Original Article

Developing an intelligent prediction system for successful aging based on artificial neural networks

Abstract

Background: Due to the growing number of disabilities in elderly, Attention to this period of life is essential to be considered. Few studies focused on the physical, mental, disabilities, and disorders affecting the quality of life in elderly people. SA[1] is related to various factors influencing the elderly's life. So, the objective of the current study is to build an intelligent system for SA prediction through ANN[2] algorithms to investigate better all factors affecting the elderly life and promote them. **Methods:** This study was performed on 1156 SA and non-SA cases. We applied statistical feature reduction method to obtain the best factors predicting the SA. Two models of ANNs with 5, 10, 15, and 20 neurons in hidden layers were used for model construction. Finally, the best ANN configuration was obtained for predicting the SA using sensitivity, specificity, accuracy, and cross-entropy loss function. **Results:** The study showed that 25 factors correlated with SA at the statistical level of $P < 0.05$. Assessing all ANN structures resulted in FF-BP[3] algorithm having the configuration of 25-15-1 with accuracy-train of 0.92, accuracy-test of 0.86, and accuracy-validation of 0.87 gaining the best performance over other ANN algorithms. **Conclusions:** Developing the CDSS for predicting SA has crucial role to effectively inform geriatrics and health care policymakers decision making.

Keywords: *Artificial neural network, clinical decision support system, elderly, successful ageing*

Raoof Nopour, Hadi Kazemi-Arpanahi[1]

Department of Health Information Management, Iran University of Medical Sciences, Tehran, Iran, [1]Department of Health Information Technology, Abadan University of Medical Sciences, Abadan, Iran

Introduction

Improvements in hygiene conditions and medical progression have increased the global concept of aging.[1] Attention to this particular period of human life is crucial because of increasing physical and cognitive disorders in older adults.[2] Aging can be defined as the period of the human lifespan in which biological function decreases and mortality increases.[3] There is no consensus about the years in which the elderly period begins.[4] It differs among nations with various cultures and different medical conditions. Still, globally the average age at which the old age starts is 65 years old, considering the global burden augmentation.[5] World Health Organization (WHO) estimated that the number of elderly people will be doubled in comparison with the current numbers, specifically in the countries having low and middle economic income level, by 2050.[6] Other researchers forecasted that the number of older adults with cognitive disorders such as dementia, chronic disease, and other disabilities would increase the elderly's population growth by that year.[7,8] During the aging period, general physical and mental disorders would be increased and this leads to the limitation in social engagement and independence among the elderlies. Therefore, preventing physical, mental, and social disorders is crucial in elderly people and increases the satisfaction of life among them.[9,10] Due to these problems found in the elderly, there has emerged one concept named successful aging (SA).[11] This concept is multi-dimensional and defined in many ways by various gerontologists' pundits.[12] There are no precise or exclusive definitions of the SA so far, and various gerontologists' pundits have defined this concept considering the different factors. Depp and Jeste defined SA based on optimal physical function with a reduced disability, optimal mental function, well being, satisfaction of life, social activities and creative and helpful roles, absence of disease, long life span, optimal general health, optimal personality, and pleasant environmental and financial factors. Martin *et al*. introduced the definition of SA based on mental and social abilities, prophylactic and remedial adaptations, mental, corporeal, and

Address for correspondence:
Dr. Hadi Kazemi-Arpanahi, Department of Health Information Technology, Abadan University of Medical Sciences, Abadan, Iran.
E-mail: h.kazemi@abadanums.ac.ir

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social peace. Martin *et al*. presented SA as release from incapacitation, independent activity, satisfaction in life, energetic participation in life, life span, pleasant adaptation, and dominance/development.[13,14] Rowe and Kahn[15] defined SA based on three dimensions: low probability of disablement and unhealthy conditions, high level of corporeal or mental function, and high social participation. Early prediction of disabilities affecting SA can improve the pleasure of life among the elderly by detecting these factors in the initial stages of elderly age.[16] Machine learning (ML) based methods have a critical application in detecting various conditions such as mental disorders and chronic disorders in health care.[17-19] Also, an ML-based technique namely artificial neural networks (ANNs) has a beneficial role in health care.[20,21] Previous research has focused on limited factors predicting the elderly's health condition by ML-based approach and ANNs.[22-24] Therefore, this study aims to build a predictive system based on ANN for predicting SA in the elderly.

Methods

This cross-sectional research was performed on adults over 60 who lived in Abadan City in Khuzestan province, the south of Iran. The data of 1156 elderly pertaining to SA and non-SA from January 2016 to August 2021 existed in one database and was investigated in this study. The number of SA and non-SA people were 1059 and 97, respectively. The predictors affecting the SA were categorized in six classes, including the demographic factors, chronic diseases, life satisfaction scales, independence rate indicator, quality of life (QoL) indicator, and lifestyle. All variables and scales defining the classes are given in Table 1.

In our study, SA was a dichotomous variable. It is a multi-facet notion, and to identify the SA in elderly, several factors including general physical health, cognitive function, social function, social engagement, and life engagement were measured**.** So**,** all mentioned aspects of an elderly person were examined and measured to identify SA and non-SA. The criteria included the following: 1) the physical health of the elderly was examined and the successful elderly participants should not have a debilitating disease or they had the number of chronic diseases ≤2) Mental and physical function [getting a score of 90–100 from the Barthel score or functional domain, score ≥26 from mini-mental state examination (MMSE), and score ≥5 from geriatric depression scale (GDS)]. 3) Social function, social engagement, and life engagement (getting a score between 20 and 35 from the life satisfaction earned by Diener scale (DLSS), have any social or religious activities outside the home).[25]

We first investigated the database of the missing values in attributes in all input and target classes. In the conditions that the lost values were observed in the output class values (including the SA and non-SA), we excluded the examples with this situation. For the independent variables with a high rate of missing values (more than 20%), we used the K-Nearest Neighborhood (KNN) algorithm with a predetermined amount values of K (1,3,5,7, and so on) to impute the missing values with similar values existing in the nearest records. Then, we removed the noisy values and smoothed the dataset with suitable values by using the KNN algorithm. Also, all records were investigated case by case regarding their existing redundancy. After cleaning the dataset, due to the imbalance in the numbers of SA and non-SA samples in the database, we used the synthetic minority oversampling technique (SMOTE) to rectify this challenge. In the last step of the preprocessing process, we applied the statistical technique of feature selection (FS) by using the phi coefficient to embed the better predictor for SA model construction. FS is the process of reducing the dimension of the dataset without decreasing the ML algorithms' performance compared to the original datasets. The benefits of the FS are increasing the efficiency and speed of training in algorithms, preventing from overtraining, better generalizability of the models, decreasing memory storage location, and improving learning accuracy.[26-28] In the current study, the Phi and Creamers correlation coefficient was leveraged in this respect. Also, we considered $P < 0.05$ significant level.

The ANNs are the abstraction structure of the human brain trying to imitate human behaviors. Their structure generally [Figure 1] includes three layers namely input, output, and calculational or hidden layers. Their structure includes nodes similar to neurons in the brain. The input layers get the various type of data such as images, signals, and so on from the environment and normalize the data and transfer it to the hidden layers. In these layers, there are some calculation nodes for the calculation process, and finally, the calculation results are transferred to the output layer for presenting the calculation results.[29-31] There are various models of ANNs for training the data.[32] In order to develop the intelligent model for predicting the SA by ANNs, we used various configurations consisting of the FF-BP and cascade forward back propagation (CFBP) for high speed of calculation process and high precision.[33] We used the Tansig transfer functions to normalize the input values and adapt to transfer data between nodes in ANN. Also, Levenberg Marquardt (LM) was used for training data for its high-speed training process. The maximum number of training epochs and time were 1000 and unlimited by default, and considering the high-speed training method, it is not challenging.[34,35] To evaluate the two various configurations, we first investigated the performance trends of each configuration using sensitivity (Formula 1), specificity (Formula 2), and accuracy (Formula 3) by various number of ANN's neurons included in the hidden layer. The 5 neurons, 10 neurons, 15 neurons, and 20 neurons were selected for evaluating each configuration performance. In this study, 70% of dataset were leveraged for training process, and 30% for testing and validation of

Table 1: The specs of SA and non-SA records

Class type	Scales used for variables in the questionnaire	Feature type	Features (values)
Demographic variable		Input	age (years), gender (man, woman), literacy level (non, elementary, having diploma certification, and having academic certification), marital status (widowed, divorced, single, married) occupation type (without job, retired, self-employment, housekeeper)
Socioeconomic variable		Input	income (under and on the poverty line), family support (Yes, No), insurance (Yes, No)
Comorbidity		Input	hypertension (negative, positive), CVA (negative, positive), bone diseases (negative, positive), renal diseases (negative, positive), liver diseases (negative, positive), lung disease (negative, positive), muscle diseases (negative, positive), depression (negative, positive), healing from diseases (negative, positive), eye disease (negative, positive), diabetes (negative, positive), neoplasm (negative, positive), and other unhealthy conditions (negative, positive)
Functional domain	Scores ranged from 0-100. 0-20 scores mean severe dependence. 21-60 scores mean high dependence. 61-90 scores mean medium dependence. 91-99 scores mean low dependence. A score is 100 means independent.	Input	Activities of daily living (ADLs) daily living (ADL) (The independence level obtained from the t-test) (Yes, No), sports activities (Yes, No), exercise time (No, <30 minutes, >30 minutes), type of exercise (non, aerobic, non-aerobic, both)
Lifestyle domain	Scores 42-98 mean an unfavorable lifestyle. 155-99 mean middle lifestyle. Scores 211-156 mean a desirable lifestyle.	Input	Stress management (low, high), social, interpersonal relationships (weak, strong), preventive measurement (Yes, No), appraisal of nutritional level (pleasant, unpleasant), malnutrition (Yes, No), physical activity (rare, frequent), The general definition of lifestyle (desirable, middle, and undesirable)
QoL (obtained from questionnaire SF 36)	Degrees categorized from 0-100. Higher grades are equaled to better QoL. A Score <70 is unpleasant A score >70 is pleasant	Input	General health (negative, positive), pain assessment (negative, positive), fatigue (negative, positive), physical dysfunction (negative, positive), physical activity (rare, frequent), social function (negative, positive), mental dysfunction (negative, positive), the general QoL (optimal, non-optimal)
Life satisfaction	Scores ranged from 5-35. Higher scores mean better satisfaction. >20 is satisfied. <20 is not satisfied	Input	Life satisfaction (pleasant, unpleasant)
SA		Target	SA and Non-SA

all ANN's predictive models. We also analyzed the two configurations of the ANNs by using the Binary Cross Entropy Loss function (BCEL) (in formulae 1-3, True Positive (TP) and True Negative (TN) are equaled to the SA and non-SA cases truly categorized by algorithms. False Negative (FN) and False Positive (FP) are SA and non-SA samples incorrectly classified by algorithms).

$$\text{Formula 1: Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Formula 2: Specificity} = \frac{TN}{TN + FP}$$

$$\text{Formula 3: Accuracy} = \frac{TP + TN}{TP + FN + FP + TN}$$

Results

After excluding the samples having the lost data existing in the output values, 5 and 1 case pertaining to the non-SA and SA cases were excluded. 1054 and 96 cases pertaining to SA and non-SA remained in the study. As a result of the SMOTE method, the cases related to successful adults increased to 1000 cases. The results of Phi and Crammers V to detect the most critical factors at $P < 0.05$ are shown in Table 2.

As shown in Table 2, the variables of income level, age, family aid, cardiovascular accident (CVA), osteopathy, hypertension, muscle diseases, liver disease, cancer,

Table 2: The results of detecting the best factors for the SA

Variables	Features (Codes in the dataset)	Features (*n* %)	Phi and Crammers V coefficient	*P*
Age	60-70 years old (1)	60-70 years old (59%)	0.455	0.01
	70-80 years old (2)	70-80 years old (28%)		
	>80 years old (3)	>80 years old (13%)		
Gender	Women (1)	Women (56%)	0.577	0.13
	Men (2)	Men (44%)		
Education	Academic (1)	Academic (5%)	0.17	0.25
	Diploma (2)	Diploma (10%)		
	Elementary (3)	Elementary (30%)		
	No literacy (4)	No literacy (55%)		
Marital status	Divorced (1)	Divorced (10%)	0.23	0.13
	Married (2)	Married (15%)		
	Widowed (3)	Widowed (70%)		
	Singled (4)	Single (20%)		
Occupation type	Self-employment (1)	Self-employment (18%)	0.11	0.16
	Retired (2)	Retired (31%)		
	Housekeeper (3)	Housekeeper (22%)		
	No job (4)	No job (29%)		
Income level	On poverty line (0)	On the poverty line (25%)	0.505	0.04
	Under poverty line (1)	Under poverty line (75%)		
Family aid	No (0)	No (58%)	0.33	0.01
	Yes (1)	Yes (42%)		
Insurance situation	No (0)	No (73%)	0.21	0.16
	Yes (1)	Yes (27%)		
Hypertension	Negative (0)	Negative (64%)	0.56	0.001
	Positive (1)	Positive (36%)		
CVA	Negative (0)	Negative (69%)	0.43	0.001
	Positive (1)	Positive (31%)		
Osteopathy	Negative (0)	Negative (55%)	0.45	0.001
	Positive (1)	Positive (45%)		
Kidney disease	Negative (0)	Negative (85%)	0.36	0.25
	Positive (1)	Positive (15%)		
Lung disease	Negative (0)	Negative (90%)	0.29	0.21
	Positive (1)	Positive (10%)		
Liver disease	Negative (0)	Negative (87%)	0.27	0.01
	Positive (1)	Positive (13%)		
Muscle disease	Negative (0)	Negative (43%)	0.35	0.02
	Positive (1)	Positive (57%)		
Depression	Negative (0)	Negative (58%)	0.13	0.012
	Positive (1)	Positive (42%)		
Convalescence	Negative (0)	Negative (33%)	0.08	0.12
	Positive (1)	Positive (67%)		
Ocular disease	Negative (0)	Negative (69%)	0.17	0.213
	Positive (1)	Positive (31%)		
Diabetes	Negative (0)	Negative (47%)	0.54	0.001
	Positive (1)	Positive (53%)		
Neoplasm	Negative (0)	Negative (86%)	0.34	0.001
	Positive (1)	Positive (14%)		
Other diseases	Negative (0)	Negative (51%)	0.07	0.16
	Positive (1)	Positive (49%)		

Contd...

Table 2: Contd...

Variables	Features (Codes in the dataset)	Features (*n* %)	Phi and Crammers V coefficient	*P*
ADL	No (0)	No (18%)	0.35	0.001
	Yes (1)	Yes (82%)		
Exercise lengths of time	None (0)	No (58%)	0.15	0.02
	<0.5 hours (1)	<0.5 hours (24%)		
	>0.5 hours (2)	>0.5 hours (18%)		
Type of exercise	None (0), Soft exercise (1), Strenuous exercise (2)	None (69%), Soft exercise (25%), Strenuous exercise (6%)	0.12	0.1
Stress management	Low (0)	Low (63%)	0.36	0.02
	High (1)	High (37%)		
Social interpersonal relationship	Weak (0)	Weak (38%)	0.25	0.001
	Strong (1)	Strong (62%)		
Appraisal of nutritional level	Unpleasant (0)	Unpleasant (68%)	0.116	0.001
	Pleasant (1)	Pleasant (32%)		
Malnutrition	No (0)	No (67%)	0.27	0.001
	Yes (1)	Yes (33%)		
Satisfaction of life	Desirable (0)	Desirable (59%)	0.611	0.001
	Undesirable (1)	Undesirable (41%)		
The general definition of lifestyle	Desirable (1)	Desirable (15%)	0.454	0.001
	Middle (2)	Middle (74%)		
	Undesirable (3)	Undesirable (11%)		
General health	Negative (0)	Negative (37%)	0.636	0.001
	Positive (1)	Positive (63%)		
Body pain	Negative (0)	Negative (77%)	0.155	0.11
	Positive (1)	Positive (23%)		
Physical dysfunction	Negative (0)	Negative (80%)	0.116	0.015
	Positive (1)	Positive (20%)		
Mental dysfunction	Negative (0)	Negative (85%)	0.15	0.001
	Positive (1)	Positive (15%)		
Social dysfunction	Negative (0)	Negative (64%)	0.14	0.001
	Positive (1)	Positive (36%)		
Preventive measurement	No (0)	No (39%)	0.43	0.03
	Yes (1)	Yes (61%)		
Fatigue	Negative (0)	Negative (55%)	0.09	0.166
	Positive (1)	Positive (45%)		
QoL	Optimal (1)	Optimal (65%)	0.751	0.001
	Non-optimal (2)	Non-optimal (35%)		
Physical activity	Rare (1)	Rare (71%)	0.15	0.07
	Frequent (2)	Frequent (29%)		

diabetes, depression, activities ADLs, exercise length of time, stress management, social interpersonal ability of relationship, appraisal nutritional level, malnutrition, satisfaction of life, general definition of lifestyle, mental dysfunction, general health, social dysfunction, physical dysfunction, preventive measurement, and quality of life gained meaningful correlation with SA variable at $P < 0.05$. So, they were used for model construction and analysis. Other variables in Table 2 correlated with $P > 0.05$ were ignored and not considered for ANN construction. The results of comparing different configurations of the ANNs for predicting the SA using sensitivity, specificity, and accuracy in each training, testing, and validation mode are shown in Figure 2.

Comparing the selected ANN configuration showed that the FF-BP with 15 neurons in the hidden layer with $\text{accuracy}_{\text{-train}} = 0.925$, $\text{accuracy}_{\text{-test}} = 0.86$, and $\text{accuracy}_{\text{-validation}} = 0.87$ obtained the best performance than other ANN configurations. The CF-BP acquired the lowest performance with $\text{accuracy}_{\text{-train}} = 0.59$, $\text{accuracy}_{\text{-test}} = 0.054$, and accuracy-$_{\text{validation}} = 0.585$. Evaluating the CF-BP type of

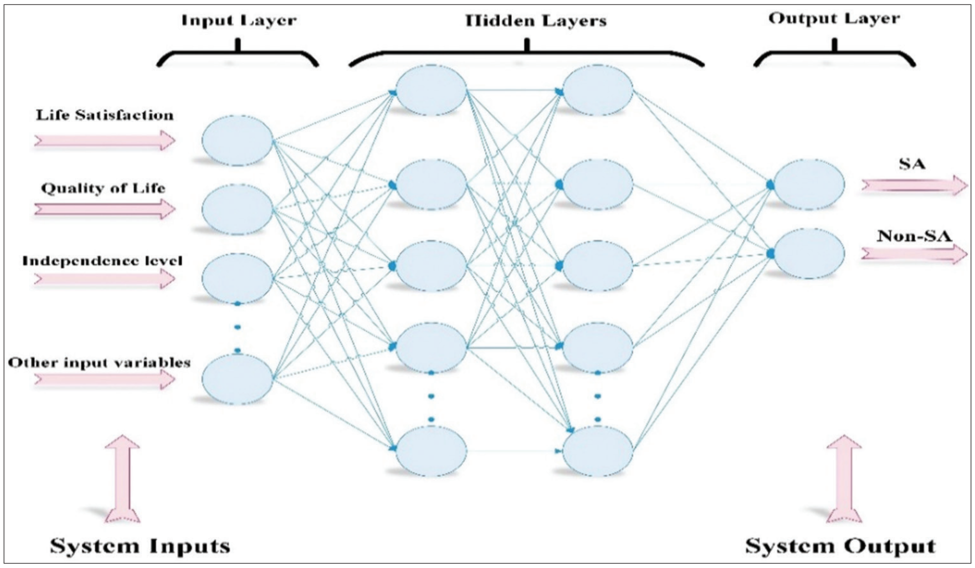

Figure 1: General schema of the ANN for predicting the SA

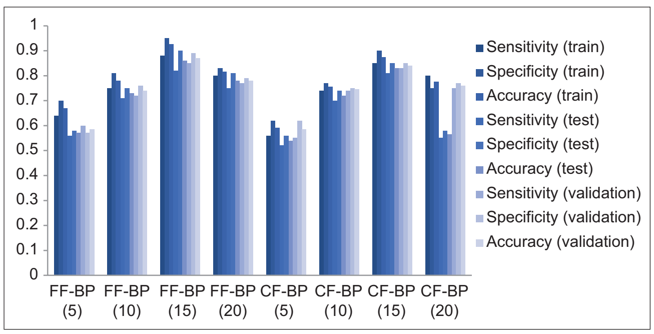

Figure 2: Performance measurements of all ANN configurations

ANN with 20 neurons in the hidden layer showed that in the test state with accuracy$_{\text{-test}}$ = 0.565, we had a high decrease in performance rate in test mode than in train mode with accuracy-test = 0.775. This shows that in this selected configuration of the ANN, the probability of overfitting the algorithm was high. The result of investigating the cross-entropy loss function of each selected FF-BP and CF-BP configuration is shown in Figure 3.

Based on Figure 3, the FF-BP with 15 neurons gained the lowest error rate in test mode than other algorithms. The error rate in this algorithm in all train, test, and validation modes was closer to each other than others. So, it showed that the FF-BP with configuration had the best generalizability of different algorithms in terms of performance. Also, the CF-BP algorithm with the most difference between the test and train mode showed the lowest capability in predicting the SA among the elderly than other algorithms. It shows that the overtraining process will occur when increasing the nodes in hidden layers, specifically more than 20 nodes. Generally, we acquired that the FF-BP algorithm with the structure of 25-15-1 with accuracy-train = 0.925, accuracy-test = 0.86, and accuracy-validation = 0.87 gained the best performance than other ANN algorithms. Also, the Binary Cross Entropy Loss function (BCEL), which was most near 10^{-2}, obtained a more generalizable performance to anticipate the SA. The predictive SA factors' strength based on relative importance (RI) in FF-BP model is shown in Figure 4.

Based on Figure 4, life satisfaction with RI = 0.19, hypertension with RI = 0.17, and CVA with RI = 0.14 resulted as the best factors related to SA among aged people by FF-BP. The factors of occupation with RI = 0.01, age, and income level with RI = 0.02 were having lower importance than others. The CDSS [Figure 5] as an intelligent tool to predict the SA was designed in MATLAB R2013-A based on the ANN. The gerontologists can give the information on these factors to the system to get the predictive recommendations about the SA or non-SA in people.

Discussion

In the current study, we aimed to predict SA based on different factors including social engagement, cognitive and physical health conditions. To this end, we used the ANN's algorithms to predict the SA. The data of 1156 people SA and non-SA older adults more than 60 years was used in this regard. We first cleaned our dataset in this study by filling in missing values and removing the noisy data. Then we used the SMOTE to balance the number of SA and non-SA cases in our dataset. We applied statistical techniques in the next step to get our database's best variables predicting the SA as a dimension reduction process. The $P < 0.05$ was set as a meaningful level. Then we used the six configurations of ANN to train the algorithms and obtained the best solution to predict the SA through best ANN configuration. To get the best model, we compared and analyzed all ANN configurations using sensitivity, specificity, accuracy, and cross-entropy loss function in the train, test, and validation

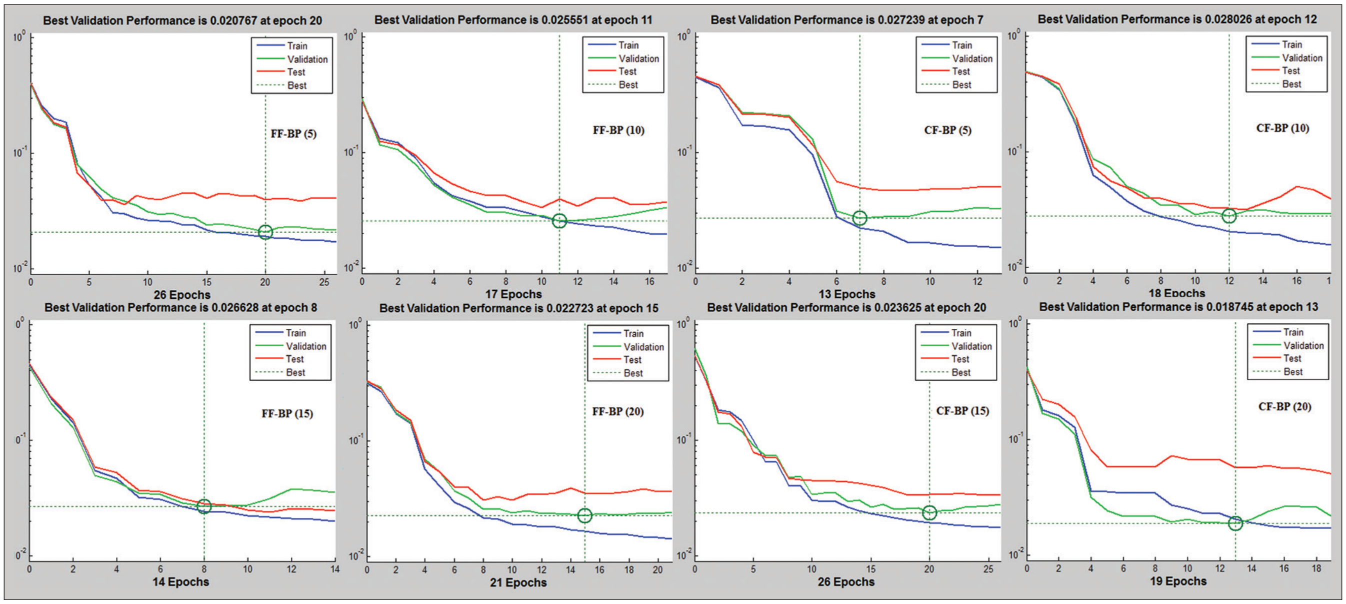

Figure 3: The cross-entropy loss function of FF-BP and CF-BP algorithms

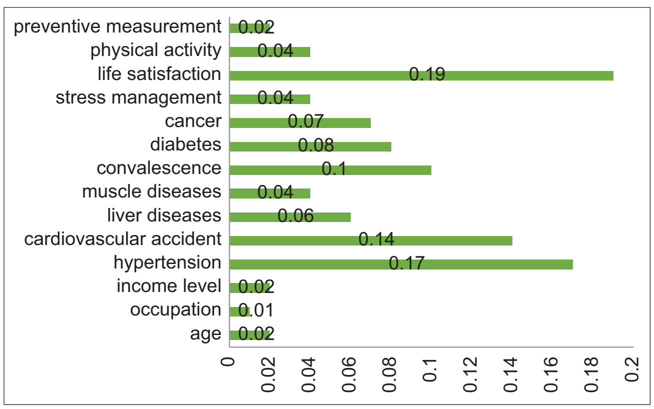

Figure 4: The relative importance of successful ageing predictors

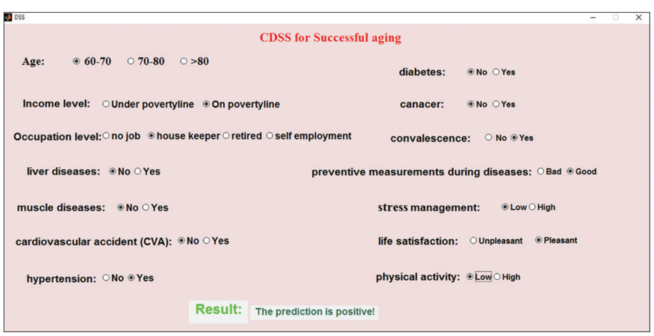

Figure 5: The CDSS User Interface designed in MATLAB for SA prediction

modes. Finally, the best SA predictors were reported by using the RI obtained for the best ANN configuration. There are few studies concerning predicting SA using ML techniques. Most of which pertained to physical or mental factors predicting SA among the elderly. Cai *et al.*[16] investigated the SA prediction using the physical fitness factors through ML algorithms. They concluded that the deep learning model with area under the curve (AUC) = 0.9, accuracy = 0.893, and positive predictive value = 0.858 obtained better performance than other ML algorithms. Also, age was considered as the best predictor regarding SA. In our study, similar to the Cai and *et al.*[16] the age variable was obtained as an essential factor affecting the SA. Byeon *et al.*[36] developed a predictive mode for social participation among Korean elderlies using the ANN and QUEST algorithms. They concluded that the subjective health status and age with the highest rate of normalized importance were the best factors. Like the Byeon study, we concluded that age is an important determinant for social engagement prediction and SA. In the study of NA,[37] the gradient boosting machine (GBM) with specificity of 0.825 and sensitivity of 0.967 was recognized as an optimal algorithm for predicting cognitive impairments among the elderly. Their study concluded age as the essential factor for cognitive impairment prediction.[37] Byeon *et al.*[38] concluded that diabetes and age are the essential factors for predicting physical disabilities among the elderly by ML algorithms. Comparing the prior investigated study shows that age is crucial for predicting physical, cognitive, and social factors. This study considered all of these factors and confirmed that they have an essential role in predicting SA among the elderly. We resulted that the FF-BP with 15 neurons in the hidden layer with accuracy-train of 0.92, accuracy-test of 0.86, and accuracy-validation of 0.87 obtained the best performance than other ANN configurations in predicting the SA. There were some limitations in this study. We used the imputation method for replacing the missing values, and with this condition, the generalizability of our models may be affected. All of our variables were qualitative and our models' accuracy may be influenced by these factors. The SMOTE technique may influence the generalizability of our models by propagating the records belonging to minority class numbers. Also, this study may not use some factors associated with SA. In future research, we suggest using more data to generalize the prediction models better. When the conditions are met, use actual data values for more realistic and generalizable results. Also, considering more factors affecting as much as possible increases ANN's models' accuracy for forecasting SA among older adults.

Conclusions

The early various factors pertaining to the increase of elderly longevity with pleasant quality can augment the success of the elderly. The current study showed that the ANN's algorithms have a potential role in predicting SA among older adults. The systems based on these intelligent methods can be used as a crucial tool in the timely detection of disabilities of elderlies in various dimensions. Therefore, they can improve the healthy living conditions in the elderly and reduce the socio-economic outcome of these disabilities at the societal level.

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This study was approved by the Abadan University of Medical Sciences, as a research project.

Ethical considerations

This article is extracted from a research project at Abadan University of Medical Sciences with the ethical code of IR.ABADANUMS.REC.1401.029.

Abbreviations

1. SA = Successful Aging
2. ANN = Artificial Neural Network
3. FF-BP = Feed Forward Back-Propagation
4. CDSS = Clinical Decision Support System.

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Conflicts of interest

There are no conflicts of interest.

Code of Ethics

IR.ABADANUMS.REC.1401.029.

Authors' Contributions

R.N. and H.K-A. contributed to the design and implementation of the research. Analysis of the data was performed by R.N. The manuscript was drafted and edited by H.K-A.

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