alerts and reminders:**
  These systems are used as alarm system. They can warn clinical staff when a patient’s conditions get worse, e.g. the system can be connected to an ECG. Reminders also take care of reminding staff on what actions need to be taken before an event occurs.\(^6\)

### 3. The Bayesian network in Artificial Intelligence in Medicine

#### 3.1 The use of the Bayesian network in healthcare

The use of Bayesian networks in healthcare is nothing new. They have been use for dealing with uncertain knowledge involved in diagnosis, selecting the right treatment alternative and for predicting outcomes of medical treatments for over a decade. Even the clinical epidemiology has used the Bayesian network to construct different disease models. The use in the various fields can be explain by the simple fact that Bayesian networks are capable of dealing with reasoning with uncertainty which makes them suitable as models for decision-support in real-life practice. The increasing complexity in the field of healthcare has, as mentioned before, led to the need of a deeper understanding for medical processes. In practice observations and patient data have a high factor of uncertainty and still the physicians need to get a overall understanding. In this situation Bayesian networks take part in the medical system as decision-making support.\(^7\)

#### 3.2. The characteristics of a Bayesian network

The Bayesian network is a probabilistic one. It represents the probability distribution of a set of random variables and consists of a graphical structure \(G\) and an associated distribution \(\text{PR} = (\text{Pr}, G)\)

The graphical structure \(G\) is an acyclic graph, that means that the graph has no directed cycles. All nodes are connected by directed arcs with each other. The network visualizes variables as nodes in the network,

\[
G = (V(G), A(G))
\]

with nodes

\[
V(G) = \{V_1, \ldots, V_i\}, \ n > 1,
\]

and arcs

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Each node \( V_i \) represents a random variable that takes a finite set of values. The arcs then represent the probabilistic influences between the different variables in form of causality relations. \( \Pr \) is the joint probability distribution that is represented in a factorised form. There is a specified set of conditional probability distribution for every variable in the digraph. It is expressed in \( \Pr(V_i \mid \pi V_i) \) and describes the joint effect of a specific combination of values for parents \( \pi(V_i) \) on probability distribution over the values of \( V_i \) (202). The different sets altogether describe the over all joint probability distribution.

\[
\Pr(V_1, \ldots, V_n) = \prod_{i=1}^{n} \Pr(V_i \mid \pi(V_i))
\]

This formula expresses the joint probability distribution which factorises over the diagraphs topology.

**3.3. Two ways of constructing a network: manual construction vs. learning the network**

There are two different common ways of constructing a Bayesian network: constructing it manually of constructing it through learning. In the following abstract I will describe the two methods briefly.

Two ways of constructing a network: manual construction vs. learning

**3.3.1. Manual construction**

Most networks in real-life applications nowadays are constructed manually. They have five different stages of development and for each stage expert knowledge of at least one human is needed as well as a literature study and the analysis of available patient data. The five stages that can be identified in the construction progress are the following:

1. **Selection of relevant variables:**
   In this stage the important variables are identified as well as the values that these variables may adopt. This identification is based on expert knowledge, descriptions of the domain and on the analysis of the purpose that the network shall have.

2. **Identification of the relationships among the variables:**
   After identifying the important variables the variables’ relationships in form of dependence and independence need to be figured out. In a probabilistic network all variables have this kind of relationships. These dependence and independence relationships need to be expressed graphically. To make this expression appropriate to the relationships it should present, the graphical structure is usually

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built upon causality between the variables, which means that the arcs express the causality in form of their directions.\textsuperscript{12}

3. **Identification of the qualitative probabilistic and logical constraints among the variables:**

These constraints can help to assess and to verify the probabilities that the network requires. The qualitative probabilities are derived from the properties of stochastic dominance of distribution. The logical constraints come from the functional relationships in between the variables. They help to reduce the number of probabilities that need to be assessed by the network.\textsuperscript{13}

4. **Assessment of probabilities**

There are a lot of local conditional probability distributions for each variable. There need to be filled in the network. They are assigned by the domain experts or obtained by data.\textsuperscript{14}

5. **Sensitivity analysis**

A sensitivity analysis is the last step in the construction of a Bayesian network before it will be used in real-life situation. It serves for establishing the quality and the clinical value for the network. A sensitivity analysis is normally conducted based on patient data.

The meaning of this analysis is to control the network’s output and it controls especially if the underlying probability distribution are adequate for the use in real-life.\textsuperscript{15}

3.3.2. Learning

An alternative, which is not use that often in real-life situations, is the learning of a Bayesian network. In learning data is used as base of learning and expanding the network. The network itself develops based on the data.

Data represents the most essential part in such a learning process. It has to consist of different data sets that need to fulfil certain properties to be adequate for the process of learning. These properties are as followed:

- The data has to be collected carefully. If there are biases in the data set it will have an impact on the network’s performance
- The variables and their assigned values used in the data need to be the same, that means they need to match, as the variables and values that are to be modelled in the network. If these variables and values do not match they need to be at least in a form which can easily be translated to the variables in the network.\textsuperscript{16}
- The data set should contain enough data to enable the net to identify probabilistic relationships among the different variables
- The data set has to satisfy the different conditions that need to be fulfilled for the search with search algorithms, t.ex. each case in the data need to specify a value for every mentioned variable; the network has problems to deal with incomplete data in case that values are missing.\textsuperscript{17}

In real-life situations especially the last property is hard to fulfil. It is hard to find actual patient data without any kind of missing value.

The learning process itself involves two different tasks for the network. First, the graphical structure needs to be identified (structure learning) and then the conditional probability distribution needs to be estimated to associate it with the networks digraph (parameter learning). In most of the searching algorithm that are needed for the learning these two tasks are covered simultaneously.¹⁸

There are different search algorithms that the net uses for the learning process. I will name three different examples:

- **K2**
  
  K2 is one of the early learning algorithms. It is based on a greedy search with a graph search heuristic. It is an example for the search and scoring method which means that it compares the ability of all possible digraphs to explain the actual data by generating various different graphs. Then it decides in favour for the most adequate digraph and scores.¹⁹

- **Dependence analysis**:
  
  In this analysis the dependence and independence relationships between the variables are extracted from the data set and are analysed.

- **Maximisation algorithm**
  
  The Maximisation is the only algorithm capable of dealing with missing values and hidden variables (values of the unobserved variable).²⁰ It estimates the probability distribution from the data using maximum likelihood estimation.

  The algorithm consists of two different steps. First, it computes the expected value of the relevant parameters and second, a maximisation step. In this step the expected values are maximised in consideration with the parameters.

These are three different examples for search algorithm in the learning of a Bayesian network. The maximisation algorithm, in my opinion, seems to be best fitted for the constructing of a network that is used as medical support as it can deal with missing values and hidden variables. Patient data is hardly ever complete.

There are different advantages and disadvantages with the two methods of constructing a network. On the one hand the manual construction seems to be more precise as real expert knowledge is used and the different stages have to be developed one by one. But hand human knowledge is also hard to translate into probabilities and the construction process can therefore easily be very time consuming.²¹ The learning process, on the other hand, can deal with a large amount on information and the network develops itself without any human expert help. But the data sets have to fulfil different properties and it is not easy to actually have patient data that does not miss a single value.

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3.4 Different areas of use for a Bayesian network in AIM

The Bayesian network can be used in several ways in the healthcare sector. I will now name the most important fields of healthcare which use Bayesian networks. Further I will explain how networks are used and what function they take in these fields.

3.4.1. Diagnostic reasoning

In the field of diagnostic reasoning the Bayesian network is used to make diagnostic test. In such test the network estimates the probability of having a certain disease based on the input of observed evidence composed of symptoms, signs and test results. Diagnostic test never come to a 100% or 0% probability, this means that there is nothing such a 100% true-positive or a 100% true-negative rates. This needs to be considered before making a diagnostic hypothesis. The network will just return a probability that the patient with the observed evidence has a certain disease, but this does not mean that one should not consider that there is the possibility of having certain symptoms and test results without having a certain disease.22

The network is never going to be “sure” about anything. In diagnostic reasoning the Bayesian networks often also are equipped with a test-selection method. This method indicates which test is best to be ordered to decrease the level of uncertainty about a disease present in a specific patient. After suggesting a test the network waits for the input of the test result by the user. Based on those results the network calculates the new possibilities and even how much information will be needed to be certain about the diagnosis of the specific patient.23

3.4.2. Prognostic reasoning

Prognostic reasoning is about making prediction about what will happen in future. The knowledge on a certain fact is exploited to make prediction of this facts development as a process over time. This area of healthcare is even more uncertain than diagnosis as there are no given facts about the future of a disease. One can just make assumptions of present knowledge and make conclusion about the future based on these assumptions. The task of the Bayesian network in prognostic reasoning is to predict the outcome for a specific patient data in considerateness of the treatments. This prediction will highly depend on the available information on the patient before the treatment started.24

3.4.3 Treatment selection

Treatment selection deals with the reasoning about the effects that are to be expected as result of different treatment alternatives. The Bayesian network itself does not provide a decision-making process in the way that it concludes which method is the best. Instead the network is embedded in a decision-support system as the ones named above in the first part of this work. Integrated in this system the network can calculate the probability for each treatment and then in combination with the decision-support system name out the optimal treatment alternative.25

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3.5 The use of a Bayesian network at the Netherlands Cancer Institute

To make the use if Bayesian networks in healthcare more obvious I will try to summarise the project of five researchers at the Netherlands Cancer Institute, Antoni van Leeuwenhoekhuis in Amsterdam. This part of my work will present the main aspects of their work with the “oesophagus network” and it will show up the difficulty in assessing probabilities during the construction stage of the network. I want to show how problematic the construction of a network and how the performance in real-life situations is measured. Further on this part of the work is supposed to give the reader a notion on how complex the probabilities are that a network requires to be proper working.

3.5.1. Background information

The project’s background

Every year about 80 patients get the diagnosis of oesophageal cancer at the Netherlands Cancer Institute, Antoni van Leeuwenhoekhuis. Based upon protocol 75% of the patients are assigned to a therapy that shows a positives response of the patient to the treatment.26 But at least one out of four patients develops complication as result of the treatment. These complications can be very serious and result in death.27 Five researchers, L.C. van der Gaag, S Renooij, C.L.M. Witteman (Institute of Information and Computing Sciences, Utrecht University), B.M.P. Aleman and B.G. Taal (Department of Radiation Oncology and Gastroenterology, The Netherlands Cancer Institute, Antoni van Leeuwenhoekhuis) try to reach a better response rate through developing a decision support system for patient specific therapy selection for oesophageal cancer. The core part of this system is a probabilistic network which describes the presentation of characteristics of the cancer and the pathophysiological processes of invasion and metastases.28

Oesophageal cancer

The oesophageal cancer is the consequence of a lesion of the oesophageal wall that has developed a tumour. A lesion of the oesophageal wall is typically associated with smoking and drinking habits.29

The tumour can have different characteristics that have an impact on the prospective growth. Such characteristics are the location of the tumour in the oesophagus, the histological type of the tumour, the length and the macroscopic shape. Tumours typically invade the oesophageal wall and upon further growth neighbour regions, depending on characteristics even the liver and the lungs. The depth of the invasion and the extent of existing metastases have great impact on a patient’s life expectancy. These two factors are also captured as the stage in which the cancer is in and they influence which treatment is chosen for treating a patient and even which effects and complications can be expected by the physicians. At Netherlands Cancer Institute several different treatment alternatives can be conducted.30

The oesophagus network

The oesophagus network captures the most modern knowledge on oesophageal cancer. It was constructed with two medical experts (see above).

The core piece of the support system constructed at the Netherlands Cancer Institute is a probabilistic network that encodes statistical variables and their relationships in a graphical structure. The strength of the relationships is indicated by the conditional probabilities (124). Each variable in the network represents a diagnostic or prognostic factor that is relevant for establishing the stage of a patient’s cancer. The establishment of a patient’s stage of cancer is, as named before, essential to be able to predict the effects and complications of a treatment applied to the patient.\(^{31}\)

The oesophagus network includes over 70 different statistical variables and more than 4000 probabilities. The graphical structure and the associated probabilities together capture the joint probability of distribution over the represent variables. Probabilistic influence between the variables is denoted graphically in form of links of causality (arcs, see text above).\(^{32}\)

When a patient’s symptoms and test results are entered in the network, it is able to compute the most likely stage of a specific patient’s cancer. It can even compute the appropriate treatment alternatives in form of probability distributions over the variables.

The network contains 40 variables that require about 1000 probability assessments. The variable that models the cancer’s state, for example, requires the number of 144 probability assessments.\(^{33}\)

### The patient’s data

The patient’s data used in the study consisted of records of 156 persons diagnosed with oesophageal cancer at the Antoni van Leeuwenhoekhuis. For each patient there were various diagnostic symptoms and test results available. For each patient the stage of the tumour was recorded through a physician. The cancer could take one of the following stages according to the developmental stage of the disease: I, IIA, IIB, III, IVA, IVB in the order of advanced disease. Furthermore three intermediate and unobservable variables (presence of haematogenous metastases, extent of lymph node metastases, invasion of the primary tumour into the different layers of the oesophageal wall) were stated whose values were speculated by the physicians.\(^{34}\)

### 3.5.2. Constructing a network in a real-life situation and the problem of probability assessment

As mentioned before was the network constructed with the help of two medical experts in the field of oesophageal cancer. Especially in the construction of the network they played a crucial role. In the first stage of the net, as describe earlier in this work, the statistical variables needed to be identified. This was done in a sequence of 11 interviews of 2 till 4 hours each. During these interviews the relevant diagnostic and prognostic factors to be captured as statistical variables were identified and their relationships were expressed by using the heuristic guideline of causality; e.g. “What could cause this effect?” etc.\(^{35}\) The information gained from the interviews was then depicted in a graph by taking direction of the causality for directing the links (arcs) between the related variables.

After the qualitative part of the network was constructed the quantitative part needed to be worked on. The probabilities required for this part of the net needed to be assessed. A literature search was obtained and historical patient data was collected but it was not enough information to guarantee a reliable assessment of all the thousands of probabilities needed for

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\(^{34}\) Van der Gaag, L., Renooij, S., Wittemann, C.L.M., Aleman, B.M.P & Taal, B.G. (2002). p 127

the network. This meant for the project of constructing the oesophagus network that the experts’ knowledge and their clinical experience would be the only source for obtaining the required probabilities.

The problems that arose from this situation were not unexpected for the researchers. Although experts are seen as useful in the construction process by assessing the required probabilities and by fitting in probabilities in probabilities within the context of the network, there is the chance of biases occurring as, under normal circumstances, an expert often uses shortcuts or heuristics in real-life situations. And this can easily lead to problems in the way that the network and the expert represent probabilities and come up with those probabilities in different ways. This is why the way the network deals with uncertainties might differ and not match to the expert way of doing so. Because of the knowledge of this problem different methods of knowledge and probability representation have been developed to avoid any kind of biases. In this project the researchers focussed on the model of a probability scale to assess probabilities. The probability scale is a horizontal or vertical line with some numeral anchors. The experts were asked to unambiguously mark the line with their assessment for all conditional probabilities in form of a single variable given a single conditioning context on the same line. This method is generally seen as to be easy to understand and it takes little time. Further, the experts were supposed to mark four assessments on one line. This was meant to allow comparing and verifying of the assessments by the experts. But the experts in this project had problems with assessing the probabilities. The scale had three different numeral (0, 50, 100) anchors. Unexpected to all expectations the expert had problems with this form of probability assessment. They found it hard to mark four assessments on one line and generally had problems with the mathematical notation of conditional probabilities.

As the probabilities are the most essential part in the network there needed to be another form of presentation. The researchers decided in favour for a frequency format. A frequency format transcribes all probabilities in terms of frequencies. The experts were presented with examples in form of small abstracts and were then asked to judge on the abstract in form of a frequency statement. But the experts had problems with this format of representation as well. It was hard for them to visualize the numbers of patients mentioned in the frequency abstract as there is not such a high number of cases of oesophageal cancer in the Netherlands. The experts could not relate to the numbers mentioned in the abstracts.

As a result of testing the different methods for assessing probabilities the researchers came to the conclusion that they needed a new method to be able to obtain the thousands of probabilities that were needed for the network. Through their experience with the earlier trials of assessing the probabilities they had come to the conclusion that there are two most important parts that have an impact on the assessment are the presentation format of probabilities and the response scale.

As it showed before the experts had problems with the mathematical notation. In the new method constructed for this research, there was no more use of mathematical notations. Requested probabilities were translated into text fragments that were stated in the terms of likelihood. By this the researchers tried to avoid difficulties with the assessment of probabilities as it had been shown before with the frequency format.

fragments the experts were presented to a scale with numerical and verbal anchors. The 7 verbal anchors were expressions of frequencies like “fifty-fifty”, “probable” etc.\textsuperscript{44} The experts again were asked to note their assessment for a specific probability on the line of the scale. The scale was presented next to the fragment text and there were always two or three such examples on one sheet. This, as before with the first try of using a scale-based model, should allow the experts to think about their judgement, maybe even fine-tune their assessment.\textsuperscript{45}

There were several small studies conducted\textsuperscript{46} to be able to implement the scale but I will not name this studies here as this is supposed to be a brief summary of the whole construction process.

When the new method had been constructed the experts were interviewed again to assess the probabilities. It took five interviews approximately two hours each to assess all required probabilities for the oesophagus network.\textsuperscript{47} Through the new assessment the experts were able to assess about 150 up to 175 probabilities an hour.\textsuperscript{48} In an interview after assessing these probabilities the experts mentioned that the new method was easy to understand and to work with. The fragment texts reminded them of old cases which made the assessment of the required probabilities much easier and the fragment texts and the numerical and verbal anchors at the same time left no need for explanations of mathematical terms.

After all probabilities had been assessed the researchers took the expert assessments and made them subject to a sensitivity test of the network

3.5.3 Evaluation of the project

To get a notion of the functioning of the network a sensitivity test in form of a preliminary evaluation study was conducted. For the study patient data from the Antoni van Leeuwenhoekhuis was used. For each patient all diagnostic symptoms and test results were entered in the network and the network was supposed to compute the most likely stage of the patient’s cancer. Finally, the computed stage was compared to the stage in the recorded data.\textsuperscript{49} The sensitivity test was done in two single studies. In the first study patient data from the collection, all data on diagnostic symptoms and test results were entered into the network and the proper stage of their oesophageal cancer was computed. The network was able to establish the correct stage for 51% of the patients in this study.\textsuperscript{50}

In the second study the researchers tried to find out why the network performed relatively poor. Three major problems could be identified. The first one was that there were actually incorrect diagnoses, which was confirmed by the two medical experts, among the patient data. Another problem were other anomalies that the network could not handle, e.g. if there were inconsistent information of test results in the data the network had problems evaluating them. The third problem could also be found in the data. Often there was no clear distinction between facts and findings from diagnostic tests.\textsuperscript{51} Sometimes facts were mentioned in the medical patient records without establishing the way this fact had become clear. This form of information cannot be handled by the network. It needs to know how facts were assessed to be able to state e.g. the presence of absence of metastases in its analysis. Absence of such diagnostic findings for stating facts led often to an incorrect result.\textsuperscript{52}

\textsuperscript{44} Van der Gaag, L., Renooij, S., Wittemann, C.L.M., Aleman, B.M.P & Taal, B.G. (2002). p 133
\textsuperscript{45} Van der Gaag, L., Renooij, S., Wittemann, C.L.M., Aleman, B.M.P & Taal, B.G. (2002). p 133
\textsuperscript{46} Van der Gaag, L., Renooij, S., Wittemann, C.L.M., Aleman, B.M.P & Taal, B.G. (2002). p 135
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\textsuperscript{52} Van der Gaag, L., Renooij, S., Wittemann, C.L.M., Aleman, B.M.P & Taal, B.G. (2002). p 146
After having identified the difficulties of the first study the researchers decided to conduct a second one. Before the study three new statistical variables were introduced to deal with the problems of the first study. The result of this second study shows that the net identified 85% of the cancer stages for specific patients correctly.\textsuperscript{53}

\textsuperscript{53} Van der Gaag, L., Renooij, S., Wittemann, C.L.M., Aleman, B.M.P & Taal, B.G. (2002). p 146
4. Summary and Discussion

This work has presented a part of the recent research in the field of Artificial Intelligence in Medicine. The focus in this work was on the Bayesian network, its construction and its function in medicine. Through an example of the use of a Bayesian network in a real-life situation the problems that this field of research is dealing with was supposed to come clear.

Bayesian networks are one of the most recent topics in research in Artificial Intelligence in Medicine. They way of dealing with uncertainties hold the biggest advantages for all kind of diagnostic and/or prognostic work in the field of healthcare. Bayesian networks can help physicians in many different ways and can thereby better the quality of healthcare on a great level. More adequate treatments can be found, a diagnosis can be reached faster, the diagnosis can be made more precisely, etc. These are just some examples of how the sector of healthcare can profit from the use of such networks.

But there are not only advantages in the use of Bayesian networks. As shown the construction of such a network is a complex process involving experts from different fields of study. In the medical use the networks need to be manually constructed and that can take time and holds several problems. To enter the process of learning the network needs to have complete data sets which are hardly ever find in patient records which make this method of filling the network with required information impossible. So the networks need to be constructed manually in a time consuming process. As the example of the researchers working with the oesophagus network showed, such construction processes can lead to big problems. Many different factors can influence the assessment of probabilities and especially working with experts that have problems with mathematical notations this part can be the hardest of the whole construction process.

Another factor that has to be considered is the accuracy of the results computed by the network. Sometimes unknown factors can have a big impact on the results and the performance of the net. Often such factors first show up in the sensitivity test and there might be a chance that some of those are not discovered while finishing the construction of the network.

So even if the development of different Bayesian networks in healthcare has proceeded one cannot be absolutely sure about all the results computed by such networks. That means that even these networks are used in healthcare the development is far from perfect. Networks can be used but they still demand that their results are used carefully and not with too much confidence in the technical development.
5. Reference List

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