# Data Mining Classification Techniques Applied For Cancer Disease – A **Case Study Using Xlminer**

# S. Jothi<sup>1</sup>, S.Anita<sup>2</sup>

<sup>1</sup> Asst. Prof., Department of Computer Science, Jayaraj Annapackiam College for Women, Periyakulam, Theni Dt. <sup>2</sup>Lecturer, Department of Electronics and Communication Engg., St. Anne's college of Engg. & Technology, Panruti, Cuddalore Dt.

#### ABSTRACT

Data mining techniques have been used in medical research for many years and have been known to be effective. In order to solve such problems as long-waiting time, congestion, and delayed patient care, faced by emergency departments, this study concentrates on building a hybrid methodology, combining data mining techniques such as association rules classification trees. The methodology is applied to real-world emergency data collected from a hospital and is evaluated by comparing with other techniques. The methodology is expected to help physicians to make a faster and more accurate classification of cancer diseases.

**Keywords**: Data mining; Cancer Disease; XLMiner, Diagnosis; Prognosis; Classification.

#### I. INTRODUCTION

Cancer leads to approximately 25% of all mortalities, making it the leading cause of death in developed countries. Early and accurate detection of cancer is critical to the well being of patients. The most effective way to reduce cancer deaths is detect it earlier. This study paper summarizes various review and technical articles on cancer diagnosis and prognosis. In this paper we present an overview of the current research being carried out using the data mining techniques to enhance cancer diagnosis and prognosis. This study paper entitled as "Data Mining Classification Techniques Applied for Cancer Disease" was done using XLMiner. The main objective of this paper is to find out which predict the various Classes for the people are affected by Cancer. For this data collected from several people. This is helps to classify, in which

category people are affected by which type of Cancer. Informations are collected based on Bone Cancer, Bladder Cancer, Stomach Cancer, Kidney Cancer and Uterus Cancer. It gives an overview of the current research being carried

out on various cancer datasets using the data mining techniques to enhance the cancer diagnosis and prognosis. This process is done by using the data mining process and the classification algorithm.

#### II. **PROBLEM DEFINITION AND DESCRIPTION**

The data collected from individual person about their disease. We predicted various classes such as Bone Cancer, Bladder Cancer, Stomach Cancer, Kidney Cancer and Uterus Cancer. In my case study is to classify the disease belongs to the people's Symptoms. For example, Bone cancer have the symptoms of Pain in Bone, Nausea, Fracture in Bone, Vomiting. Kidney Cancer has the symptoms of Blood Pressure, Blood in Urine. Stomach Cancer has the symptoms of Nausea, Vomiting, Pain in abdomen, Blood in vomit. Uterus Cancer has the symptoms of Nausea, pain in abdomen, pain upon Urination. Bladder Cancer has the symptoms of blood in vomit, Blood in Urine, Pain upon Urination. In that my case study is to classify the disease belongs to the people's Symptoms.

# III. KNOWLEDGE DISCOVERY AND DATA MINING

This section provides an introduction to knowledge discovery and data mining. We list the various analysis tasks that can be goals of a discovery process and lists methods and research areas that are promising in solving these analysis tasks.

# 3.1. The Knowledge Discovery Process

The terms Knowledge Discovery in Databases (KDD) and Data Mining are often used interchangeably. KDD is the process of turning the low-level data into high-level knowledge. Hence, KDD refers to the nontrivial extraction of implicit, previously unknown and potentially information from data in databases. While data mining and KDD are often treated as equivalent

www.ijert.org

1

words but in real data mining is an important step in the KDD process. The following fig. 1 shows data mining as a step in an iterative knowledge discovery process.

The Knowledge Discovery in Databases process comprises of a few steps leading from raw data collections to some form of new knowledge. The iterative process consists of the following steps:

- 1) Data cleaning: Also known as data cleansing it is a phase in which noise data and irrelevant data are removed from the collection.
- 2) Data integration: At this stage, multiple data sources, often heterogeneous, may be combined in a common source.
- 3) Data selection: At this step, the data relevant to the analysis is decided on and retrieved from the data collection.
- 4) Data transformation: Also known as data consolidation, it is a phase in which the selected data is transformed into forms appropriate for the mining procedure.
- 5) Data mining: It is the crucial step in which clever techniques are applied to extract patterns potentially useful.
- 6) **Pattern evaluation:** This step, strictly interesting patterns representing knowledge are identified based on given measures.
- 7) Knowledge representation: Is the final phase in which the discovered knowledge is visually represented to the user. In this step visualization techniques are used to help users understand and interpret the data mining results.

# 3.2. Data Mining Process

In the KDD process, the data mining methods are for extracting patterns from data. The patterns that can be discovered depend upon the data mining tasks applied. Generally, there are two types of data mining tasks: descriptive data mining tasks that describe the general properties of the existing data, and predictive data mining tasks that attempt to do predictions based on available data. Data mining can be done on data which are in quantitative, textual, or multimedia forms.

Data mining applications can use different kind of parameters to examine the data. They include association (patterns where one event is connected to another event), sequence or path analysis (patterns where one event leads to another

event), classification (identification of new patterns with predefined targets) and clustering (grouping of identical or similar objects). Data mining involves some of the following key steps.

- 1) **Problem definition:** The first step is to identify goals. Based on the defined goal, the correct series of tools can be applied to the data to build the corresponding behavioural model.
- 2) Data exploration: If the quality of data is not suitable for an accurate model then recommendations on future data collection and storage strategies can be made at this. For analysis, all data needs to be consolidated so that it can be treated consistently.
- 3) Data preparation: The purpose of this step is to clean and transform the data so that missing and invalid values are treated and all known valid values are made consistent for more robust analysis.
- 4) Modelling: Based on the data and the desired outcomes, a data mining algorithm or combination of algorithms is selected for analysis. These algorithms include classical techniques such as statistics, neighborhoods and clustering but also next generation techniques such as decision trees, networks and rule based algorithms. The specific algorithm is selected based on the particular objective to be achieved and the quality of the data to be analyzed.
- 5) Evaluation and Deployment: Based on the results of the data mining algorithms, an analysis is conducted to determine key conclusions from the analysis and create a recommendations series of for consideration.

#### **DATA MINING DEVELOPMENT PROCESS**

### 4.1 ALGORITHM IMPLEMENTATION

In this paper, we have classified the disease according to the people's Symptoms using data mining techniques by implementing the algorithm. Classification is data mining technique used to predict group membership for data instances. For example, you may wish to use classification to predict whether the weather on a particular day will be "Sunny", "Rainy", or "Cloudy". Popular

classification techniques include Decision trees and neural networks. We need to use learning algorithms that can produce result in order to rank the testing examples. Algorithm which is used in classification called as decision tree. Decision tree methods build a collection of rules for use as a predictive model.

The advantage of this approach is that the rules are easy to understand, and they are frequently useful for discovering underlying business processes. The disadvantage of decision tree approach is that these models usually do not perform as well as other models. For then they developed a proprietary modification for standard decision tree algorithms.

# Step 1:

Input variables are identified. They are declared as var1 as Sex, var2 as Age, var3 as Pain in Bone, var4 as Nausea, var5 as Fracture in Bone, var6 as Vomiting, var7 as Pain in Abdomen, var8 as Blood in Vomit, var9 as Blood Pressure, var10 as Blood in Urine,var11 as Pain Upon Urination and var12 as disease.

# Step 2:

In this second step, to find out the probabilities for each attribute by using information gain. The information gain is calculated from the following formula,

Info (D) = - 
$$\binom{n}{i=1} p_i \log_2 (p_i)$$

Where pi is the probability that an arbitrary tuple belongs to the class. Here all the classes are in the probability value of 1.5

# Step 3:

Training log is used to find out the miss classify of the given class. It also used for growing the full tree using training date.

### Step 4:

In this step, the full tree rules are used for find out the decision and terminal nodes. Where the decision nodes are 4, and the terminal nodes are 5.

Step 5: In this step, the tree was constructed with the corresponding attributes. The tree has taken the root node as the attribute Pain Upon Urination. The root node is selected by that high probability value. Finally, in this step to classify the actual class to predicted classes in given data such as Bone Cancer, Bladder Cancer, Stomach Cancer, Kidney Cancer and Uterus Cancer will be get from this step. The overall elapse time to run the XL Miner for this case study is 1Sec.

# V. DATA MINING FINDINGS

The initial studies unveiled a number of relationships between variables as well as threshold values that justify further analysis. The several values of several attributes are useful predictors of retention and/or attrition. These explanations increase our confidence that the values of these attributes will continue to be predictors in the future. We have to classify how many persons are affected by Bladder Cancer, how many persons are affected by Bone Cancer, how many persons are affected by Kidney Cancer, how many persons are affected by Stomach Cancer, and how many persons are affected by Uterus Cancer by using XLMiner.

$\triangleright$	Y										
	AGE	PAIN IN BONE	NAUSEA	FRACTURE IN BONE	VOMITING	PAIN IN ABDOMEN	BLOOD IN VOMIT	BLOOD PREASURE	BLOOD IN URINE	PAIN UPON URINATION	DISEASE
İ			Y	Y	Y						BONE
	YOUN	YE	Е	E	E	N	N	N	N		CANCE
	G	S	S	S	S	О	О	О	О	NO	R
	YOUN G	N O	N O	N O	N O	N O	N O	Y E S	Y ES	NO	KIDNE Y CANCE R
ĺ			Y	Y	Y						BONE
	SENIO	YE	Е	Е	E	N	N	N	N		CANCE
	R	S	S	S	S	О	О	О	О	NO	R
	YOUN G	N O	Y E S	N O	Y E S	Y E S	Y E S	N O	N O	NO	STOMA CH CANCE R
	MIDD LE AGED	N O	Y E S	N O	N O	Y E S	N O	N O	N O	YES	UTERU S CANCE R
	SENIO R	N O	N O	N O	N O	N O	Y E S	N O	Y ES	YES	BLADD ER CANCE R
	YOUN G	N O	Y E S	N O	Y E S	Y E S	Y E S	N O	N O	NO	STOMA CH CANCE R
	MIDD		Y	Y	Y						BONE
	LE	YE	Е	Е	E	N	N	N	N		CANCE
	AGED	S	S	S	S	О	О	O	O	NO	R

										UTERU
SENIO	N	Y E	N	N	Y E	N	N	N	VEG	S CANCE
R	О	S	О	О	S	О	O Y	0	YES	R KIDNE Y
YOUN G	N O	N O	N O	N O	N O	N O	E S	Y ES	NO	CANCE R
		Y		Y	Y	Y				STOMA CH
YOUN G	N O	E S	N O	E S	E S	E S	N O	N O	NO	CANCE R BLADD
YOUN	N	N	N	N	N	Y E	N	Y		ER CANCE
G	O	O	O	O	0	S	0	ES	YES	R BONE
SENIO R	YE S	E S	E S	E S	N O	N O	N O	N O	NO	CANCE R
MIDD LE	N	Y E	N	Y E	Y E	Y E	N	N		STOMA CH CANCE
AGED	O	S	0	S	S	S	0	O	NO	R UTERU
MIDD LE	N	Y E	N	N	Y E	N	N	N		S CANCE
AGED	0	S Y	O Y	O Y	S	0	0	O	YES	BONE
SENIO R	YE S	E S	E S	E S	N O	N O	N O	N O	NO	CANCE R KIDNE
SENIO	N	N	N	N	N	N	Y E	Y		Y CANCE
R	О	О	О	О	О	О	S	ES	NO	R STOMA
SENIO R	N O	Y E S	N O	Y E S	Y E S	Y E S	N O	N O	NO	CH CANCE R
YOUN	YE	Y E	Y E	Y E	N	N	N	N	NO	BONE CANCE
G	S	S	S	S	0	0	0	О	NO	R BLADD
MIDD LE	N O	N O	N O	N O	N O	Y E S	N O	Y	VEC	ER CANCE R
AGED	U	Y	0	U	Y	۵	U	ES	YES	UTERU S
LE AGED	N O	E S	N O	N O	E S	N O	N O	N O	YES	CANCE R
arvivo.							Y			KIDNE Y
SENIO R	N O	N O Y	N O Y	N O Y	N O	N O	E S	Y ES	NO	CANCE R BONE
YOUN G	YE S	E S	E S	E S	N O	N O	N O	N O	NO	CANCE R
MIDD		Y		~	Y					UTERU S
LE AGED	N O	E S	N O	N O	E S	N O	N O	N O	YES	CANCE R
GENIO	N	Y	N	Y	Y	Y	N	N		STOMA CH
SENIO R	N O	E S	N O	E S	E S	E S	N O	N O	NO	CANCE R STOMA
MIDD LE	N	Y E	N	Y E	Y E	Y E	N	N		CH CANCE
AGED MIDD	O VE	S Y	O Y E	S Y	S	S	O	O N	NO	BONE CANCE
LE AGED	YE S	E S	E S	E S	N O	N O	N O	N O	NO	CANCE R KIDNE
							Y			Y CANCE
SENIO R	N O	N O	N O	N O	N O	N O	E S	Y ES	NO	R

									01. 1 1550	ie 8, Octobe
						v				BLADD
SENIO	N	N	N	N	N	Y E	N	Y		ER CANCE
R	O	O	O	O	O	S	O	ES	YES	R
								Lo	TES	UTERU
		Y			Y					S
YOUN	N	Е	N	N	Е	N	N	N		CANCE
G	О	S	О	О	S	О	О	О	YES	R
						3.7				BLADD
CENIO	N	N	N	N	N	Y E	N	Y		ER CANCE
SENIO R	O	O	O	O	O	S	O	ES	YES	R
IX	0	Y	Y	Y	0	5		LO	TLS	BONE
SENIO	YE	Ē	Ē	Ē	N	N	N	N		CANCE
R	S	S	S	S	О	О	О	О	NO	R
										STOMA
*******		Y		Y	Y	Y				CH
YOUN	N	E	N	E	E	E	N	N	NO	CANCE
G	О	S	О	S	S	S	О	О	NO	R KIDNE
							Y			Y
YOUN	N	N	N	N	N	N	E	Y		CANCE
G	0	O	O	O	O	O	S	ES	NO	R
										UTERU
		Y			Y					S
SENIO	N	Е	N	N	Е	N	N	N		CANCE
R	О	S	О	О	S	О	О	О	YES	R
MIDD	7.75	Y	Y	Y		.,				BONE
LE	YE	E	E	E	N	N	N	N	NO	CANCE
AGED	S	S	S	S	0	О	О	О	NO	R BLADD
						Y				ER
SENIO	N	N	N	N	N	E	N	Y		CANCE
R	Ô	Ö	Ö	o	o	S	Ö	ES	YES	R
										KIDNE
MIDD							Y			Y
LE	N	N	N	N	N	N	Е	Y		CANCE
AGED	О	О	О	О	О	О	S	ES	NO	R
							37			KIDNE
SENIO	NT	N	N	NT	N	N	Y E	v		Y CANCE
R	N	1.0	1 1 1	N	I IN		Ľ	Y		
								FS	NO	
	0	О	0	О	0	0	S	ES	NO	R
					О			ES	NO	
SENIO		О						ES N	NO	R UTERU
	О	O Y E S	O N O	O N O	O Y	O	S		NO YES	R UTERU S CANCE R
SENIO R	O N O	O Y E S	O N O Y	O N O Y	O Y E S	O N O	S N O	N O		R UTERU S CANCE R BONE
SENIO R YOUN	O N O YE	O Y E S Y E	O N O Y E	O N O Y E	O Y E S	O N O	N O N	N O N	YES	R UTERU S CANCE R BONE CANCE
SENIO R	O N O	O Y E S	O N O Y	O N O Y	O Y E S	O N O	S N O	N O		R UTERU S CANCE R BONE CANCE R
SENIO R YOUN	O N O YE	Y E S Y E S	O N O Y E	O N O Y E	Y E S N	O N O	N O N	N O N	YES	R UTERU S CANCE R BONE CANCE R UTERU
SENIO R YOUN G	O N O YE S	Y E S Y E S	N O Y E S	N O Y E S	Y E S N O	N O N O	N O N O	N O N O	YES	R UTERU S CANCE R BONE CANCE R UTERU S
SENIO R YOUN	O N O YE	Y E S Y E S	O N O Y E	O N O Y E	Y E S N	O N O	N O N	N O N	YES	R UTERU S CANCE R BONE CANCE R UTERU
SENIO R YOUN G SENIO	O N O YE S	Y E S Y E S	N O Y E S	N O Y E S	O Y E S N O	N O N O	N O N O	N O N O	YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE
SENIO R YOUN G SENIO	O N O YE S	Y E S Y E S	N O Y E S	N O Y E S	O Y E S N O	N O N O	N O N O	N O N O	YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER
SENIO R YOUN G SENIO R	O N O YE S N O	O Y E S Y E S Y E S	N O Y E S N O N	N O Y E S N O N	O Y E S N O Y E S	N O N O Y E	N O N O N O	N O N O Y	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE
SENIO R YOUN G SENIO R	O N O YE S	Y E S Y E S S	N O Y E S	N O Y E S	O Y E S N O	N O N O Y	N O N O	N O N O	YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R
SENIO R YOUN G SENIO R YOUN G	O N O YE S N O	O Y E S Y E S Y E S	N O Y E S N O N	N O Y E S N O N O	O Y E S N O Y E S	O N O N O Y E S	N O N O N O	N O N O Y	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA
SENIO R YOUN G SENIO R YOUN G MIDD	O N O YE S N O	O Y E S Y E S Y E S N O	N O Y E S N O N O	N O Y E S N O N O Y	O Y E S N O Y E S S	N O N O Y E S Y	N O N O N O	N O N O Y ES	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE	O N O YE S N O	Y E S Y E S N O Y E	N O Y E S N O N O N O	N O Y E S N O N O Y E	O Y E S N O Y E S N O	N O N O Y E S Y E	NOONOONOONNOONNOONNOONNOONNOONNOONNOON	N O N O Y ES	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE
SENIO R YOUN G SENIO R YOUN G MIDD	O N O YE S N O	O Y E S Y E S Y E S N O	N O Y E S N O N O	N O Y E S N O N O Y	O Y E S N O Y E S S	N O N O Y E S Y	N O N O N O	N O N O Y ES	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE	O N O YE S N O	Y E S Y E S N O Y E	N O Y E S N O N O N O	N O Y E S N O N O Y E	O Y E S N O Y E S N O	N O N O Y E S Y E	NOONOONOONNOONNOONNOONNOONNOONNOONNOON	N O N O Y ES	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE	N O YE S N O N O N O N	Y E S Y E S N O Y E	N O Y E S N O N O N O	N O Y E S N O N O Y E	O Y E S N O Y E S N O	N O N O Y E S Y E	NOONOONOO	N O N O Y ES	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED	N O YE S N O N O O	Y E S Y E S S Y E S S N O Y E S S N O	N O Y E S N O N O N O N O O	NOOYESS	O Y E S N O Y E S N O	N O N O Y E S Y E S	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y ES	YES NO YES	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R	N O YE S N O O N O O N O O	Y E S Y E S S Y E S S N O Y E S S N O Y E S S N O Y E S S N O Y E S S N O Y Y E S S N O Y Y E S S N O Y Y Y E S S N O Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y	NOONOONOOY	N O Y E S N O Y E S N O Y Y E S S N O Y Y E S S N O Y Y E S S N O Y Y E S N O Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y	O Y E S N O Y E S S N O	N O N O Y E S Y E S N O	NOONOONOO	N O N O Y ES	YES NO YES NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R	N O YE S N O N O N O YE	Y E S Y E S S Y E S S N O Y E S N O Y	NOOYESSNOO	NOOYESSNO	O YESS NOO YESS NOO YESS	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y ES N O Y ES N	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R	N O YE S N O O N O O N O O	Y E S Y E S S Y E S S N O Y E S S N O Y E S S N O Y E S S N O Y E S S N O Y Y E S S N O Y Y E S S N O Y Y Y E S S N O Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y	NOONOONOOY	N O Y E S N O Y E S N O Y Y E S S N O Y Y E S S N O Y Y E S S N O Y Y E S N O Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y Y	O Y E S N O Y E S S N O	N O N O Y E S Y E S N O	NOONOONOO	N O N O Y ES	YES NO YES NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R	N O YE S N O N O N O YE	Y E S Y E S S Y E S S N O Y E S S S S S S S S S S S S S S S S S S	NOOYESSNOO	NOOYESSNO	O Y E S N O Y E S N O Y O N O N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y ES N O Y ES N	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R UTERU
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R  SENIO R	O NO YE S NO NO NO YE S S S S S S S S S S S S S S S S S S	Y E S Y E S S Y E S S N O Y E S S Y E S S Y Y E S S Y E S Y Y Y E S Y Y Y E S Y Y Y E S Y Y Y E S Y Y Y Y	NOOYESSNOO	NOOYESSNOOYESS	O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O N O N O Y E S N O N O Y E S N O N O N O Y E S N O N O N O Y E S N O N O N O N O N O N O N O N O N O N	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y ES N O O	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R  SENIO R	NOOYE SOON	Y E S Y E S N O Y E S N O Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S	NOOYESS	NOOYESSNOOYESSN	O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O N O Y E S N O N O Y E S N O N O O Y E S N O N O O Y E S N O O N O O Y E S O O O O O O O O O O O O O O O O O O	NOONOONOONOONNOONNOONNOONNOONNOONNOONN	NOONOONOONOONOONOONOONNOONNOONNOONNOON	N O N O Y ES N O N N O	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R UTERU S CONCE R CONCE R UTERU S CANCE R BONE CANCE R BONE CANCE R BONE CANCE R UTERU S CANCE
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R  SENIO R	O NO YE S NO NO NO YE S S S S S S S S S S S S S S S S S S	Y E S Y E S S Y E S S N O Y E S S Y E S S Y Y E S S Y E S Y Y Y E S Y Y Y E S Y Y Y E S Y Y Y E S Y Y Y Y	NOOYESSNOO	NOOYESSNOOYESS	O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O N O N O Y E S N O N O Y E S N O N O Y E S N O N O Y E S N O N O N O Y E S N O N O N O Y E S N O N O N O N O N O N O N O N O N O N	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y ES N O O	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R UTERU S CANCE R UTERU S CANCE R UTERU S CANCE R
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R  SENIO R	NOOYE SOON	Y E S Y E S N O Y E S N O Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S	NOOYESS	NOOYESSNOOYESSN	O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O N O Y E S N O N O Y E S N O N O O Y E S N O N O O Y E S N O O N O O Y E S O O O O O O O O O O O O O O O O O O	NOONOONOONOONNOONNOONNOONNOONNOONNOONN	NOONOONOONOONOONOONOONNOONNOONNOONNOON	N O N O Y ES N O N N O	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R UTERU S CONCE R CONCE R UTERU S CANCE R BONE CANCE R BONE CANCE R BONE CANCE R UTERU S CANCE
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R  SENIO R  YOUN G	NOOYE SOON	Y E S Y E S S N O O Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S Y E S S S Y E S S S Y E S S S S	NOOYESS	NOOYESSNOOYESSN	O Y E S N O Y E S N O Y E S N O Y E S S N O Y E S S N O N O N O Y E S S N O N O N O O Y E S S N O O O O O O O O O O O O O O O O O	NOONOONOONOONNOONNOONNOONNOONNOONNOONN	NOONOONOONOONOONOONOONNOONNOONNOONNOON	N O N O Y ES N O N N O	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CCANCE R KIDNE Y CANCE R BONE CANCE R UTERU UTERU S CANCE R UTERU CANCE R UTERU CANCE R
SENIO R  YOUN G  SENIO R  YOUN G  MIDD LE AGED  SENIO R  SENIO R  YOUN G  MIDD CR  MID CR  MI	NOOYE SOO	Y E S Y E S S N O Y E S S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y E S Y Y Y E S Y Y Y Y	NOYESSNOO	NOOYESSNOOYESSNOO	O Y E S N O Y E S N O Y E S N O Y E S Y E S Y	NOONOONOONOO	NOONOONOONOONOONOONOONOO	N O N O O Y ES N O O N O O	YES NO YES NO NO	R UTERU S CANCE R BONE CANCE R UTERU S CANCE R BLADD ER CANCE R STOMA CH CANCE R KIDNE Y CANCE R BONE CANCE R UTERU S CANCE R UTERU S CANCE R UTERU S UTERU S CANCE R

	l	ı —		l					1	KIDME
							Y			KIDNE Y
YOUN	N	N	N	N	N	N	E	Y		CANCE
G	О	О	0	О	0	0	S	ES	NO	R BLADD
MIDD						Y				ER
LE	N	N	N	N	N	E	N	Y		CANCE
AGED	О	0	О	О	О	S	О	ES	YES	R KIDNE
							Y			Y
SENIO	N	N	N	N	N	N	Е	Y		CANCE
R	О	О	О	О	О	О	S	ES	NO	R STOMA
		Y		Y	Y	Y				CH
SENIO	N	Е	N	Е	Е	Е	N	N		CANCE
R	О	S	О	S	S	S	О	О	NO	R
		Y			Y					UTERU S
YOUN	N	E	N	N	E	N	N	N		CANCE
G	О	S	О	О	S	О	О	О	YES	R
						Y				BLADD ER
YOUN	N	N	N	N	N	E	N	Y		CANCE
G	О	О	О	О	О	S	О	ES	YES	R
YOUN	VE	Y	Y	Y	NT.	NT.	N.T	NI		BONE
G	YE S	E S	E S	E S	N O	N O	N O	N O	NO	CANCE R
		5		5					110	STOMA
		Y		Y	Y	Y				CH
SENIO R	N O	E S	N O	E S	E S	E S	N O	N O	NO	CANCE R
K	0	3	U	S	3	3	0	0	NO	KIDNE
MIDD							Y			Y
LE	N	N	N	N	N	N	Е	Y	NO	CANCE
AGED	О	О	0	О	О	О	S	ES	NO	R UTERU
MIDD		Y			Y					S
LE	N	Е	N	N	Е	N	N	N		CANCE
AGED	О	S	O Y	O Y	S	О	О	О	YES	R BONE
SENIO	YE	E	E	E	N	N	N	N		CANCE
R	S	S	S	S	O	O	O	O	NO	R
						**				BLADD
YOUN	N	N	N	N	N	Y E	N	Y		ER CANCE
G	O	O	O	O	O	S	O	ES	YES	R
										STOMA
CENIO	NT.	Y	N.T	Y	Y	Y	N.T	NI		CANCE
SENIO R	N O	E S	N O	E S	E S	E S	N O	N O	NO	CANCE R
										UTERU
MIDD	.,	Y			Y					S
LE AGED	N O	E S	N O	N O	E S	N O	N O	N O	YES	CANCE R
NOLD		5			5				TLS	BLADD
MIDD						Y				ER
LE AGED	N O	N O	N	N	N O	E S	N O	Y ES	YES	CANCE R
AGED	0	Y	O Y	O Y	0	3	0	ES	1123	BONE
SENIO	YE	Е	Е	Е	N	N	N	N		CANCE
R	S	S	S	S	О	О	О	О	NO	R
		Y			Y					UTERU S
YOUN	N	E	N	N	E	N	N	N		CANCE
G	0	S	О	О	S	О	О	О	YES	R
						37				BLADD
YOUN	N	N	N	N	N	Y E	N	Y		ER CANCE
G	O	0	0	0	O	S	0	ES	YES	R
										STOMA
SENIO	N	Y E	N	Y E	Y E	Y E	N	N		CH CANCE
R	O	S	O	S	S	S	O	O	NO	R
		•		• -						

									01. 1 1000	ie 8, Octobei
) (IDD		3.7			**					UTERU
MIDD LE	N	Y E	N	N	Y E	N	N	N		S CANCE
AGED	O	S	O	O	S	O	O	O	YES	R
		_	_	_	~		_	_		KIDNE
							Y			Y
SENIO	N	N	N	N	N	N	E	Y		CANCE
R	О	0	0	0	О	О	S	ES	NO	R
MIDD LE	YE	Y E	Y E	Y E	N	N	N	N		BONE CANCE
AGED	S	S	S	S	O	O	O	0	NO	R
										BLADD
MIDD						Y				ER
LE	N	N	N	N	N	E	N	Y	MEC	CANCE
AGED	О	О	0	О	О	S	О	ES	YES	R UTERU
		Y			Y					S
SENIO	N	E	N	N	E	N	N	N		CANCE
R	О	S	О	О	S	О	О	О	YES	R
		Y	Y	Y						BONE
SENIO	YE	Е	E	E	N	N	N	N	NO	CANCE
R	S	S	S	S	О	О	О	О	NO	R KIDNE
							Y			Y
YOUN	N	N	N	N	N	N	Е	Y		CANCE
G	О	О	О	О	О	О	S	ES	NO	R
						3.7				BLADD
YOUN	N	N	N	N	N	Y E	N	Y		ER CANCE
G	O	O	O	O	O	S	O	ES	YES	R
			Ŭ				Ŭ	2.0	125	BLADD
						Y				ER
SENIO	N	N	N	N	N	E	N	Y	******	CANCE
R	О	O Y	0	O	О	S	О	ES	YES	R
SENIO	YE	E	Y E	Y E	N	N	N	N		BONE CANCE
R	S	S	S	S	o	o	o	Ö	NO	R
										KIDNE
							Y			Y
SENIO	N	N	N	N	N	N	E	Y	NO	CANCE
SENIO R	N O	N O	N O	N O	N O	N O		Y ES	NO	CANCE R
							E		NO	CANCE
						О	E	ES Y	NO	CANCE R BLADD
R	О	О	О	О	О	O Y	E S	ES	NO YES	CANCE R BLADD ER CANCE R
YOUN G	O N	O N	O N	O N	O N	O Y E	E S N O	ES Y		CANCE R BLADD ER CANCE R KIDNE
YOUN G MIDD	O N O	O N O	O N O	O N O	O N O	O Y E S	E S N O	Y ES		CANCE R BLADD ER CANCE R KIDNE Y
YOUN G	O N	O N	O N	O N	O N	O Y E	E S N O	ES Y		CANCE R BLADD ER CANCE R KIDNE
YOUN G MIDD LE	O N O	N O N	N O N	N O N	N O N O	O Y E S	E S N O	Y ES	YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE
YOUN G MIDD LE AGED	N O N O	N O N O	N O N O	N O N O	N O N O Y	O Y E S N O	E S N O	Y ES	YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S
YOUN G MIDD LE AGED MIDD LE	N O N O	N O N O Y E	N O N O	N O N O	N O N O Y E	O Y E S N O	E S N O Y E S	Y ES Y ES	YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE
YOUN G MIDD LE AGED	N O N O	N O N O Y E S	N O N O	N O N O	N O N O Y	O Y E S N O	E S N O	Y ES	YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S
YOUN G MIDD LE AGED MIDD LE	N O N O	N O N O Y E	O N O N O	O N O N O	N O N O Y E	O Y E S N O	E S N O Y E S	Y ES Y ES	YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R
YOUN G MIDD LE AGED MIDD LE AGED	N O N O	N O N O Y E S Y	N O N O N O	N O N O N O	N O N O Y E S	Y E S N O	S N O Y E S N O	Y ES Y ES N O	YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R
YOUN G MIDD LE AGED MIDD LE AGED SENIO	O N O N O N O	N O N O Y E S Y E	N O N O Y E	N O N O Y E	N O N O Y E S N	O Y E S N O	E S N O Y E S N O N O	ES Y ES Y ES N O	YES NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R	N O N O YE S	N O N O Y E S Y E S	N O N O Y E S	N O N O Y E S	N O N O Y E S N O	O Y E S N O	E S N O Y E S N O N O Y	Y ES Y ES N O	YES NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y
YOUN G MIDD LE AGED MIDD LE AGED SENIO R	N O N O YE S	N O N O Y E S Y E S N N	N O N O Y E S N	N O N O Y E S N	N O N O Y E S N O N	O Y E S N O N O	E S N O Y E S N O V Y E S S N O V Y E S N	Y ES  Y ES  N O  N O	YES NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R	N O N O YE S	N O N O Y E S Y E S	N O N O Y E S	N O N O Y E S	N O N O Y E S N O	O Y E S N O	E S N O Y E S N O N O Y	Y ES Y ES N O	YES NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD	N O N O YE S	N O N O Y E S Y E S N O Y	N O N O Y E S N O	N O N O Y E S N O Y	N O N O Y E S N O O Y	O Y E S N O N O	E S N O Y E S N O Y E S S	Y ES  Y ES  N O  N O  Y ES	YES NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH
YOUN G MIDD LE AGED MIDD LE AGED SENIO R  SENIO R  MIDD LE	N O N O YE S N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y E S N O N	N O N O Y E S N O Y E	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O N O	E S N O Y E S N O Y E S N O N O Y E S N O N O Y E S N O N O N O N O N O N O N O N O N O N	Y ES  Y ES  N O  N O  Y ES	YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH CANCE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD	N O N O YE S	N O N O Y E S Y E S N O Y	N O N O Y E S N O	N O N O Y E S N O Y	N O N O Y E S N O O Y	O Y E S N O N O	E S N O Y E S N O Y E S S	Y ES  Y ES  N O  N O  Y ES	YES NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH CANCE R
YOUN G MIDD LE AGED MIDD LE AGED SENIO R  SENIO R  MIDD LE	N O N O YE S N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y E S N O N	N O N O Y E S N O Y E	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O N O	E S N O Y E S N O N O Y E S N O	Y ES  Y ES  N O  N O  Y ES	YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH CANCE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R  SENIO R  MIDD LE	N O N O YE S N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y E S N O N	N O N O Y E S N O Y E	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O N O	E S N O Y E S N O Y E S N O N O Y E S N O N O Y E S N O N O N O N O N O N O N O N O N O N	Y ES  Y ES  N O  N O  Y ES	YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD LE AGED	N O N O YE S N O O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O Y E S N O O	N O N O Y E S N O Y E S	N O N O N O N O Y E S S N O O Y E S S	N O N O Y E S	E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y Y E S N	Y ES  Y ES  N O  N O  Y ES  N O	YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD LE AGED	N O N O YE S N O N O N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O N O N O N O N O N O N O N O N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O N O Y E S	E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E E	Y ES  Y ES  N O  N O  Y ES  N O	YES NO YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R KIDNE CANCE R STOMA CH CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD LE AGED YOUN G	N O N O N O N O N O N O O N O O N O O N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O N O N O N O N O N O N O N O N O	N O N O Y E S N O O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O Y E S N O Y	E S N O Y E S N O Y E S S S S S S S S S S S S S S S S S S	Y ES  Y ES  N O  N O  Y ES  N O	YES NO YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R KIDNE Y CANCE R BLADD ER
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD LE AGED YOUN G	N O N O YE S N O N O N O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O N O N O N O N O N O N O N O N O	N O N O Y E S N O N O N O N O N O N O N O N O N O N	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O Y E S N O Y E	E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E S N O Y E E	Y ES  Y ES  Y ES  N O  Y ES  N O  Y ES	YES NO NO NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R KIDNE Y CANCE R BLADD ER CANCE
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD LE AGED YOUN G	NOONOONOONOON	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O N O N O N O N O N O N O N O N O	N O N O Y E S N O O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O N O Y E S N O Y	E S N O Y E S N O Y E S N O Y E S N O	Y ES  Y ES  N O  N O  Y ES  N O	YES NO YES NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R KIDNE Y CANCE R BLADD ER
YOUN G MIDD LE AGED SENIO R  MIDD LE AGED SENIO R  MIDD LE AGED  YOUN G  YOUN G  SENIO	NOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOON	O Y E S N O Y E S N O Y E S N N	E S NOO Y E S NOO Y E S NOO NOO NOO NOO	Y ES  N O  Y ES  N O  Y ES  N O  Y ES  N O	NO YES NO NO NO YES	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R STOMA CH CANCE R BLADD ER CANCE R BLADD ER CANCE R BLADD ER CANCE R
YOUN G MIDD LE AGED MIDD LE AGED SENIO R SENIO R MIDD LE AGED YOUN G YOUN G	NOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	N O N O N O N O N O N O N O Y Y E S S N O O N O O Y Y C O O N O O O O O O O O O O O O O O O O	NOONOONOONOONOONOONOONOONOONOONOONOONOO	NOONOONOONOONOONOONOONOONOONOONOONOONOO	O Y E S N O O Y E S N O O Y E S S	E S N O Y E S N O Y E S N O O Y E S N O O Y E S N O O Y E S N O O O O O O O O O O O O O O O O O O	Y ES  Y ES  N O  Y ES  N O  Y ES  Y ES	YES NO NO NO NO	CANCE R BLADD ER CANCE R KIDNE Y CANCE R UTERU S CANCE R BONE CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R KIDNE Y CANCE R STOMA CH CANCE R KIDNE Y CANCE R BLADD ER CANCE R BLADD ER CANCE R

										UTERU
MIDD		Y			Y					S
LE	N	Е	N	N	E	N	N	N	T/E/G	CANCE
AGED	О	S	О	О	S	О	О	О	YES	R
MIDD						3.7				BLADD
MIDD	N	N	N	N	N	Y E	N.T	Y		ER CANCE
LE AGED	O	O	O	O	O	S	N O	ES	YES	R
AGED	0	Y	Y	Y	U	S	U	ES	ILS	BONE
SENIO	YE	E	E	E	N	N	N	N		CANCE
R	S	S	S	S	O	Ö	Ö	o	NO	R
10	5	5	5	5			0	0	110	STOMA
		Y		Y	Y	Y				CH
YOUN	N	Ē	N	Ē	Ē	Ē	N	N		CANCE
G	0	S	0	S	S	S	0	0	NO	R
		Y	Y	Y						BONE
YOUN	YE	Е	Е	Е	N	N	N	N		CANCE
G	S	S	S	S	О	О	О	O	NO	R
										STOMA
		Y		Y	Y	Y				CH
SENIO	N	Е	N	Е	E	E	N	N		CANCE
R	0	S	О	S	S	S	О	0	NO	R
										KIDNE
MIDD							Y			Y
LE	N	N	N	N	N	N	Е	Y	NO	CANCE
AGED	О	О	О	О	О	О	S	ES	NO	R
						Y				BLADD ER
SENIO	N	N	N	N	N	E	N	Y		CANCE
R	0	O	0	Ö	Ö	S	Ö	ES	YES	R
IX								Lo	ILS	UTERU
MIDD		Y			Y					S
LE	N	E	N	N	Ē	N	N	N		CANCE
AGED	O	S	О	О	S	О	О	0	YES	R
MIDD		Y	Y	Y						BONE
LE	YE	Е	Е	Е	N	N	N	N		CANCE
AGED	S	S	S	S	О	О	О	0	NO	R
										KIDNE
							Y			Y
SENIO	N	N	N	N	N	N	Е	Y		CANCE
R	О	О	О	О	О	О	S	ES	NO	R
		.,								UTERU
VOLIM	NT.	Y	N.T	N.T	Y	N.T	N.T	N.		S
YOUN	N O	E S	N O	N O	E S	N O	N O	N O	YES	CANCE
G	U	Y	Y	Y	3	U	U	U	IES	R BONE
YOUN	YE	E	E	E	N	N	N	N		CANCE
G	S	S	S	S	0	O	O	O	NO	R
	2	2	2	2			)		,	

Table 1 – Data Collection



Figure 1

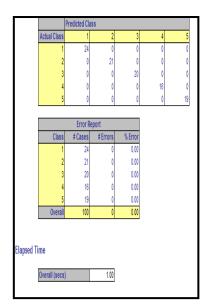
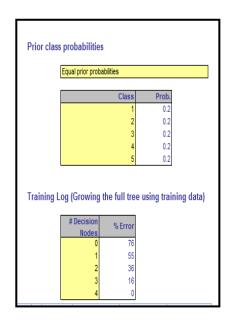


Figure 2



Full Tree Rules (Using Training Data) #Decision Nodes #Terminal Nodes SplitValue LeftChild RightChild Class Node Type NodelD Cases N/ADN URINATION Decision NAUSEA Decision O PAIN IN BONE Decision WA Terminal Termina WA N/A WA Terminal NAUSEA Decision WA WA Terminal Terminal Training Data scoring - Summary Report (Using Full Tree) Classification Confusion Matrix

Figure 4: Full Tree Rules

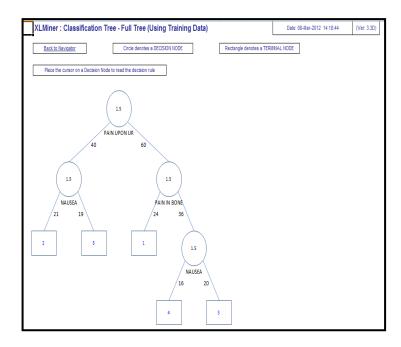


Figure 5 : Classification Tree – Full Tree

#### VI. CONCLUSION

The goal of classification is to build a set of models that can correctly predict the class of the different objects. The input to this method is set of objects (i.e., training data), the classes which these objects belongs to (i.e., dependent variables), and a set variables describing different characteristics of the objects (i.e., independent variables). Once such a predictive model is built, it can be used to predict the class of the objects for which class information is not known a priori. Hereby, we collected all the data about which type of cancer are affect the people according to their Symptoms. The above technique can be successfully applied to the data sets for any cancer (such as Bone Cancer, Bladder Cancer, Stomach Cancer, Kidney Cancer, Uterus and so on), as it was successfully demonstrated on the bone, bladder, stomach, Kidney and ovarian cancer in this research. The early and accurate detection as well as classification of cancer using the XLMiner tool will help in the selection of treatment options.

### **BIBLIOGRAPHY**

- 2. Agarwal R, Imielinski T, Swami AN. "Mining Association rules between Sets of Items in Large Databases." SIGMOD. June 1993, 22(2):207-16
- 3. Agarwal R, Srikant R,"Fast Algorithms for mining Association Rules", VLDB. Sep 12-15-1994, Chile, 487-99, pdf, ISBN 1-55860-153-8.
- 4. Mannila H,Toivonen H, Verkamo AI. "Efficiant Algorithms for Discovering Association Rules." AAAI workshop on Knowledge Discovery in Databases (SIGKDD). July 1994, Seattle, 181-92, ps.
- 5. Implementation of the algorithm in C# Retrieved from http://en.wikipedia.org/wiki/Apiriori\_al gorithm.
- 6. http://www.scribd.com/doc/28249613/ Data-Mining-Tutorial
- 7. Sarvestan Soltani A., Safavi A. A., Parandeh M. N. and Salehi M., "Predicting Breast Cancer Survivability

using data mining techniques," Software Technology and Engineering (ICSTE), 2<sup>nd</sup> International Conference, 2010, vol.2,pp.227-231.

8. Shelly Gupta et al./ Indian Journal of Computer Science and Engineering (IJCSE) ISSN: 0976-5166 Vol. 2 No. 2 Apr-May 2011 189