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Association Rule- Spatial Data Mining Approach for Exploration of Endometrial Cancer Data

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Abstract - Cancer is increasing the total number of unexpected deaths around the world. Until now, cancer research could not significantly contribute to a proper solution for the cancer patient, and as a result, the high death rate is uncontrolled. The present research aim is to extract the significant factors for responsible for endometrial cancer. We subsequently employed association rule mining algorithms in order to discover most of the significant factors . The Association Rule Mining methods are used to mine attribute relationships. The Support and Confidence values are estimated for all item-sets. Minimum Support and Confidence values are used to select frequent patterns. Classification technique is applied to assign labels for the transactions. Learning phase is carried out for transaction pattern identification. Testing process handles the pattern matching and label assignment task.

Keywords- Endometrial Cancer, association rule mining, Spport

I. INTRODUCTION

The conditions in which the people live in are shaped by multiple elements of the society. The various conditions which affect health such as environmental, social, political and economic factors may be difficult to investigate. Demographic research shows that disease and disability are not randomly distributed in the population. Endometrial cancer is a gynecological malignancy which predominantly affects older and post menopausal women. The main aim of this study was to determine the factors using Data Mining Techniques which are significantly associated with endometrial cancer. These Techniques have wide application because it is supported by 2 methods which are Massive databases and Data mining algorithms. Huge amounts of healthcare data is collected by the health care industry which unfortunately, are not "mined" to discover hidden information for effective decision making. Hidden patterns and relationships are often discovered. The only remedy for this situation is by using Advanced data mining techniques . Medical profiles could predict the likelihood of patients getting a cancer disease. It enables the knowledge relationships between medical factors related to cancer disease, to be established. Data mining technology provides a user-oriented approach for hidden patterns in the data. This knowledge can be used by the healthcare administrators to improve the quality. Numerous fields associated with medical services like prediction of effectiveness of surgical concepts, medical tests, medication, and the discovery of relationships among clinical and diagnosis data as well employ Data Mining methodologies [1]. Therefore, data mining has developed into a vital domain in healthcare. It is possible to predict the efficiency of medical treatments by building the data mining applications. The real-life data mining applications are attractive since they provide data miners with varied set of problems, time and again. Working on cancer disease patient's databases is one kind of a real-life application which tries to utilize the knowledge and experience of several specialists collected in databases towards assisting the diagnosis process [2]. In the recent past, the data mining techniques were utilized by several authors to present diagnosis approaches for diverse types of cancer diseases [3, 4,5].

Documenting socioeconomic variations in cancer may be a step towards decreasing health disparities by identifying the socio economic groups or areas that are at the greatest risk of cancer morbidity and mortility. The analysis of socioeconomic gradients in cancer serve as an indicator of the impact of cancer prevention programs and reveal the underlying conditions which create risk factors, and influence health care system access and utilization. There are several data mining techniques developed and applied to discover new and interesting pattern relationships from large spatial data. Association rule mining technique is applied mainly to correlate the presence of a set of items with another set of items among massive databases. The main aim of association rule is to generate hypothesis rather than testing them that is commonly achieved through statistical techniques [6].

II. ASSOCIATION RULE

Association rule mining is being applied to search for hidden relationships between factors by finding factors frequently appearing together in the cancer database. The Mining Association rule is one of the important tasks of data mining which identifies interesting association and correlation among large data set of items. The concept of Association rule was introduced as a powerful tool for discovering correlations among massive databases.

Association rule typically consists of three parts – an antecedent (X), a consequent (Y) and a measure of the interestingness of the rule (support%, confidence% and lift), as represented in the following equation;

$$X \rightarrow Y \text{ (support\%, confidence\%,)}$$

The antecedent and the consequent are a set of one or more predicates. The support of a rule measures the frequency of collective occurrence of all the antecedent and consequent predicates of a rule in the dataset [3]. Each rule has an associated support and confidence, which is defined as:

Support is an estimate for Pr[X∩Y]/Total number of records

Confidence is an estimate for Pr[x∩Y]/Pr[X]

The support is the ratio of transactions that satisfy both X and Y to the number of transactions in databases. The confidence is the conditional probability of Y given X. Since users are interested in large support and high confidence, two thresholds are used to find strong association rules [7]. Criteria value filters the data based on the confidence value. Thus classical association rule mining algorithms aim to extract association rules with support and confidence greater that user- specified threshold. The goal of spatial data mining is to automate the extraction of interesting, useful but implicit spatial patterns. The process of Association rule has the following sequences

i) Understanding of the problem domain and identification of the final goal of the process
ii) Data Collection
iii) Preprocessing of data is carried out to refine the data
iv) Encoding of data
v) Data Mining- selection of association rule, selection of algorithm for data exploration,running the algorithm to generate patterns and
vi) Interpretation , presentation and explanation of mined knowledge

III. APPLYING ASSOCIATION RULES

Association rules are nothing different from classification rules except that does not predict only class labels but also predict all other attribute. It is used to produce a combination of attributes. An association rule is the number of instances for which it predicts correctly and this is often called its support. Confidence is the number of instances that it predicts correctly and expressed as proportion of all instances to which it applies called accuracy. The user have to specify the minimum coverage and accuracy values and look for only those rules whose values are at least of the specified minimum value

Associative Classifier

The cancer symptoms and its class labels are used in the learning process. Learned class patterns are used in the prediction process. The system is divided into four major modules. They are Data preprocess, approximation process, disease prediction and rule mining. Data preprocess module is designed to clean noisy transactions. The approximation process is designed to convert the data values into categorical values. Disease prediction module is designed to forecast the disease severity levels. Rule mining module is designed to fetch symptom patterns.

Data Preprocess

The data preprocess module is designed to import data from textual data collection. The cancer patient diagnosis details are imported and updated into Oracle database. Redundant data values are removed from the database. Incomplete data values are assigned by the system. Aggregation based data substitution technique is used for the incomplete data assignment process. Cleaned dataset is referred as optimal dataset. The training set is selected from the optimal dataset. The testing is carried out on the unlabeled transactions.

Approximation Process

The approximation process is initiated to convert data values into categorical attributes with experts advice. The data values are divided into small intervals. The interval data are assigned with category information. Classification is applied on the categorical data values.

Disease Prediction

Pruning-Classification Association Rule (PCAR) combines minimum frequency items with minimum frequency item sets. It first deletes infrequent items from item sets, and then classifies item sets based on frequency of item sets. The number of candidate item sets is greatly reduced and item sets need not to be combined or decomposed.

Rule Mining

The association rule mining technique is applied to predict the disease severity. The disease symptom rules are also identified with label information. The rules are updated and used in future prediction process. The rule base is automatically updated by the frequent patterns with its labels.

IV. DATA AND METHODOLOGY

The dataset used for this analysis consisted of women diagnosed with Endometrial cancer from Mysore, Chamrajnagar, Hassan, Mandya and Madikeri districts mainly. The data for the present study on cancer was collected from the Cancer hospital records. Between 1995 and 2010, 325 endometrial cancer patients were diagnosed. Patients were divided into groups based on age at diagnosis, parity, diet, menopausal status, religion, education, occupation. The data was recorded in MS-Excel sheet. The permutations and combinations between the cancer and its associated habits were made. Association rules were generated and the confidence /supporting values were calculated for each type

V. RESULTS

Table 1: Descriptive characteristics of the study

PATIENT CHARACTERISTICS	NUMBER OF CASES	PERCENTAGE
AGE		
LESS THAN 50	71	21.935
51-60	103	31.790
MORE THAN 60	150	46.296
DIET		
VEG	87	26.85
NON VEG	237	73.14
MARITAL STATUS		
MARRIED	312	96.29
UNMARRIED	12	3.703
PARITY		
NO CHILDREN	72	22.22
1-2 CHILDREN	102	31.48
MORE THAN 2	150	46.29
AGE AT MENOPAUSE		
BELOW 50	89	27.46
ABOVE 50	235	72.53

Association rule mining mainly helps to identify the factor (if the occurrence of the disease is not due to heredity) which has more influence to cause the disease. For the present study , association rule mining technique is applied to examine all the existing association between cancer and the habit. According to our analysis seen in the table below there is a strong association rule when the patient was multiparous, when she is more than 60 years of age, undergone menopause and following a non veg diet and when these factors are involved the occurrence of cancer is high.

S NO	Combination of Factors	No of Records	Support	Confidence
1	age,diet,no of kids,menopause(2,2,3,2)	56	0.1728	1
2	age,diet,no of kids,mar stat(2,2,3,1)	65	0.2006	1
3	age, no of kids, mar stat,menopause(2,3,1,2)	68	0.2099	1
4	**diet, no of kids, mar stat, menopause(2,3,1,2)**	**91**	**0.2809**	**1**
5	**age,diet,mar stat, menopause(2,2,1,2)**	**91**	**0.2809**	**1**

S NO	Combination of Factors	No of Records	Support	Confidence
1	age,diet,no of kids(2,2,3)	65	0.2006	1
2	age,no of kids,menopaus(2,3,2)	68	0.2099	1
3	age,no of kids,mar stat(2,3,1)	79	0.2438	1
4	diet, no of kids,menopause(2,3,2)	91	0.2809	1
5	age,diet,menopause(2,2,2)	91	0.2809	1

6	diet,mar stat,age(2,1,2)	108	0.3333	1
7	no of kids, mar stat,menopaus(3,1,2)	115	0.3549	1
8	age,mar stat,manopause(2,1,2)	121	0.3735	1
9	diet, no of kids,mar stat	123	0.3796	1
10	**diet,mar stat,menopause(2,1,2)**	**166**	**0.5123**	**1**

VI. DISCUSSION

The present study investigated associations between secondary cancer factors and the risk of endometrial cancer development among women who were between the age group of 40 to 85. This study demonstrated that a woman who has was above the age of 60, who has undergone menopause, and who consumed a non vegetarian diet were highly associated with the risk of endometrial cancer development. Women who have undergone menopause after the age of 50 have relative risk of the disease when compared to those who had undergone menopause at the age of 45.

Most investigators who have found patient age to be an independent prognostic factor in women with endometrial carcinoma have included clinically staged patients in their analysis [8,9,10,11,12,13,14,15,16]. The frequent association between older age in endometrial carcinoma patients on the one hand and, conversely, deep myometrial invasion and aggressive histologies always raises the possibility that the poor outcome in older patients is entirely the result of such an association. Multiple investigators, however, have found that outcome differences based on age remain even after controlling for imbalances in pathologic features [17,18,19,20,21,22,23,24,25]. In contrast, others [26,27,28,29,30] have reported that the prognostic significance of age is lost after adjusting for such imbalances. While some [31,32,33,34,35] have found age to be an independent predictor for outcome, others [36,37,38,39,40] have not. The data in the literature also suggest that there is incremental increase in the risk of dying from endometrial carcinoma with increasing age. In a review of 819 patients with Stage I-II endometrial carcinoma from the Gynecologic Oncology Group database, Zaino et al. demonstrated that the RR increased from 1 for patients who were age $\leq$ 45 years (reference) at the time of diagnosis to 2 for patients age 55 years, 3-4 for patients age 65 years, and to 4-7 for patients age $\geq$ 75 years.[41].

Reproductive factors may also influence the risk of endometrial cancer by affecting relative estrogen/ progesterone exposures. The menstrual cycle, pregnancy, miscarriage, induced abortion, and menopause are also associated with fluctuating levels of estrogen and progesterone. The uterus, being a sex hormone-dependent organ, responds to hormonal changes in the body brought about by a woman's reproductive experiences. According to epidemiological studies, late age at menopause is known to be a risk factor for cancers[42,43,44]. Women who reach menopause at a late age are more likely to have a higher risk of the cancer, The higher cancer risk in women with a late menopause is most likely explained by both the longer duration and higher level of exposure to estrogen and progesterone experienced by these women. They also may experience a larger number of anovulatory cycles resulting in a lack of cyclic progesterone.

It has been postulated that a diet high in meat may increase the risk of endometrial cancer; however, few nutritional epidemiologic studies have evaluated endometrial cancer as an endpoint (Bandera et al. 2007). Several case-control studies have evaluated red meat and endometrial cancer, and results from these studies have been summarized in a meta-analysis (Bandera et al. 2007). The results of the meta-analysis, based on data from seven studies, indicated a significant 51% increased risk of endometrial cancer per 100g/ day of red meat consumption (Meta OR = 1.51, 95% CI: 1.19-1.93). Meat and fish cooked at high temperatures can produce HCAs, potent experimental mutagens, or carcinogens (Dolara et al, 1979; Sinha and Knize et al, 1998; Sinha and Rothman et al, 1998; Wong et al, 2005). Heterocyclic amines begin to form at temperatures of 150^{o} C or higher, and their production can be increased up to three-fold when the cooking temperature is increased from 200 to 250^{o}C [45]. Frying, broiling, grilling, and baking are associated with formation of large amounts of HCAs [46]. In our population, deep-frying is the most common high-temperature method for cooking red meat and fish. It has been reported that deep-frying also generates fumes containing mutagenic compounds[47][48]. These mutagens or carcinogens have been linked to an increased risk of cancers among Western populations [49][50].

VII. CONCLUSION

New classification approach that use association rule mining and classification has become a significant tool for knowledge discovery. The association rule mining and classification techniques are integrated under the associative classification process. Interesting relationships and correlation among cancer and a set of habits which is useful for decision making in any area of science particularly in spatial epidemiology was proposed by association rule data mining technique. Biological functions through biological data could be also analyzed through the proposed data mining strategy.

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