Predicting anxiety and depression in elderly patients using machine learning technology

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Anxiety and depression are two important mental health problems among the geriatric population. They are often undiagnosed and directly or indirectly responsible for various morbidities. Early and timely diagnosis has immense effect on appropriate management of anxiety and depression along with its co-morbidities. Owing to time constraint and enormous patient load, especially in developing county such as India it is hardly possible for a physician or surgeon to identify a geriatric patient suffering from anxiety and depression using any psychometric analysis tool. So, it is of utmost importance to develop a predictive model for automated diagnosis of anxiety and depression among them. This Letter aims to develop an appropriate predictive model, to diagnose anxiety and depression among older patient from socio-demographic and health-related factors, using machine learning technology. Ten classifiers were evaluated with a data set of 510 geriatric patients and tested with ten-fold cross-validation method. Highest prediction accuracy of 89% was obtained with random forest (RF) classifier. This RF model was tested with another data set from separate 110 older patients for its external validity. Its predictive accuracy was found to be 91% and false positive (FP) rate was 10%, compared with gold standard tool.

1. Introduction: Population is ageing globally [1]. Both developed and developing countries in the world are experiencing the growth in the absolute number of geriatric population [1]. Worldwide, there were 607 million people at the elderly age group in the year 2000, which increased to 901 million in 2015. It has been projected by United Nations to grow 1.4 billion in 2050 and 2.1 billion by the year 2050 [1]. In terms of proportion of elderly population to total population in 2000, it was 10% but it increased to 12% in 2015 as shown in Fig. 1 [2]. In India, the proportion of elderly population was 7.7% in 2000, increased to 8.9% in 2015 as shown in Fig. 2 [2, 3].

According to World Health Organization (WHO), a healthy person should possess a healthy mind along with physical fitness [3]. Changes in mental health and thought processes are one of the most important age-related changes among the elderly people throughout the world. Anxiety and depression are two important mental health disorders associated with it [4]. Vulnerability and associated consequences of anxiety and depression also increase as age progresses [5]. It is often found that, elderly patients presented to a physician or surgeon, suffering from multiple somatic symptoms such as dyspepsia, fatigue, headache, body ache, and joint pain are truly the manifestations of underlying anxiety and depression [6]. Some important morbid conditions such as hypertension (HTN), irritable bowel syndrome, chronic obstructive pulmonary disease, asthma, diabetes, obesity, and coronary artery diseases are significantly associated with the anxiety and depression among the elderly patients [6–9]. Even, anxiety, and depression are associated with the increased risk of death among the patients suffering from coronary heart disease [10, 11]. Suicidal tendencies are significantly higher among the depressed elderly [12]. WHO estimates that globally there are 7–12 and 4–7% of the older population suffering from depression and anxiety, respectively [5]. Systematic review and meta-analysis articles estimated that the prevalence of anxiety and depression ranges between 7 and 49% in various countries in the world [13]. India is one such country with very high prevalence of anxiety, depression, and other mental health disorders among them. It contributes almost 12% of global burden of the disease and projected to be increased to 20% in 2030. Literature suggests that prevalence of anxiety and depression ranges from 10 to 48% of the elderly population in different places in the country [13, 14]. Considering worldwide increasing trend of anxiety, depression, and other mental diseases, WHO announces the world health day theme for the year 2017 as ‘Depression: Let’s talk’ to give special emphasis to the problems [15].

Anxiety and depression can happen to any elderly individual at any time. Although, it is preventable and treatable, yet difficult to diagnose in proper time by the general physicians (GPs). This is due to the lack of obvious symptoms among the elderly [12, 16]. Often diagnosis has been made several years after its onset. Moreover, proper diagnosis of anxiety and depression for appropriate management can only be made by the psychiatrists or psychologists. Owing to scarcity of trained manpower especially in developing countries such as India, it is very difficult to diagnose and treat anxiety and depression among the elderly patient in proper time to minimise the morbidity and mortality associated with it. There are some valid and reliable psychometric analysis tools to screen the elderly individual suffering from anxiety and depression. Some of them are 30 or 15 items geriatric depression scale, Hamilton anxiety and depression scale, hospital anxiety and depression scale (HADS) etc. [16–18]. Those can be used by the general practitioners also. However, the problem is that it takes at least 5–30 min to complete such tools. During very busy outpatient department (OPD) hours at a hospital or clinic in developing countries, it is practically not possible for a GP or specialist to administer such a tool. As doctor population ratio is also unfavourable compared with developed countries. Even, at indoor PDs, it often seems to be an undoable task due to high patient load. As a result, proper diagnosis and management initiates at a late stage of the disorder which contributes to the higher incidence of morbidity and mortality associated with it. So, an automated disease prediction system for older patients suffering from anxiety and depression is required. It will help a lot to the GP and specialists in all fields of specialisation to screen the patient for underlying diseases. The system will also refer them to concerned specialist for appropriate diagnosis and management at an early stage. This will help to improve overall mental health status of a country. Not only that, consequences associated with it can also be minimised.
Globally almost 6.6% of disability adjusted life year loss for the elderly people can be averted [5]. Various socio-demographic factors and disease conditions play a vital role in the development of anxiety and depression in the elderly patients. Age, sex, marital status, socio-economic conditions, family environment, literacy, job security, past history of depression, chronic medical conditions are strongly associated with the anxiety and depression among the older people [19–21]. Those factors can be used as predictors for the development of an automated anxiety and depression prediction system. Predictor variables can be put into the automated system by any one, not necessarily to be a medical or paramedical person including patient himself and based on it prediction can be made within seconds.

2. Materials and methods: After obtaining ethical clearance from the Institutional Ethics Committee of R.G. Kar Medical College and Hospital, Kolkata, West Bengal, India, data were collected from 520 geriatric patients attended at the general OPD of that hospital between January and August 2016. They were evaluated for anxiety and depression by the investigator using HADS and classified into two different classes, i.e. ‘anxiety and/or depression present’ and ‘anxiety and depression absent’ [22]. Feature selection approaches are applied to reduce the feature dimension and various classifiers were evaluated with the selected features using machine learning technology in Waikato Environment for Knowledge Analysis (WEKA) (version 3.8.0) (http://www.cs.waikato.ac.nz/ml/weka/documentation.html). System default values of various parameters have been applied for each classifier. Training and testing have been done using ten-fold cross-validation method. The classifier having highest predictive accuracy was selected for further external validation. For that purpose, data of selected features were collected from another 110 geriatric patients attended at the general OPD of that hospital between September and October 2016 and prediction was made. At that same time, those 110 geriatric patients were also classified into two above-mentioned classes using HADS. Finally, a confusion matrix was generated for the predictive model with respect to HADS classification. Accuracy was calculated from that confusion matrix. The methodology has been depicted in Fig. 3, followed by concise description of each step.

2.1. Data collection: R.G. Kar Medical College and Hospital, Kolkata, is one of the most important government-operated tertiary care institution in eastern India. There, general OPD operated from Monday to Saturday by the GP. Informed consent was taken from every patient before data collection. Data of age, sex, literacy, residence, marital status, current medical conditions (pain at multiple sites, diabetes, HTN, hearing problem, visual impairment, mobility impairment, and insomnia) were collected by the investigator from 520 geriatric patients attended at that OPD for various problems. Those features were selected after extensive literature review and consulting with the psychiatrists at that hospital. Those features represented different probable causative dimensions of anxiety and/or depression among the geriatrics. These are personal attributes (age, sex), socio-demographic attributes (literacy, residence, marital status, and recent bereavement), economic conditions (employment status, socio-economic status, and PI), past medical history (past history of anxiety and depression, family history of depression, any kind of addiction, pain at multiple sites, diabetes, HTN, hearing problem, visual impairment, mobility impairment, and insomnia) (Table 1). Then, statuses of anxiety and depression were evaluated using HADS.

2.2. Hospital ADS: It is a psychometric analysis scale administered by the physicians for screening of anxiety and/or depression among the patients simultaneously. It was originally constructed by Zigmond and Snaith in 1983 [22]. It consists of 14 questions, of which seven to evaluate anxiety and seven to evaluate depression. Responses are scored from 0 to 3 in ordinal scale. A patient can score, depending on response, between 0 and 21 for either...
Table 1 Methodology in a nutshell

| Step involved | Description |
|---------------|-------------|
| data collection/features | age, sex, literacy, residence, marital status, recent bereavement, employment status, socio-economic status, PI, past history of anxiety and depression, family history of depression, any kind of addiction, pain at multiple sites, diabetes, HTN, hearing problem, visual impairment, mobility impairment, and insomnia were collected from 520 geriatric patients. At the same time, they were also evaluated for anxiety and depression using HADS scale and characterised into two groups, i.e. anxiety and/or depression present and both anxiety and depression absent. The following depression present and both anxiety and depression absent were made with the selected classifier, and at the same time those 110 geriatric patients were also classified using HADS. Confusion matrix was evaluated for those two classification systems and accuracies of the machine learning classifier were obtained considering the classification made by the HADS as gold standard. |
| feature selection in WEKA | selected evaluators in WEKA are CFS subset, GR, OR, PC, and SU. Features are selected with these attribute evaluators and listed in Table 2 |
| classification with selected attributes/features external validation | ten classifiers (BN, NB, Log, MLP, SMO, KS, RS, J48, RF, and RT) have been chosen to predict anxiety and depression in elderly patients and statistics for each classifier have been mentioned in Tables 3 and 4. Data of selected features were collected from another 110 geriatric patients and predictions of anxiety and depression were made with the selected classifier, and at the same time those 110 geriatric patients were also classified using HADS. Confusion matrix was evaluated for those two classification systems and accuracies of the machine learning classifier were obtained considering the classification made by the HADS as gold standard. |

anxiety or depression. Systematic review and meta-analysis of large number of published articles identified the cut-off point 8 out of 21 for anxiety or depression [23]. This scale and cut-off point is valid and reliable for the geriatric population in all levels of health care [24]. With this questionnaire, average 5 min is required to identify a person suffering from anxiety and/or depression. Using the score of the HADS, every geriatric patient was classified initially into one out of four categories, i.e. No anxiety–No depression, Only Anxiety, Only Depression, and Anxiety–Depression both. Later on, these four outcomes had been grouped into two outcome variables, i.e. ‘anxiety and/or depression present’ and ‘anxiety and depression absent’. These groupings were made as the aim was to screening of the geriatric patients for anxiety and/or depression and referred to psychiatrist and psychologists for appropriate management, who are most probably suffering from either anxiety or depression or both.

2.3. Features selection or attribute evaluation algorithms: Initially, there were 20 features to predict the outcome (Table 1). Owing to effect of collinearity and interaction within the features, the predictive accuracy of a learning algorithm may suffer. So, to find out the redundant features and minimise the feature dimension, five different attribute evaluators were applied with filter approach. Finally, best fitted set of features were identified and applied for subsequent predictive modelling. The following section contains brief description of attribute evaluators.

Correlation feature selection (CFS) subset evaluator [25] evaluates the merit of a subset of attributes considering the individual predictive capability of each attribute along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low collinearity are preferred. One R (OR) [26] evaluates the worth of an attribute by using the OR classifier which generates simple rules for each feature and select the rule having minimal error. Principal component analysis (PCA) [27] reduces the features dimensions by choosing enough eigenvectors to account for some percentage of the variance in the original data. Gain ratio (GR) and symmetrical uncertainty (SU) [28] evaluators are based on measurement of entropy of a system which measures GR and system’s uncertainty with respect to class, respectively.

2.4. Classification algorithms: This is a binary class classification problem. Different machine learning algorithms can handle this kind of health-related classification issues very efficiently [29]. Ten different classifiers were employed and evaluated to select the optimal one with the selected set of features. These are Bayesian Network (BN), logistic, multiple layer perceptron (MLP), Naïve Bayes (NB), random forest (RF), random tree (RT), J48, sequential minimal optimisation (SMO), random sub-space (RS), and K Star (KS). These ten different classifiers represent different principles applied in machine learning. Such as BN and NB are based on Bayesian principle, logistic based on regression principle, MLP follows feed forward artificial neural network modelling, RT, and J48 are decision tree-based classifiers, whereas RF is an ensemble learning method, SMO used for training of support vector machine (SVM), KS is an instance-based classifier which uses entropy-based distance function and RS is a meta classifier based on bagging.

BN [30] classifier represents data in the form of nodes in directed acyclic graph. Relationship between the nodes follows conditional probabilistic principles. The network is trained based on the relationship among nodes and whole network. Logistic classification (Log) [31] is applied where the outcome variables are categorical. Each attribute or variable or feature has some contribution in prediction of expected outcome in a data set. Predictive capability of each attribute is measured using maximum-likelihood estimation statistics. Logistic model calculates the probability of prediction of a binary outcome using input data set. This model uses likelihood ratio and Wald test to test statistical significance. MLP [32] is a basic and simple artificial neural network that can be used for supervised learning. This network composed of a set of inputs and a single output. Output depends on weighted sum of the input nodes. To obtain desired result, for complex data MLP is required. Input weighted sum of previous layer has to be fed to the next layer. The final output unit will activate when the input crosses a threshold. When the target output is achieved, then all these computations will be stopped. Number of hidden layers and nodes in a layer depend on applications. NB classifier [33] is supervised learning method based on probabilistic attitude of each attributes to the specific class. The probability is calculated using NB algorithm. RT classifier constructs a tree or directed acyclic graph based on stochastic process that considers K randomly chosen attributes at each node. It has an option to allow estimation of class probabilities. RF [33] is an assembly of random decision tree classifier. Prediction output of RF classifier is made of all prediction outputs by individual classifier. The base learner that has been used in RF is RT. This classifier selects features randomly with the help of bagging concept. The RS [34] is a meta classifier used in WEKA. It uses reduced error pruning tree as default base classifier. This method constructs a decision tree-based classifier that maintains highest accuracy on training data and improves on generalisation accuracy as it grows in complexity. The classifier consists of multiple trees constructed systematically by pseudo-randomly selecting subsets of components of the feature vector, that is, trees constructed in randomly chosen subspaces. Then, final classification result is decided by simple majority voting rule. SMO provides a simple and optimised training algorithm for SVM. Usually, to solve complex problems quadratic programming, optimisation is

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applied for learning SVM, which makes computation procedures slower. SMO provides an easy way out for this problem. It divides the large problem into smaller ones and solves them separately with less memory requirement [35]. SMO can handle a large set of data as memory requirement is linear, not quadratic. J48 [28] classifier uses C4.5 decision tree algorithm for tree-based classification. It splits the input data into different trees based on the range of values for the attribute set. KS [36] is an instance-based classifier. That means the class of a test instance is based on the class of those training instances that are similar to it. Similarity between test and training sets is determined by some similarity function. KS differs from other instance-based learners as it uses an entropy-based distance function to measure similarity.

3. Results: Among 510 geriatric patients, there were 281 (55%) males and 229 (45%) females. Mean (±standard deviation) age was 68.5 (±4.85) years. Among them, 48.2% suffering from some kind of mental health problems either anxiety or depression or both and 51.8% patients were free from those mental health issues. To reduce the feature dimension, various attribute evaluations were applied and result has been reported in Table 2.

After comparing various feature selection algorithms in Table 2, out of 20 initial features, 11 has been identified as most important. These were age, sex, marital status, employment status, PI, pain at multiple sites, recent bereavement, diabetes mellitus, HTN, visual impairment, and hearing impairment. Information about PI is not hesitate to tell the true figure due to socio-cultural beliefs and norms. So, it has been removed from the selected feature set. Finally, ten features were selected for the next stage.

Ten classifiers were evaluated with the selected set of features and confusion matrix generated after ten-fold cross-validation has been reported in Table 2.

Furthermore, the classifiers have been compared in terms of accuracy (Accu), true positive (TP) rate, FP rate, precision/predictive value (PPV), F-measures (F), and area under the receiver operating characteristic (ROC) curve (AUC). It is summarised in Table 3 and depicted in Fig. 4.

It is clear from Table 4 and Fig. 4 that RF is the appropriate classifier for this data set. It has the highest accuracy (89%), TP rate (89%), precision/PPV (89.1%), F-measure (89%), and AUC (94.3%). It has the lowest FP rate (10.9) also.

Table 2 Comparison of five different attribute evaluator algorithms

| Order | Attribute evaluator/feature selection algorithms |
|-------|--------------------------------------------------|
| 1     | CFS best fit OR PCA GR SU                       |
| 2     | Search method: ranker                           |

Table 3 Confusion matrix of ten classifiers

| Classifier | Classified as | a | b | Kappa |
|------------|---------------|---|---|-------|
| BN         | a             | 184| 62| 0.5944|
|            | b             | 41 | 223|       |
| NB         | a             | 223| 23 | 0.5949|
|            | b             | 81 | 183|       |
| Log        | a             | 200| 46 | 0.4501|
|            | b             | 95 | 169|       |
| MLP        | a             | 193| 53 | 0.5567|
|            | b             | 60 | 204|       |
| SMO        | a             | 231| 15 | 0.5118|
|            | b             | 111| 153|       |
| KS         | a             | 185| 61 | 0.5055|
|            | b             | 65 | 199|       |
| RS         | a             | 219| 27 | 0.7491|
|            | b             | 37 | 227|       |
| J48        | a             | 220| 26 | 0.7569|
|            | b             | 36 | 228|       |
| RF         | a             | 221| 25 | 0.7803|
|            | b             | 31 | 233|       |
| RT         | a             | 206| 40 | 0.7014|
|            | b             | 36 | 228|       |

Table 4 Evaluation of the classifiers in terms of different metrics

| Classifier | Accu | TP | FP | PPV | F | AUC |
|------------|------|----|----|-----|---|-----|
| BN         | 79.8 | 79.8| 15.5| 81.8| 79.7| 88.9|
| NB         | 79.6 | 79.6| 19.6| 81.4| 79.4| 85.3|
| Log        | 72.4 | 72.4| 27  | 73.4| 72.3| 81.1|
| MLP        | 77.8 | 77.8| 22.1| 77.9| 77.8| 85 |
| SMO        | 75.3 | 75.3| 23.4| 79.7| 74.6| 75.9|
| KS         | 75.3 | 75.3| 24.7| 75.3| 75.3| 81.4|
| RS         | 87.5 | 87.5| 12.4| 87.5| 87.5| 91.7|
| J48        | 87.8 | 87.8| 12  | 87.9| 87.8| 86 |
| RF         | 89   | 89  | 10.9| 89.1| 89  | 94.3|
| RT         | 85.1 | 85.1| 15  | 85.1| 85  | 85 |

N.B. – a: anxiety and/or depression present and b: anxiety and depression absent.

Fig. 4 Bar diagram showing accuracy (%), FP rate (%), and AUC (%) of ten different classifiers

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Table 5 Confusion matrix for prediction by machine learning technology (RF) versus gold standard (HADS) result on test data set

|       | Gold standard test (HADS) | Total |
|-------|----------------------------|-------|
|       | a                          | b     |       |
| a     | 47                         | 6     | 53    |
| b     | 4                          | 53    | 57    |
| total | 51                         | 59    | 110   |

N.B. – a: anxiety and/or depression present and b: anxiety and depression absent.

Table 6 Evaluation of RF classifier on test data set

| Metrics                  | Performance |
|--------------------------|-------------|
| accuracy                 | 91%         |
| TP rate                  | 92%         |
| FP rate                  | 10%         |
| precision                | 89%         |
| specificity              | 90%         |
| F-score                   | 90%         |
| diagnostic odds ratio    | 104         |

4. Discussion: Machine learning technology is a new promise for the development of an automated disease diagnostic system. Researchers from both medical and engineering fields are trying to address this issue together. In this Letter, an endeavour has been made to predict one of the most important age-related mental changes, i.e. anxiety and depression among the older people, from socio-demographic and medical factors, using machine learning technology. A considerably large number (510) of elderly patients were interviewed and screened for anxiety and depression. This data set was used for predictive modelling. Study conducted by Suhasini et al. [37] tried to predict mental health problems of 400 psychiatric patients, not exclusively on older patients, using machine learning technology. However, this kind of study specially focusing on elderly patient is hardly available in literature. Study conducted by Bhakta and Saw [38] on prediction of depression among elders living in a slum at Kolkata found that among four different classifiers (BN, logistic, MLP, and SMO) BN and SMO algorithms predicted depression with an accuracy of almost 90%. In this Letter, at first relevant features were selected using attribute evaluator in WEKA. Ten features were found to be effective. Then, ten machine learning classifiers were evaluated and RF had the highest predictive accuracy with ten-fold cross-validation test. This RF model was tested on another 110 elderly patients for its external validity. Its predictive accuracy was found to be 91% and FP rate was only 10%, compared with gold standard HADS. This Letter will pave the way for future research work in search for better classifier with appropriate features especially suitable for the geriatric patients. Moreover, this can be extended to identify older persons suffering from underlying mental health problems, from general population at community level.

5. Conclusion: This Letter illustrates the promise of machine learning technology in the field of automated disease prediction system. A prediction model based on small number of sample size is hardly generalisable. Multi-centric research with large data set, comparing with different classifiers and appropriate use of optimisation techniques will help to build a generalised predictive model. That will lead to develop an efficient and effective automated system which can predict anxiety and depression among the elderly patient within seconds. That will help physicians and surgeons to address different health-related issues with proper emphasis on the mental health status of older patients.

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