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Original Article

Detecting Depression in Elderly People by Using Artificial Neural Network

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Introduction: The possibility of depression is common in the elderly. Novel technologies allow us to monitor people related to depression. Hence, a model was provided to detect depression in elderly based on artificial neural network (ANN).

Methods: The present study is an applied descriptive-survey research. Forty elderly people were randomly selected from the Elderly Care Center in Gonbad Kavous, Golestan, Iran in 2019. Data were obtained through interview. The data were randomly divided in to two groups of training and testing. In training phase by using first dataset (70%), three layers network is considered. Interrelation weights between variables, optimum transfer function and optimum number of hidden layer were obtained. The sum of squared errors, receiver operating characteristic curve criterion and accuracy were used to select the optimum ANN. The optimum model tested and validated ($p < 0.001$) with second dataset (30%).

Results: The sigmoid transfer function in hidden and output layers with 5 nods (SSE = 131), one hidden layer with 15 neurons was considered as optimum model. Receiver operating characteristic curve criterion and accuracy were obtained equal to 0.913 and 94.79% respectively. The confusion matrix was showed high sensitivity (97.45%) and specificity (99.25%) in the diagnosis of depression. Age, gender, income, polarity outgoing messages to family, incoming calls, time active in the day, polarity incoming messages from family, time sleep in the day were obtained as a significant set for input layer of the optimum model. In addition, the optimum model has been quite successful in identifying normal and depressed elderly.

Conclusion: This research applied an ANN model for detection of depression in the elderly. ANN can be used as a computational tools for early diagnosis of depression in the elderly People.

Keywords: Aged, Prediction, Depression, Artificial Neural Network

Introduction

Aging is a biological phenomenon and natural process and describes people who are 60's years old and over (1). Statistics show that the most of countries will be broadly facing the aging population phenomenon. Therefore, the most critical challenge of this century is increasing elderly population (2). Alicia (2) has stated that limited social communication in the elderly affects their mental health and can lead to depression and disability. According to Alicia (2) depression is a mood disorder and Flores-Pacheco et al. (3) has stated that genetic, biochemical, psychological and social factors are related to depression. In the researches, depression in the elderly is defined as a psychological problem that often does not receive enough attention to diagnose and treat it (3).

Cole et al. (4) shows that demographic variables such as age, gender, and ethnicity that affect depression can be used to predict depression. In addition, Dean et al. (5) have stated that living alone is an important factor in the development of depressive disorder so that older people living alone experience higher levels of depressive symptoms. As mentioned, the complex interaction of various factors can be effective in elderly depression. Therefore, regression models cannot identify such relationships. Detienne et al. (6) believe that the relationships between psychological variables are very complex, so optimum artificial neural network (ANN) models can be used instead of regression models.

Today, with scientific and technological advances, it is possible to diagnose diseases in the early stages. Some algorithms have been made in computer science to support the detection of depression. Prediction models are designed to assist healthcare professionals and patients with decisions about the use of diagnostic testing, starting or stopping treatments, or making lifestyle changes (7).

A set of research has been conducted in diagnosing of the clinical illness, but to our knowledge, little research has been done on elderly depression. Therefore, the main purpose of this research was to provide an ANN model that will help diagnose depression in the elderly.

Methods

Study design

In this applied descriptive-survey study, a three layers ANN model was used to determine the effective weight of the independent variables on predicting the depression symptoms in the participants. The first layer (input layer) contains the input variables (socio-demographic variables, physiological variables and social contact). The second layer is the middle layer (the hidden layer) and the third layer is determined based on the response variable. In this study, the output layer with two neurons was considered because of the variable type of depression/normal response. The ANN was used to model algorithms for prediction depression symptoms.

Data collection and tools

This section includes data collection for the elderly who are monitored for a week. In this part, the participants were required to have complete physical and cognitive abilities, the ability to use own mobile phone to make calls or send text messages, understanding questions. They also should to sign an informed consent form that they were willing to take part in the research. In this research, 40 older adults 60's years old and above who was selected randomly from elderly Care Center of Gonbad Kavous, Golestan, Iran in 2019. Participants had experience loss of a loved one at least in 2 month before. After sufficient explanation, data was obtained from those who were willing and eager to participate in the research. The Researcher completed the depression scale and socio-demographic information, physiological information and social contact via interviews. The variables of the research can be categorized as bellow.

Socio-demographic variables

Age, gender, marital status, living alone, family numbers, income, employment status, homebound status, place of residence (rural or urban), number of chronic non- communicable diseases, ethnicity, history of alcohol use, history of drug use, history of use of psychopharmacological agent.

Physiological variables

Average distance travelled (km); average steps in the day; average calories spent (calories); average time sleep in the day (Min) and average amount of minutes active in the day (Min) (7).

Social contact

Average incoming / outgoing calls from/to family (daily calls); average incoming /outgoing calls from/to friends (daily calls); average duration of incoming calls from family/ friends (minutes); average polarity incoming/ outgoing messages to family/ friends; average polarity incoming messages from family/ friends (7).

Afterward, Geriatric Depression Scale (GDS) with 30 item is used. The scale asked the participants to answer the items according to their feelings over the past week. The GDS (8) was developed as a screening tool for older adults and consist of 30 and 15 item versions (9). Both the 30 and 15 item (8) versions of the GDS demonstrate good reliability and validity among older adults with chronic (10) and postoperative pain (9). In addition, Otto's findings (11) support the use of the GDS as a reliable questionnaire among African American older adults. The depression score equals the sum of the items' scores. The score range of 5-8 indicates mild depression, a score between 9 and 11 represents moderate depression, and a score of 12 or above shows severe depression. Cronbach's alpha coefficient was 0.9, the split half coefficient was 0.89, and the test-retest coefficient was 0.58 in the Persian version (8).

Ethical considerations

Before collecting data, written permission was taken from Gonbad Kavous University (Permission no: 150666) and Gonbad Kavous Welfare Organization (Permission no. 933/97/100/3226). All of the participants were informed about objective of the research in detail and written and oral informed consents were taken from elderly individuals after assuring confidentiality of their information.

Data analysis

Accordingly, two psychologists independently assessed the elder adults for the diagnosis of depression. Afterward, the data were randomly divided in-to two parts of training (70%) and testing (30%).

In the training phase, a three layers network is considered with 27 numbers of input neurons according to the number of independent variables. For the output layer, two neurons were considered, representing two classes, including a normal class and the depression class (mild, moderate, sever). Initially, correlation weights were randomly assigned in the range of -1 to 1. Then the outputs of the model were compared with the interviewed outputs. Thereafter, the weights (the degree of correlation between each of the precursor neurons with the later layer neurons) were modified using the error propagation learning algorithm (a method to determine the weights between layers' neurons). This process of training and determining weights was repeated until the system error reached to 0.001.

The number of hidden layer can affect the performance of the neural network. The number of neurons in the middle layer was considered to be between 2 and 20 neurons. According to the best results, the appropriate number of middle layer neurons was determined.

It is noted that, the sum squares error (SSE) mean and Receiver Operating Characteristics (ROC) curve criterion was used to select the best neural network model. This curve is one of the most important criteria for evaluating the performance of classified or multi-layered models. The Area under Curve (AUC) of the ROC curve can be values from zero to one. The best model is one in which the AUC value is close to 1. The ROC curve is a curve in which the Y axis is true positive rate or sensitivity and the X axis is false positive rate or specificity. In this part, high sensitivity in the designed system can be a testament to the system's reliability in diagnosing depressive disorder. In addition, the specificity means that if a person does not have a depressive disorder, the system is more likely to show a lack of depression. In addition, the accuracy as an index indicates the proximity of a measurement to the actual value.

In the next, after selecting the best structure with optimum (input/hidden/output) layer, the network was validated and tested with a second dataset (30% of remaining data) that had no role in modeling. Finally, in the phase of model validation, a descriptive comparison was made between the outputs of the ANN optimum model with the GDS and the clinical interview. Data were analyzed using SPSS 22 software.

Results

This study incorporated 40 participants aged 60 years and above with mean 67 years. Men (n = 17, 42.5%) and women (n = 23, 57.5%) of research are living in urban (n = 26, 65%) and rural (n = 14, 35%) with 6,000,000 Rial average income (SD = 13.57), monthly. All participants were alone and the number of family members varied from 1 to 7 persons. Around 12.5% (n = 5) of the participants had no chronic disease, the proportion of homebound was only 2.5% (n = 1). Participants had 2.5% (n = 1) with history of alcohol use, 12.5% (n = 5) history of drug use and 17.5% (n = 7) psychotic drugs use. Overall, 30% (n = 12) of the participants did not show any symptoms of depression. In other words, depressive symptoms were observed in 70% (n = 28) of the participants [5% (n = 2) of the participants had mild depression, 25% (n = 10) had moderate depression and 40% (n = 16) had severe depression]. Participants walked an average of 0.8 km per day.

They had activity equal to 30 min per day and time sleep equal to 360 min/day. They had, averagely, 2 time call to family, 1 time/day call to friends, 1 time/day call from family with 5 min per day, 1 time call from friends with 4 min per day, 1 outgoing messages to family and also their friends, 1 incoming messages from family and their friends.

In this section, data preparation, cleaning and discretization were performed. Therefore, data sets and subsets were formed using participants' variables and levels of depression. The information classified in ANN method was analyzed using statistical methods. The aim of the section was to obtain a set of ANN models for the diagnosis of depression in the elderly.

Results in the past researches indicated that the type of the transfer functions in the hidden and output layers are affecting on the performance of ANN (1). Hence, in the first step, all combinations of the ANN with 2, 3, 4, and 5 nods were evaluated by using sigmoid and hyperbolic tangent functions in the hidden layer and sigmoid, linear and hyperbolic tangent function in the output layer. In this case, result indicated that the ANN model by using the sigmoid transfer function in hidden and output layers and 5 nods had the sum of square error (SSE = 131) lower than other ANN combination models (SSE = 131 to 345) (Table 1).

The number of hidden layer is another factor in performance of the ANN model. Hence, in the second step, first step procedure using ANN sigmoid 5 transfer function with 2, 3, and 4 hidden layers was repeated. Result indicated that the increased number of hidden layers could not effect on the ANN fit significantly (Table 2).

Table 1. The error sum of square for combination transfer function in one hidden and output layers

Output layer														
	Transfer function		**Sigmoid**				**Hyperbolic tangent**				**Linear**			
Hidden layers		**nod**	**2**	**3**	**4**	**5**	**2**	**3**	**4**	**5**	**2**	**3**	**4**	**5**
	Sigmoid	2	136	136	135	139	269	267	262	256	332	328	322	310
		3	137	134	143	135	266	264	260	252	325	324	312	307
		4	135	132	133	132	261	253	251	250	321	318	308	301
		5	134	133	132	131*	260	248	243	238	317	313	301	295
	Hyperbolic tangent	2	273	271	264	261	298	295	291	290	345	344	343	342
		3	265	263	260	257	296	293	289	283	343	342	340	341
		4	261	255	250	243	292	287	285	279	342	341	338	339
		5	256	252	248	240	290	281	280	273	341	340	335	337

Table 2. Optimum number of hidden layer in ANN-sigmuid5 transfer function

	Number of hidden layers			
	1	2	3	4
Sum of square error (SSE)	131	136	137	134

The number of neurons in the hidden layer is a factor that affects the function of the neural network. In order to increase the accuracy of the system, the number of different neurons for the hidden layer in the ANN was investigated. The best results were obtained with 15 optimum neurons in the hidden layer of the ANN-Sigmoid 5. It means that, less and upper than 15 neurons in the hidden layers will reduce the accuracy of the network (Table 3).

Another diagnostic criterion of the model is the ROC. In the ROC, a value of 0 to 0.5 represents the random classification class and a value of 0.5 to 1 represents the overall diagnostic capability of the model. In this research, ROC for the proposed model was obtained 0.913 (confidence interval = 95% and $p < 0.001$).

The predicted correct ratios indicate the correct grid alignment in the training set. Classification accuracy ratio (true prediction index ratio) for the ANN model was 94.79 (confidence interval = 95% and $p < 0.001$).

The confusion matrix was used to evaluate the performance of the designed system. The sensitivity and specificity of the ANN for normal and depression classes are shown in the table 4. The high sensitivity of the ANN indicates a high level of confidence in the diagnosis of depression. In addition, a high specificity in the designed system means that if the elderly are not depressed, the designed system shows a non-depressive disorder with a high probability.

From the total sample of population (n = 40), 70% of sample population (n = 28) was used to generate the ANN model and 30% (n = 12; 5 women and 7 men) for model evaluation. Using the GDS and clinical interview, the normal or depressed status of the elderly (n = 12) was identified. Also, using the ANN optimum model (input = 27 variables, hidden layer = 1 with 15 neurons and 5 nods, output layer = 4), the normal or depressed status of each elderly person was determined. Table 5 shows that, the ANN model has been quite successful in identifying normal and depressed elderly.

Table 3. Selecting the optimum ANN model for elderly depression data

Neurons	Proposed model input/hidden/output	SSE	ROC	Non-accuracy %	Accuracy %
2	27/2/4	0.1317	0.702	13.27	86.73
3	27/3/4	0.1272	0.716	12.02	87.98
4	27/4/4	0.1107	0.737	11.82	88.18
5	27/5/4	0.1082	0.749	10.10	89.90
6	27/6/4	0.1074	0.773	9.76	90.24
7	27/7/4	0.1064	0.792	9.38	90.62
8	27/8/4	0.1031	0.811	9.09	90.91
9	27/9/4	0.1019	0.823	8.02	91.98
10	27/10/4	0.1003	0.836	7.97	92.03
11	27/11/4	0.0964	0.879	7.69	92.31
12	27/12/4	0.0902	0.892	6.54	93.46
13	27/13/4	0.0881	0.898	6.41	93.59
14	27/14/4	0.0865	0.903	6.33	93.67
15	27/15/4	0.0831*	0.913*	5.21*	94.79*
16	27/16/4	0.0849	0.907	5.49	94.51
17	27/17/4	0.0881	0.901	6.63	93.37
18	27/18/4	0.0912	0.823	7.13	92.87
19	27/19/4	0.1023	0.802	7.69	92.31
20	27/20/4	0.1073	0.782	8.25	91.75

*Significant and selected ANN after training based on optimal indices (Minimum SSE, maximum ROC and Accuracy)

Table 4. Model sensitivity and specificity

ANN	Depression classes	Sensitivity (%)	Specificity (%)
0	Normal	91.30	99.23
1	Depress	97.43	99.25

Table 5. Model evaluation

Elderly No.	Age	Depression level based on the ANN model	Depression level based GDS	Depression level based on clinical interview
1	68	Normal	Normal	Normal
2	69	Depressed	Normal	Mild
3	71	Depressed	Mild	Moderate
4	65	Normal	Normal	Normal
5	72	Depressed	Moderate	Moderate
6	76	Depressed	Severe	Severe
7	78	Depressed	Severe	Severe
8	63	Normal	Normal	Normal
9	66	Depressed	Mild	Mild
10	75	Depressed	Severe	Moderate
11	74	Depressed	Severe	Severe
12	78	Depressed	Severe	Severe

Discussion

Diagnosis of the disease based on clinical symptoms is a major problem in mental health topics. Recognizing the severity of depression from the symptoms of depression is no exception. Depression is a common mental illness worldwide and can negatively affect a person’s feeling, thinking, behavior, and ability to function (12).

A significant portion of the world's population is 60’s years and older. The elderly population is increasingly grow and will be the portion of the population with the highest rate in the future. It is necessary to have a specific attention for mental health of this portion of the population. Depression is the most mental problem of the elderly which was reported by researchers. A set of researches have been conducted to evaluate the effective factors on depression. The risk factors of depression can be named such as; loneliness (13), couple burnout and divorce (14), number of family member (15), people whose spouse has passed away, place of residence (16), low income, poor socioeconomic status (17), the number of chronic non-communicable disease (18), low education (19), increased age, female gender, being single, cognitive impairment, disabling gastrointestinal diseases, and neurological and cardiac disorders (20), poor social support, low self-esteem (11). Alicia (2) also reported a set of physiological variable (i.e. average distance travelled (km), etc.) and social contact (i.e. average ingoing and outgoing calls to friends, etc.). In addition, the variables of household size, income, age, chronic illness, place of residence, and ethnicity were found to have significant effect on depression (1).

Conclusions

This study assessed the important factors affecting elderly depression. The subsequent factors were socio-demographic, physiological and social contacts. There was a correspondence between the findings of the present study and other studies in variables of age, gender, income, average polarity outgoing messages to family, average incoming calls from friends (daily), average amount of time active in the day (min), average polarity incoming messages from family, average time sleep in the day (min), respectively.

In addition, results of this research proposed an artificial neural network model using computer system for detection of depression in the elderly. This model is able to automatically monitoring human-computer interactions and generating alerts to attention of the elderly condition. The importance of this research is in the development of computational tools for mental health that allow early diagnosis of depression in the elderly and give them early attention for timely treatment. The ultimate goal of this research is to provide the necessary conditions to improve the quality of life of the elderly.

Study limitations

Depression is related to many factors. In our research, physiological and social factors were investigated. In another study, it is suggested that other factors affecting depression, such as genetics and biochemistry, be considered along with the factors considered in this study. In addition, a significant number of elderly people in the Gonbad Kavous Elderly Care Center could not enter the project due to physical illnesses, unwillingness to participate in the project, and not having the necessary conditions to enter the project. Therefore, one of the problems of the research was the small number of research samples. Therefore, to generalize the research results to the target community, it is recommended to implement the model at the regional and national levels to enable the generalization of its results for macro-planning. Finally, the ANN model has been successful only in separating depressed elderly from normal, and this model is not able to determine the level of depression (low, medium, severe). Therefore, it is recommended to use fuzzy-logic systems in determining the level of depression in future research.

Conflict of interest

There was no conflict of interest in this study.

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Authors' contribution

Author designed the study, collected and analyzed the data, drafted the manuscript, reviewed the draft, and read and approved the final version of the manuscript.

References

1. Allahyari E. Predicting elderly depression: an artificial neural network model. Iranian Journal of Psychiatry and Behavioral Sciences. 2019; 13(4): e98497.
2. Martínez A, Benítez R, Estrada H, Hernández Y. Predictive model for detection of depression based on uncertainty analysis methods. Proceedings. 2018; 2(19): 1-10.
3. Flores-Pacheco S, Huerta-Ramírez Y, Herrera-Ramos O, Alonso-Vazquez O. Factores familiares y religiosos en adultos mayores y su relación con síntomas depresivos. Journal of Behavior, Health & Social Issues. 2012; 3(2): 89–100.
4. Cole MG, Dendukuri N. Risk factors for depression among elderly community subjects: A systematic review and meta-analysis. The American Journal of Psychiatry. 2003; 160(6): 1147-56.
5. Dean A, Kolody B, Wood P, Matt GE. The influence of living alone on depression in elderly persons. Journal of Aging and Health. 1992; 4(1): 3-18.
6. Detienne KB, Detienne DH, Joshi SA. Neural networks as statistical tools for business researchers. Organizational Research Methods. 2003; 6(2): 236-65.
7. Shipe ME, Deppen S, Farjah F, Grogan EL. Developing prediction models for clinical use using logistic regression: an overview. Journal of Thoracic Disease. 2019, 11(4): 574-84.
8. Yesavage JA, Sheikh JI, Yesavage JA, Sheikh JA, Yesavage JA, Sheikh J, et al. Geriatric depression scale (GDS): recent evidence and development of a shorter version. Clinical Gerontologist. 1986; 5(1-2): 165-73.
9. Andrasik F, Goodie JL, Peterson A, editors. Biopsychosocial assessment in clinical health psychology. The Guilford Press; 2015.
10. Sheikh JI, Yesavage JA. Geriatric depression scale (GDS): Recent evidence and development of a shorter version. Clinical Gerontologist, 1986; 5(1-2): 165-73.
11. Rudy TE, WeinerDK, Lieber SJ, Slaboda J, Boston JR. The impact of chronic low back pain on older adults: A comparative study of patients and controls. Pain. 2007; 131 (3): 293-301.
12. Pedraza O, Doston VM, Willis FB, Graff-Radford NR, Lucas JA. Internal consistency and test-retest stability of the geriatric depression scale-short form in African. American older adults. Journal of Psychopathology and Behavioral Assessment. 2009; 31 (4): 412-6.
13. Osubor VI, Egwali AO. A neuro fuzzy approach for the diagnosis of postpartum depression disorder. Iran Journal of Computer Science. 2018; 1: 217–225.
14. Sajadi H, Mohaqeqi Kamal H, Vameghi M, Forozan AS, Rafei H, Nosratabadi M. Systematic review of prevalence and risk factors associated with depression and its treatment in Iranian elderly. Salmand Iranian Journal of Ageing. 2013; 7(4): 7-15. [Persian]
15. Mirza M. modeling the factors influencing the prediction of divorce, research project (150666). Gonbad Kavous University: 2020.
16. Park M, Unutzer J, Grembowski D. Ethnic and gender variations in the associations between family cohesion, family conflict, and depression in older Asian and Latino adults. Journal of Immigrant and Minority Health. 2014; 16(6): 1103-10.
17. Ghaderi S, Sahaf R, Mohammadi Shahbalaghi F, Ansari G, Gharanjic A, Ashrafi K, et al. Prevalence of depression in elderly Kurdish community residing in Boukan, Iran. Salmand Iranian Journal of Ageing. 2012; 7(1): 57-66. [Persian]
18. Rajabizadeh GH, Ramezani A. Prevalence of depression in Kermanian geriatrics-2002. Journal of Rafsanjan University of Medical Sciences & Health Services. 2004; 3(1): 58--66. [Persian]
19. Djernes JK. Prevalence and predictors of depression in populations of elderly: a review. Acta Psychiatrica Scandinavica. 2006; 113(5): 372-87.
20. Papadopoulos FC, Petridou E, Argyropoulou S, Kontaxakis V, Dessypris N, Anastasiou A, et al. Prevalence and correlates of depression in late life: A population based study from a rural Greek town. International Journal of Geriatric Psychiatry. 2005; 20(4): 350-7.