World Applied Sciences Journal 27 (5): 656-662, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.27.05.1077

The Role of Hot-Tea Drinking and the Food Insecurity on the Esophageal Cancer among Women in the North of Iran (Gilan Province)

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Abstract: Although tea may exert opposing influences on chronic disease, information on the balance and suitable of tea intake and food insecurity are important factors for overall diet quality, particularly in Iran, who have a much higher hot-tea drinking than north (Gillan) populations. The objective of this cross-sectional study was to test the hypothesis that hot-tea drinking and food insecurity could be creates esophageal cancer among women in the north of Iran (Gilan Province). The subjects were 710 women aged 40 to 70 years (210 women has the esophageal cancer), they are selected randomly in the Gilan Province of the north of Iran. The food insecurity (such as hunger and hidden hunger) in the province according to the 24-hour food-recall questionnaire was 29.8% and 46.2%, respectively. Only 27% of the study population was secure in terms of having access to all key nutrients. The accuracy of the questionnaire for screening for hunger in the population was 93.3%, respectively; and the corresponding value for hidden hunger was 87.6. Our findings indicate that the over 91 % of selected people (that have the esophageal cancer) and over 70 % of the selected people (that have not the esophageal cancer) drink the hot tea and all selected women has suffered from the esophageal pains. Average value of the esophageal cancer predicted using fuzzy cognitive maps is equal to 83% (for 36 monthes).

Abbreviations: FCM, fuzzy cognitive maps
Key words: Esophageal cancer · Hot tea · Food insecurity · Fuzzy cognitive maps

INTRODUCTION

Nowadays one of the principle challenges of any country is improving the chronic disease and cancers. One of most important of cancers is the esophageal cancer in Iran. No doubt, the esophageal cancer is an outcome of the interaction and combination of different factors. Cancer of the oesophagus is one of the commonest: causes of death in adults (especially women) in north of Iran, where the incidence of this cancer is among the highest in the world [1, 2].

One of main factors is food insecurity, there is evidence that food insecurity, particularly transitory food insecurity, has been getting worse in Malawi. In 2001–2003 Malawi suffered a food crisis. This was manifested in a six- fold increase in food prices, which left around 3.5 million people food insecure [3]. The crisis was the combined result of climatic shocks, mis-management of the country's strategic grain reserve, poor crop estimates and a chaotic delayed response in terms of maize imports [3, 4]. Few universally valid indicators of food security are applicable in crises. Nutritional status, if properly measured, is widely accepted as comparable across different contexts. However, while nutritional status can be one indicator of food security status, it may equally reflect elements of health status, care practices, water quality and other determinants of nutrition [5, 6].

The possible role of hot-tea drinking in the aetiology of oesophageal cancer raised by Dr Greenberg [7, 8] was one of the factors considered by Bashirov and others in a paper on the epidemiology of oesophageal cancer in the Aktubinsk province of Kazakhstan - an area where there is a very high incidence of this disease [9].

According to literature, food insecurity and hot-tea drinking are majore factors to creating oesophageal cancer in north of Iran. With this in mind, the objective of this

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cross-sectional study was to test the hypothesis that hot tea intake and food insecurity could be creates esophageal cancer among women in the north of Iran (Gilan Province). The subjects were 710 women aged 40 to 70 years (210 women has the esophageal cancer), they are selected randomly in the Gilan Province of the north of Iran. The Fuzzy Cognitive Maps method based on real coded genetic algorithm has been used for prediction of the role of hot-tea drinking and the food insecurity on the esophageal cancer among women in the north of Iran (Gilan Province). The results gained are comparable with other modern methods.

MATERIALS AND METHODS

Method of this paper has been based on the analytical and descriptive Research using fuzzy cognitive maps (FCM) method. This analytical and descriptive type research has been carried out using the questionnaire as the research tool for gathering the required data. Data's gathering involved both reference material and a questionnaire survey. Sampling was simple random sampling and the data-gathering instrument was the questionnaire. The author had already undertaken research in this field, which had stimulated the prediction tchniques used to analyze this case study, based on FCM Method.

This cross-sectional study was conducted on a total of 710 women aged 40 to 70 years (210 women has the esophageal cancer), they are selected randomly in the Gilan Province of the north of Iran. Eligible individuals were followed and encouraged to come to the study setting for an interview, anthropometric measurements and dietary assessment. The participation rate was 94%. Participants were required to sign an informed consent to participate in the program. Approval for this study was obtained from the Research Committee of the Food and Nutrition Security Office of the Islamic Azad University (Medical Sciences section). The area has previously been selected and described in detail as a reliable representative sample of the general population in terms of socioeconomic status, lifestyle, general health status and population composition [10].

Information on food consumption was obtained with a validated 24-hour food-recall questionnaire over 3 non-consecutive days. These results were compared with data from the Household Food Security Scale [11] to assess the applicability of this short scale for the surveillance of food insecurity. The short questionnaire had six questions. If the participants responded to two or more of the six items, they were considered food insecure. The questions were validated (in the local language) by a pilot study before starting the main research. To do this, the questionnaire was distributed to 50 individuals with the same characteristics and from the same area as the main study participants. The pilot study was carried out on the first 50 subjects of the whole study group. After assessment and evaluation of the results of this pilot, the next individuals (n = 710) were studied as the main part of the research. The results were then statistically analyzed to ensure that the short-scale questionnaire was valid for assessing household food insecurity in the main part of the research. For prediction of role of hot tea, it is used FCM method.

Predicting the time series for recognizing the numerical or explanatory levels is a new approach. This approach has been presented using the Fuzzy Cognitive Maps together with a learning method enjoying the advantage of the real-coded genetic algorithm. In fuzzy cognitive maps framework, the systems are described through their reciprocal concepts and relationships [12]. The suggested prediction method combines the fuzzy cognitive maps with the fuzzy set grain model, one of the advantages of which being the modeling and predicting in two numerical and explanatory levels. Comprehensive activities have been performed in mind considering two main goals. First, estimating the quality of the suggested structure and second, testing the effects of the prediction technique parameters on the prediction quality. The gained results in comparison with other fuzzy based prediction techniques show that the suggested structure produces higher accuracy in numerical and explanatory levels [13].

The main aims and in other words, the motive of selecting the Fuzzy cognitive maps are as follows:

- Application of the Fuzzy cognitive maps for predicting the time series: The motive for using this specific technique is a result of its simple and comprehensive structure, consisting of the reciprocal relationship concepts, conforming to a given range. The Fuzzy cognitive maps are capable of acquiring the behavior of a given dynamic system. Recently the introduced genetic optimization based learning algorithm (genetic algorithm) allows for automatic expanding of the Fuzzy cognitive maps from the genetic data. This learning approach is flexible considering the input data. For example, both observations in successful time points of t and t+1 can be used for learning the map and if some observations are removed from the historical data, all the remained couples still can be successfully used for learning [14].

- The possibility of design and expanding the absolute predicting systems, based on the Fuzzy cognitive maps which are capable of predicting in two numerical and explanatory levels [15].

The desired steps for implementing are according to the description given in Figure 1.

The Fuzzy cognitive maps prediction system realizes a series of well-delineated steps as shown in Fig. 1. The input signal is preprocessed in a preprocessing module, which plays a dual role. First, it extracts feature(s) of interest for the linguistic prediction. They include change of signal, which is defined as a difference between two consecutive values of a given input signal and the signal's amplitude. The change constitutes an additional time series. Second, both signals are normalized linearly to the unit interval. In order to avoid artificial enlargements of small signal changes, the normalization of change signal is carried out based on the range of the original time-series signal. More specifically, the maximum possible change value is determined and the normalization is performed with respect to this value. As a result, from the preprocessing module, two normalized signals, i.e., input and change, are obtained. The first value of input signal is dismissed to have equal length of both signals [16].

After preprocessing, information granules of the signal determining its current status are extracted and linked in fuzzification module. This process involves linguistic descriptors (labels), which are given as a set of fuzzy sets. Based on their definitions, membership values are calculated for each value of both signals. The linguistic descriptors can be defined uniformly or independently for each signal. Consider K time series as an input to this module and number of corresponding linguistic descriptors denoted by the N1, N2,…, Nk. In the first phase, these signals are represented in terms of membership values of given fuzzy sets, which results in having N1+ N2+ …+Nk fuzzy time series. Next, granularization process takes place, which links fuzzy time series with the use of fuzzy operators. Each of these time series expresses the level the given signal can be characterized by corresponding linguistic descriptors. We provide unique linguistic labels over the entire time series by choosing the descriptors with the highest values at each time point. The presence of the next, data divider, module is caused by organization of our experimental setup and thus, it does not belong to the proposed prediction method per se. In particular, it serves for experimental evaluation of the prediction method dividing the input data set into training and test subsets. The former subset is used to develop appropriate Fuzzy cognitive maps, whereas the latter one is separate and is used to test prediction accuracy on unseen data. The actual learning of Fuzzy cognitive maps is performed in the Real Coded Genetic Algprithm module, which establishes Fuzzy cognitive maps based on training data. This process exploits the genetic learning algorithm, which is described in Section II. Number of nodes in candidate Fuzzy cognitive maps corresponds to number of granular time series from the output of fuzzification module. The nodes depict complete signal description within the assumed fuzzy domain, i.e., each node corresponds to a single combination of linguistic descriptors of granular time series. We emphasize that all Fuzzy cognitive maps's parameters that define the model are established automatically, i.e., without any substantial intervention of a model's designer [17, 18]. A fully developed Fuzzy cognitive map is used by linguistic prediction module to carry out the signal prediction in fuzzy domain (linguistic prediction) on the test data.

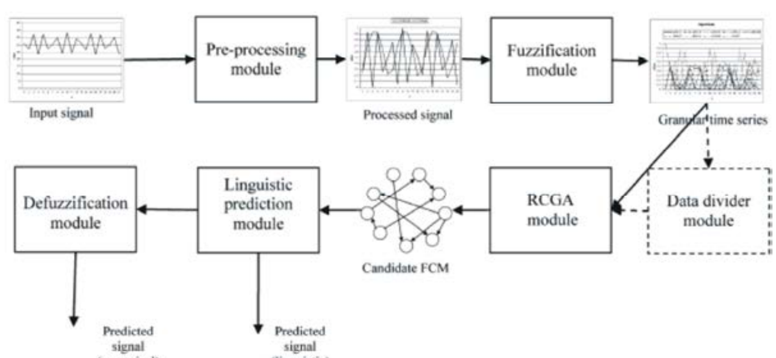

Fig. 1: Diagram of the suggested prediction method

This process involves a model simulation according to scenario defined in data divider module. Linguistic prediction uses fuzzy operations on granular time series obtained from simulation. Numerical prediction requires fuzzy values to be defuzzified. Defuzzification module performs this process according to a predefined defuzzification method on granular time series, which is obtained from simulation and then is carried out on the test data. The numerical prediction is performed based on the defuzzified values. In addition to defuzzified signal value, other signal features defined in preprocessing module may be also used as a supplement, or correction coefficient, during prediction.

RESULTS

At first, an optimized signal was exploited for prediction from among the 4 signals (40-47, 48-55, 56-63, 64-70 years). The signal with min change standard deviation and max range standard deviation will be selected. Table 1 shows the change value and range in different levels. Domain is obtained by $\frac{x - x_{\min}}{x_{\max} - x_{\min}}$ change is obtaind by $\frac{|x|}{x_{\max} - x_{\min}}$.

According to Table 1, the signal of 64-70 years has the min change standard deviation and the max range standard deviation and therefore is selected as the input signal of the prediction. Real Coded Genetic Algorithm learning parameters (whose values have been established experimentally) include the following: 1) single-point crossover, 2) mutation method: randomly chosen from random mutation, nonuniform mutation and Mühlenbein's mutation, 3) selection method: randomly chosen from roulette wheel and tournament, 4) probability of recombination: 0.9, 5) probability of mutation: 0.5, 6) population size: 100 chromosomes, 7) maximum number of generations: 10 000 and 8) maximum fitness function value: 0.999. After a candidate fuzzy cognitive maps is constructed from the training data by the Real Coded Genetic Algorithm module, the prediction is carried out at two levels, linguistic and numerical. Figure 2 presents predictions in 36 month in future.

According to the prediction data, Our findings indicate that the over 91 % of selected people (that have the esophageal cancer) and over 70 % of the selected people (that have not the esophageal cancer) drink the hot tea and all selected women has suffered from the esophageal pains. Average value of the esophageal cancer predicted using fuzzy cognitive maps is equal to 83% (for 36 monthes). The mean square error reached to its minimum value using the above function: 0.076. The R^2 value reached to 99% which indicates the model validity. The Cronbach alfa value is 98%, confirming the validity of the model. In addition, interviews with the experts based on the Delphi method confirmed the above values in 97% of the cases.

The food insecurity (such as hunger and hidden hunger) in the province according to the 24-hour food-recall questionnaire was 29.8% and 46.2%, respectively. In addition, Food insecurity significantly increased the risk of underweight in the study subjects (RR = 53.2, CI: 4.9–65.5), while it decreased the risk of overweight and obesity (RR = 0.30, CI: 0.18–0.49 and RR = 0.32, CI: 0.16–0.62, respectively).The prevalence rates of hunger and hidden hunger according to the 24-hour food-recall questionnaire were 11% (CI: 40–47), 18% (48-55), 28%(56-63) and 43% (CI: 64–70), respectively. Only 27% (CI: 40–58) of the study population was secure in terms of having access to all key nutrients (including protein, calcium, vitamin A and vitamin B2). Of the total respondents, 40% reported that they could not afford to eat balanced meals. At the same time, 28% of the respondents gave affirmative responses to two or more of the six items, indicating food insecurity. The accuracy of the questionnaire for screening for hunger in the population was 93.3%, respectively; and the corresponding value for hidden hunger was 87.6.

It found that the majority of people in the areas investigated consume hot beverages and excessively hot tea, the tea being consumed about 3-4 times a day in large quantities but from small glasses in order to ensure that it is kept hot. The tea-drinking habits of 210 resophageal-cancer patients and 500 healthy controls were compared. Of the oesophageal patients, 65% consumed more than 6 glasses of tea at one time.

DISCUSSION

Bashirov *et al*. concluded that the difference between the groups was too small to establish hot tea as the main factor responsible for the increased incidence of cancer of the oesophagus in the Kazakhs [19]. In the earlier study cited in your editorial Kaufman and others found that among other bad eating habits the drinking of very hot tea was prevalent among 63 (49-6%) cesophageal-cancer patients as compared with 17 (23-6%) controls. These workers found no differences as between Kazakh tribes resident in the city of Guryev, but the standardised morbidity-rate per 100,000 inhabitants of Guryev. city was 240-2 for Kazakhs and 93-4 for Russians [20].

Table 1: Selected women Domains

63-70			56-63			48-55			40-47		
Change	Domain	Quantity	Change	Domain	Quantity	Change	Domain	Quantity	Change	Domain	Quantity
0.806	0.636	5.8	0.656	0.521	5.2	0.771	0.731	6.6	0.821	0.487	5.5
0.781	0.611	5.62	0.648	0.513	5.14	0.75	0.71	6.42	1.106	0.772	7.41
0.616	0.446	4.43	0.414	0.279	3.28	1.04	1	8.90	0.503	0.169	3.37
0.828	0.659	5.96	0.471	0.336	3.73	0.48	0.44	4.10	0.573	0.239	3.84
0.677	0.508	4.88	0.656	0.522	5.21	0.342	0.301	2.92	1.124	0.79	7.53
0.709	0.539	5.10	0.903	0.768	7.16	0.515	0.475	4.41	0.546	0.212	3.66
0.447	0.278	3.22	1.135	1	9.00	0.925	0.885	7.91	0.813	0.479	5.45
0.57	0.401	4.10	0.718	0.583	5.69	0.811	0.77	6.94	0.863	0.529	5.78
0.407	0.238	2.93	0.249	0.114	1.97	0.767	0.727	6.56	0.505	0.172	3.39
0.456	0.286	3.28	0.306	0.171	2.42	0.539	0.499	4.61	1.18	0.847	7.91
0.315	0.145	2.27	0.135	0	1.07	0.977	0.937	8.36	1.314	0.98	8.80
0.461	0.291	3.32	1.127	0.993	8.94	0.493	0.453	4.22	1.252	0.918	8.39
0.798	0.628	5.74	0.463	0.328	3.67	0.697	0.657	5.97	0.745	0.411	4.99
0.513	0.344	3.69	0.265	0.13	2.10	0.551	0.51	4.71	0.378	0.044	2.53
0.402	0.232	2.89	1.052	0.917	8.34	0.82	0.779	7.01	0.854	0.52	5.72
0.432	0.262	3.11	0.179	0.045	1.42	0.794	0.754	6.79	1.251	0.917	8.38
0.875	0.705	6.30	0.186	0.051	1.47	0.331	0.291	2.83	1.132	0.798	7.58
0.588	0.419	4.24	0.997	0.862	7.90	0.228	0.188	1.95	0.834	0.5	5.59
0.505	0.335	3.63	0.334	0.199	2.65	0.144	0.104	1.23	0.696	0.362	4.67
0.944	0.775	6.80	0.292	0.158	2.32	0.342	0.302	2.92	1.334	1	8.94
0.914	0.744	6.58	0.969	0.834	7.68	0.638	0.598	5.46	1.326	0.992	8.88
1.169	1	8.42	1.08	0.945	8.56	0.947	0.907	8.10	0.8	0.466	5.36
0.649	0.48	4.67	0.549	0.415	4.36	0.86	0.82	7.36	1.032	0.698	6.91
0.316	0.147	2.28	0.749	0.614	5.94	0.56	0.52	4.79	0.838	0.504	5.61
0.783	0.614	5.64	0.464	0.329	3.68	0.793	0.753	6.79	0.439	0.105	2.94
0.383	0.214	2.76	0.527	0.392	4.18	0.865	0.825	7.40	1.037	0.703	6.95
0.169	0	1.22	1.125	0.99	8.92	0.293	0.253	2.51	0.71	0.376	4.76
1.052	0.883	7.57	1.092	0.958	8.66	0.04	0	0.34	0.91	0.576	6.09
0.228	0.059	1.64	0.761	0.627	6.04	0.913	0.873	7.81	1.297	0.964	8.69
0.998	0.829	7.18	0.819	0.685	6.50	0.26	0.22	2.23	0.901	0.567	6.04
0.384	0.214	2.76	0.402	0.267	3.19	0.165	0.125	1.41	1.106	0.772	7.41
0.235	0.066	1.69	0.285	0.151	2.26	0.871	0.831	7.45	0.334	0	2.24
0.727	0.558	5.23	1.116	0.982	8.85	0.634	0.594	5.42	0.979	0.645	6.56
0.521	0.352	3.75	0.711	0.576	5.64	0.297	0.256	2.54	1.054	0.72	7.06
0.723	0.553	5.20	0.484	0.349	3.84	0.931	0.891	7.96	0.86	0.526	5.76
1.115	0.946	8.03	1.069	0.934	8.48	0.715	0.675	6.12	1.111	0.777	7.45
		1.2			1.1			0.3		2.2	Min
		8.4			9			8.9		8.9	Max
0.625	0.455		0.650	0.515		0.614	0.574		0.904	0.570	average
0.068	0.068		0.107	0.107		0.076	0.076		0.080	0.080	Variance

64-70 years is selected min variance of change & max variance of domain

It found that the majority of people in the areas investigated consume hot beverages and excessively hot tea, the tea being consumed about 3-4 times a day in large quantities but from small glasses in order to ensure that it is kept hot. The tea-drinking habits of 210 resophageal-cancer patients and 500 healthy controls were compared. Of the oesophageal patients, 65% consumed more than 6 glasses of tea at one time. Among resophageal-cancer patients the most frequently encountered habits were: (1) consumption of excessively hot food; (2) consumption of hot tea; (3) overeating before going to bed; (4) habitual hasty eating; and (5) many years of eating dry uncooked solids. These findings certainly seem to justify further investigations.

The prevalence of food insecurity according to this short questionnaire was about 36% in the study population. Gulliford and colleagues reported a similar figure of 25% from Trinidad and Tobago [21]. The percentages of affirmative responses to the six questions in our study were 18%, 24%, 15%, 27%, 26%

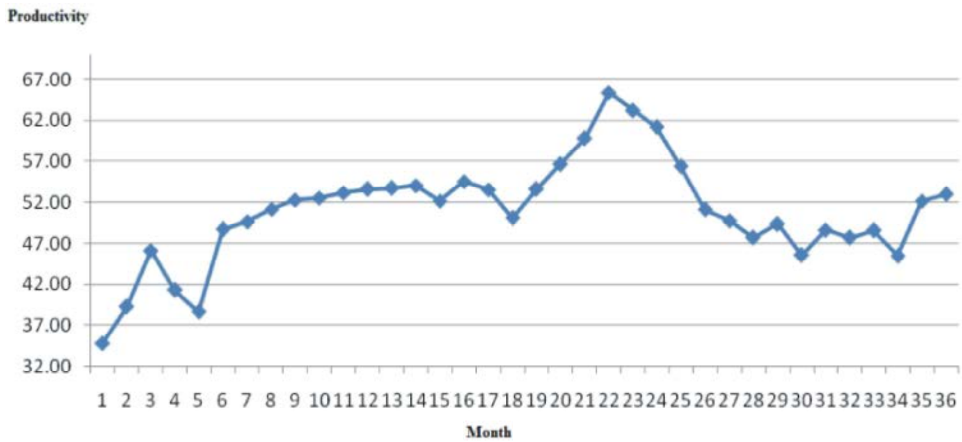

Fig. 2: Predictions in case study

Table 2: Camparison of methods based on error

Approach	Error %
Song - Chissom method	0.129
Chen's method	0.34
Markov method	0.578
Hwang method	0.245
Fuzzy time series method	0.09
proposed method	0.076

and 46%, respectively. In comparison with similar figures from the United States, the current population survey and Caribbean studies showed that the prevalence of food insecurity based on the affirmative responses to six items of the food security measurement was relatively high in Iran [22]. Our findings showed an association of food insecurity and BMI in the study population. Food insecurity increased the rate of underweight and decreased the rates of overweight and obesity. Some studies have reported an association between food insecurity and BMI. In a nationally representative sample of 6,506 individuals from Finland, Sarlio-Lahteenkorva and Lahelma showed that underweight subjects were at higher risk for food insecurity than obese or normal subjects [23]. Townsend et al. found an association between food insecurity and overweight in the female population, whereas there was no such association in male subjects. A study from the United States showed that although mild or moderate food insecurity was associated with a higher risk of obesity, severe food insecurity was associated with a lower risk of obesity [24]. Another research study reported an association of food insecurity with underweight but not with obesity.

The results gained from the suggested method in comparison with the results of the other methods showed that the prediction methods based on the existing fuzzy sets have been tested only on one or two data sets. On the contrary, our paper includes comprehensive tests and comparing the results with all the rival methods, as shown in Table 2. Table 2 makes a comparison between the results of the predicting data relating to 36 month based on the error level. As can be seen from the results, the Fuzzy Cognitive Maps (FCM) method incurs the minimum error possible. The second better method, that is the Fuzzy time method gained the score 0.09. The other methods including the Sung-Chism, Chen, Markove and Hwang methods achieved the next ranks.

One possible follow-up is the comparison of the proposed method with other models, such as the Hidden - Markov models and Bayesian network.

ACKNOWLEDGEMENT

This work was supported by a grant from Islamic Azad University, Zanjan Branch, Zanjan, Iran.

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