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Screening of anxiety and depression among the seafarers using machine learning technology

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ABSTRACT

Background: Seafarers are vulnerable to suffer from various mental health disorders, most commonly anxiety and depression. So, periodic screening for anxiety and depression, is necessary for health and well-being. Machine learning technology can be used as a quick and automated screening procedure to identify the at risk seafarers for early referral to psychological counselling and treatment.
Objectives: To compare performance of different machine learning algorithms for screening of anxiety and depression among the seafarers.
Methods: Total 470 seafarers were interviewed at Haldia Dock Complex, India, after taking necessary permission and ethical clearance. Various socio demographic, occupational, and health related information were collected. Then status of anxiety and depression was assessed by Hospital Anxiety and Depression Scale. Five machine learning classifier i.e. Catboost, Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machine, were evaluated using Python.
Result: Catboost appeared to be the best one for this purpose with accuracy and precision 82.6% and 84.1% respectively.
Conclusion: This research emphasizes the application of machine learning technology in the field of automated screening for mental health illnesses. Using this technology, time consuming, anxiety and depression screening procedure can be replaced by an automated computer based technique with reasonable amount of accuracy.

1. Introduction

World Health Organization (WHO) defines “health as a state of complete physical, mental and social well-being and not merely an absence of disease or infirmity” and also include the ability to lead a “socially and economically productive life” [1,2]. WHO, farther clarifies the mental health as “a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community” [1]. So, mental conditions have been recognised as one of the most important dimension of health and well-beings of every individual. Depression and anxiety are two important states in the wide spectrum of mental health disorders. Disability due to those mental health problems are gradually increasing worldwide. It was estimated that lifetime prevalence of depression among high and low-middle income countries are 14.6% and 11.1% respectively [3]. On the other hand, a systematic review and meta regression found that, global current prevalence of anxiety disorders is 7.3% (4.8–10.9%), and ranges from 10.4% (7.0–15.5%) in high income countries to 5.3% (3.5–8.1%) in low-middle income countries [4]. It is estimated by WHO that globally 23% of Disability Adjusted Life Years (DALY), lost due to mental health disorders especially anxiety and depression [5].

Anxiety and depression are major public health problems worldwide [5]. It affects all age group, from paediatrics to geriatrics, both women and men [5]. Effects of anxiety and depressive disorders on health and well-beings are multidimensional. On one hand, it is responsible for multiple somatic symptoms like acid reflux, gastritis, palpitation, tremor, insomnia or hypersomnia, significant weight loss or gain and on the other hand, different psycho social manifestations like social withdrawal, depressed mood, suicidal ideation or attempt suicide, decrease productivity in workplace, lack of concentrations are directly attributed to anxiety and depression [6]. Anxiety and depression are the important risk factors for other lifestyle diseases like

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hypertension, ischemic heart diseases, diabetes, as well as intentional and unintentional injuries [5,7,8]. Depression and suicidal ideation are closely interrelated and at worst, depression can lead to suicide. It is also adversely associated with different communicable diseases like HIV, Tuberculosis [9]. People suffering from anxiety and depression are often stigmatised by the society and excluded by the family. They also underperform in educational institute and work place. As a consequence, they increasingly deprived of different economic and social opportunities and pushed to lead a poor quality of life [9]. Economic burden of it, is enormous and often unmeasured and vitiates the cycle of poor health and poverty. Poor and middle income families are mostly affected. In this perspective, to give due importance to the increasing problems of mental health disorders, WHO declared the theme for the year 2017 as “Depression: Let's Talk” [10].

The causes of anxiety and depression are multifactorial, including biological, economic, social, environmental and cultural. Diagnosis of it is made by psychiatrists or psychologists according to Diagnostic and Statistical Manual of Mental Disorders (DSM)-5 [11] or International Classification of Diseases (ICD) 10 [12]. Shortages of psychiatrists and psychologists are the most important barriers to identifying the patients and providing treatment and care in low- and middle-income countries [5]. There are only 5 psychiatrists per 10 million people in low and middle income countries [5]. Sometimes social stigma acts as a hurdles in between patients and psychiatrists [9]. Often, it remains undiagnosed and sufferings continues and the disease became more and more severe. There are some questioner type screening tools like Hospital anxiety and depression scale (HADS), Hamilton Anxiety and Depression Rating scale, which efficient enough to identify the patients, more likely suffering from anxiety and depression [13]. Those screening tools are most effective when applied by the trained health professionals. Predictive accuracy depends upon individual insight and depth of understanding of the questions [14]. Due to those limitations, screening tools are mostly applied for research purpose only and to some extent in hospital settings. There is no such mechanism to find out individuals suffering from anxiety and depression from apparently healthy general population. So, it is of utmost importance to develop a system to screen at risk population who are more likely suffering from anxiety and/or depression. To address the limitations of existing questionnaire based screening tools, the new system should be based on clearly defined objective criteria. In general, different socio demographic variables and co morbid conditions like gender, age, marital status, educational status, occupation, hypertension, diabetes, insomnia, palpitation, etc. significantly associated with the anxiety and depression and also have been proposed as important predictors for the development of anxiety and depression [15–17]. Machine learning technology can be applied to formulate an efficient and effective model to predict anxiety and depression from different predictor variables and subsequently a quick, reliable, automated screening methodology can be designed to identify the at risk individual and referred them to psychiatrists or psychologists for farther diagnostic evaluation and management [18].

Shipping industry is indispensable for economic growth and sustainable development of the society and therefore indirectly plays an important role in all of the sustainable development goals (SDGs) set by the United Nations [19]. Seafarers are the most important member of that industry. A sailor, mariner, seaman, or seafarer is a person who navigates or assists as a crew member in the operation and maintenance of water borne vessels. Due to their work schedule, life style, job profile, and other factors, they are more vulnerable to suffer from various mental health disorders, most commonly anxiety and depression [20,21]. Moreover, mental health and well-beings of everyone has been given a priority as evident from the target 3.4 of SDG-3 [19]. So, periodic screening, followed by necessary treatment for anxiety and depression, is necessary for their physical and mental health and well-being as well as to increase performance at work place. Occupational health specialists have to do this job by interviewing the seafarers with gold standard schedule like Hamilton anxiety and depression rating scales (HAM A and HAM D), Hospital Anxiety and Depression Scale (HADS) etc. It takes approximately 20–30 min to complete an interview for this purpose only. Most of the time, these mental health screening procedures for the seafarers have been ignored by employers, especially in developing countries due to shortage of expert manpower and time. As an alternative, machine learning technology can be used as a quick and automated screening procedure to identify the at risk seafarers for early referral to psychological counselling and treatment centre. This digital health technology will lead to create a mentally healthy workforce for the industry and enables them to lead a socially and economically productive life.

2. Materials and methods

2.1. Study population

The seafarers working at Haldia Dock Complex, a riverine major port in India, under Kolkata Port Trust, were interviewed, using a predesigned and pretested questionnaire, between January 2016 to August 2016. Total 470 seafarers, both permanent and contractual, were interviewed within that period. Those seafarers were do the all kind of shipping related activities in the port. They help to navigate the waterborne vessels in and out from the deep sea to river port. They do their job in shift duty manner. According to their working pattern, job profile of sailors can be grouped mainly into 2 (two) categories. One category is sailors working in Deck Department, includes Pilot; Chief Mate; Second Mate; Third Mate, Able Seaman, Ordinary Seaman, Cook, Cook Mate, Basun, Basun Mate etc. They do the job of sailing, piloting the vessel and loading and unloading the cargo, preparing and serving foods; cleaning, maintaining cabin and receiving, issuing, and inventorying stores, and management of passenger during voyage and another category is sailors working in Engine Department include Chief Engineer, Second Engineer/First Assistant Engineer, Third Engineer/Second Assistant Engineer, Fourth Engineer/Third Assistant Engineer, Fifth Engineer/Junior Engineer. They do the job of maintaining the propulsion and other kinds of mechanical systems on board the vessel. Though all categories of sailors working together in a water borne vessel, there may be some common health problems and there may be some specific health problems according to their category due to specific job profile, duration of service and different working condition in the vessel. Informed consent had been obtained from every study participant before being interviewed. Sailors already suffering from any mental health disorder, as diagnosed by qualified doctor, or had history of drug addiction were excluded from the study. Necessary permission was taken from the port authority for the study and ethical clearance was obtained from the institutional ethics committee at R. G. Kar Medical College and Hospital, Kolkata.

2.2. Study variables

Based on literature review [15–17,20,21] several socio demographic and occupational factors and co morbid conditions were put into the interview questionnaire and considered as predictor/independent variables/features (Sample dataset is in Fig. 1.). Those

Employment_Status	Job_Profile	Type_Vessel	Rank_Sailor	age	marital_status	family_type	education	PCI	duration_service	htn	DM	IHD	BMI	Anxiety_Depression
contractual	Engine	Non-ship	Non-Officer	36	married	joint	X	7200.00	8	Yes	No	no	18.83	No Anxiety-No Depression
contractual	Engine	Non-ship	Non-Officer	33	single	joint	XII	7666.67	4	No	No	no	19.60	No Anxiety-No Depression
permanent	Deck	Ship	Non-Officer	46	married	nuclear	XII	10000.00	20	No	No	no	18.83	Only Depression
permanent	Deck	Ship	Non-Officer	48	married	joint	Grad	12400.00	19	No	No	no	19.15	No Anxiety-No Depression
contractual	Deck	Non-ship	Non-Officer	40	married	nuclear	XII	7000.00	10	Yes	Yes	no	25.40	Only Anxiety
contractual	Deck	Non-ship	Non-Officer	44	married	joint	XII	6400.00	9	Yes	Yes	yes	25.22	Anxiety and Depression
permanent	Engine	Non-ship	Non-Officer	48	married	nuclear	XII	15000.00	20	No	Yes	yes	18.51	No Anxiety-No Depression
permanent	Deck	Non-ship	Non-Officer	34	married	joint	X	16000.00	9	No	No	no	18.59	No Anxiety-No Depression

Fig. 1. Sample Data Set with features and label.

variables are age, educational qualification (X/XII/Graduate level), type of family (nuclear/joint), marital status (married/divorced/single), per capital monthly family income in Indian Rupees, employment status (permanent/contractual), job profile (deck worker/engine worker), rank in the organization (officer/non officer), type of vessels where posted (ship/other than ship), duration of service as a sailor in years, presence or absence of hypertension, diabetes, ischemic heart disease, and Body Mass Index (BMI). The status of anxiety and depression during interview were assessed by HAM-A and HAM-D [22,23]. Those two scale are considered as one of the most valid and reliable screening tools for anxiety and depression among adult individuals [22,23]. The HAM-A was one of the first rating scales designed to measure severity of anxiety, which is the still widely used in both research and clinical practice. The scale consists of 14 domains to measures both psychic and somatic anxiety. Sum of the score from all parameters ranges between 0 and 56. Score less than 14 was considered as not significant anxiety (labelled as “No Anxiety”), otherwise suffering from significant anxiety disorder (labelled as “Anxiety”) [23]. HAM D scale was used to measure the level of depression. Scoring is based on first 17 items on the scale. HAM D score between 0 and 7 was conceded normal (labelled as “No Depression”) otherwise labelled as “Depression” [22]. As per HAM A and HAM D score a person can be labelled either “No Anxiety-No Depression” or “No Anxiety-Depression” or “Anxiety-No Depression” or “Anxiety-Depression”. Except “No Anxiety-No Depression” group, all others are need to be treated by the psychiatrist for mental health disorder. The basis of the any medical screening technique is to find out the affected individual for necessary referral to the doctors for confirmation of the diagnosis and necessary management. As this research work is to test the applicability and suitability of the machine learning technology as a medical screening tool, so we decided to group all the outcome into two labels, “No Anxiety-No Depression” and “Anxiety and/or Depression”. “Anxiety and/or Depression” group is suffering from either anxiety or depression or both and they are to be referred to psychiatrist for diagnostic evaluation and proper management. Another advantage of this binarification is solving a binary classification problem is easier and less complex than multiclass problem.

2.3. Feature selection

Feature selection is one of the most important step in machine learning framework. It eliminates the irrelevant and redundant features from the set of original predictor variables. In this research work, among the 14 predictors, 4 features were in ratio scale (age, per capita monthly income, BMI, duration of service) and others 10 features (educational qualification, type of family, marital status, employment status, job profile, rank in the organization, type of vessels where posted, presence or absence of hypertension, diabetes, ischemic heart disease) were categorical in nature. Dummy variables were created for the categorical features. So, there were 16 features with in the final data set (One extra dummy variable is for education qualification and another from marital status as both the features have three class). In this study recursive feature elimination (RFE) method was applied to identify the optimal number of features. To find the optimal number of features cross-validation is used with RFE to get the accuracy score of different feature subsets and select the best scoring collection of features. The result (Fig. 2.) shows that all the features are important to obtain highest level of accuracy. So, we decided not to drop any predictor from the original feature set.

2.4. Machine learning classifiers and training and testing dataset

A final data set with all the 14 features and 1 target and 470 instances are prepared for classification purpose. This dataset has been divided into 2 datasets based on period of data collection. Data collected between January, 2016 to July, 2016 i.e. 414 instances has been used for training and validating the machine learning classifiers/models. Data collected on the month of August 2016 i.e. 56 instances has been used to test the previously trained model for its external validity. A pictorial view of classification methodology for screening of anxiety and depression among the seafarers is given in Fig. 3.

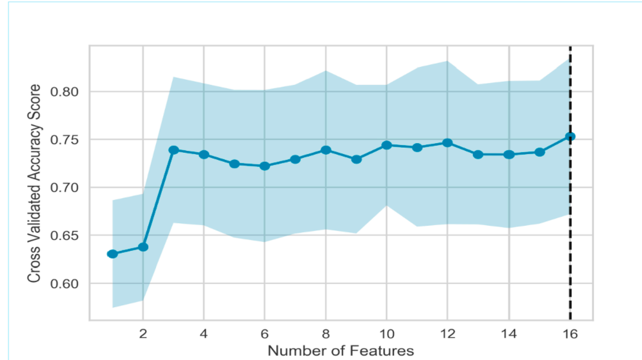

Fig. 2. Recursive feature elimination with accuracy score.

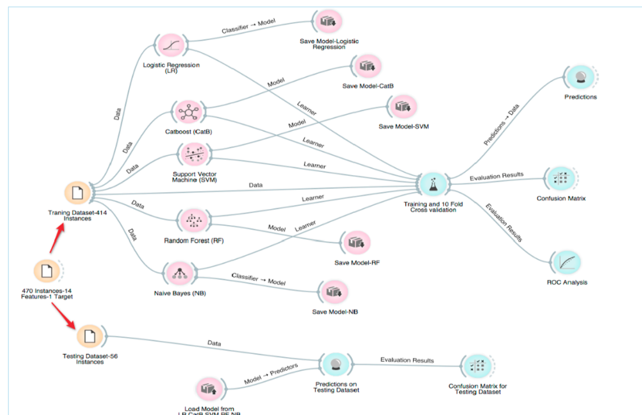

Fig. 3. Workflow of the Data mining Task.

In data mining, classification means mapping of input instance to a decision class variable. Classifier does this job by learning from a dataset of input and class variables. So classifier is a function that can be defined by Equation (1).

$$f_c : I \rightarrow D \tag{1}$$

Where, I represent a set of attribute variables and D represents a set of decision class. $I = \{i_1, i_2, \ldots, i_n\}$ and $D = \{d_1, d_2, \ldots, d_n\}$. and f_c represents the classification function which maps an input attribute instance (I) to a decision class (D).

The network for the system has been trained with 10-fold cross validation method. In this method provided data set is randomly divided into 10 equal sized parts. One of these parts used as test set and remaining 9 sets are used for training. In next iteration from these 9 sets 1 is selected as test data and former data set is included in training set. In this way variability is reduced using different partition. At the end, all the results, collected from different iterations, are averaged and final result is shown.

Five machine learning classifiers (Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machine and Catboost), those can handle the binary outcome variable (labels) with mixture of categorical and continuous features, are selected for comparison purpose. Among them ‘CatBoost’ is a state-of-the-art algorithm uses gradient boosting on decision tree.

A brief description of these 5 machine learning classifiers are given in this section.

2.4.1. Logistic regression (LR)

Logistic classifier is based on multinomial logistic regression model where parameters are estimated using ridge estimator [24]. Statistically logistic function (F(x)) is defined by Equation (2).

$$F(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{e^x + 1} \tag{2}$$

Let, there are n_1 number of classes, n_2 number of observations and n_3 number of features. Then parameter matrix (β) for each feature with each class will be a {n_3 x (n_1 – 1)} matrix, calculated from Equation (3).

$$P_j(X_i) = e^{X_i\beta_j} \Big/ \textstyle\sum_{j=1}^{n_1-1} e^{X_i\beta_j} + 1 \tag{3}$$

Here, $P_j(X_i)$= The probability for class j except last class, j = 1 … n_1, i = 1 … n_2, X_{ij} = feature set for observation i with respect to class j. Probability of last class is calculated with Equation (4).

$$1 - \sum_{j=1}^{n_1-1} P_j(X_i) = 1 \Big/ \textstyle\sum_{j=1}^{n_1-1} e^{X_i\beta_j} + 1 \tag{4}$$

The negative multinomial log-likelihood of the model is calculated with Equation (5).

$$L = -\sum_{i=1}^{n_2-1}\left\{\left(\sum_{j=1}^{n_1-1} Y_{ij} * \ln P_j(X_i)\right) + \left(\left(1 - \sum_{j=1}^{n_1-1} Y_{ij}\right) * \ln\left(1 - \sum_{j=1}^{n_1-1} P_j(X_i)\right)\right)\right\} + r_v * (\beta^2) \tag{5}$$

Here, Y_{ij} = represent the matrix for decision class variable and r_v = ridge factor.

After that matrix β is found for which L value is minimum using Quasi Newton method. With these values of parameters in matrix β classification has been made. In this research work, logistic regression model with default parameter values in “scikit learn” python library was applied. For optimization “lbfgs” solver algorithms is used which supports only L2 penalty. Maximum 100 number of iterations taken for the solvers to converge.

2.4.2. Naïve Bayes classifier (NB)

Naïve bayes is a classifier based on the theory of Bayes Network with independent prediction assumptions [25]. It assumes that presence of a feature in a decision class is not dependent on presence of another feature in that class. For this strong assumptions of feature independence, it is called Naïve. Suppose X = {x_1, x_2, …, x_n} is a set of feature and C = {c_1, c_2, …, c_m} is a set of class. From Bayes theorem the posterior probability of each class variable with given feature can be calculated using Equation (6).

$$P(C_i|X_j) = \frac{P(X_j|C_i)\,P(C_i)}{P(X_j)} \tag{6}$$

Where, i = 1,2, …m and j = 1,2, …, n, $P(X_j|C_i)$ = Probability of feature X_j with given class C_i, $P(C_i)$ = Prior probability of class C_i and $P(X_j)$ = Prior probability of feature X_j.

After that the classifier find out the maximum probability for class variables. The class with highest posterior probability value will be the result of classification. In this study parameters of prior probabilities was set to 0 and variance was set to $1e^{-9}$.

2.4.3. Random forest (RF)

Random Forest is an ensemble learning method which select features randomly with bagging [26,27]. It was first proposed by Ho. Let there are n number of features (F_1, F_2 … F_n). Using bagging procedure, m number of features are selected from these feature set randomly, where m < n always. With these m feature set a decision tree is generated. Next time, another m number of features are selected randomly with replacement. With each selected features a decision tree is generated. Final decision is obtained in voting or averaging method. If the decision class set for n number of feature set is {C_1, C_2 … C_n} and bagging selects t times m number of samples randomly with replacement. Then an unknown sample S will be predicted with Equation (7).

$$\bar{f} = \frac{1}{t}\sum_{p=1}^{t} f_p(S') \tag{7}$$

Where, p is the count of trees generated by bagging. f_p is a function of F and C which represents the decision tree of F and C. This equation represents the average of all decisions taken on t number of classes. This final decision also can be chosen by voting with maximum number of occurring classes. The parameters set the random forest ensemble learning method are number of estimator 100, minimum sample split 2, min sample leaf 1 and minimum impurity split to $1e^{-7}$ as threshold for early stopping of the tree growth. “gini” impurity function is applied to measure the quality of split.

2.4.4. Support vector machine (SVM)

Support Vector Machine [26] is a supervised machine-learning algorithm used in classification and regression problem. With a given training set, it tries to find out an optimal hyperplane in multidimensional space, which can easily classify the testing data set. The overlapping and dispersed data points in a real world application makes hindrance in hyperplane creation. To overcome the problems in real world application some tuning parameters like kernel, margin, regularization and gamma are used in SVM classifier. Based on the aforementioned parameters SVM can be trained for linear and nonlinear classification problem. In this study SVM classifier is trained with non-linear Radial Basis Function (RBF) kernel (Equation (8)).

$$\kappa(x, x') = \exp(-g * |x - x'|^2) \tag{8}$$

The parameter of SVM for this study was radial bias function kernel with gamma co efficien to 1/number of features, tolerance for stopping criteria $1e^{-3}$ and “one over rest” (ovr) strategy for decision function shaping.

2.4.5. Catboost (Cat)

CatBoost [28] is a supervised machine-learning algorithm to classify categorical data using gradient boosting on decision trees. At first a series of under fitted shallow decision tree model are build up on sampled training data set. The decision tree is created in a top-down approach by dividing the training dataset into similar instances. The homogeneity among the instances is measured with entropy. The decision trees are act as weak learners in this ensemble learning method. After creating the decision trees, each tree model tries to reduce the residual error in prediction with Log loss function. The weighted cumulative sum of these predictions produces final predicted value in the classifier with learning rate one. For this research purpose different training parameters were set accordingly, like Root Mean Squared Error (RMSE) as loss function, number of iteration 1000, learning rate 0.03, L2 regularization co efficient 3, and evaluation by area under the curve (AUC) estimation.

3. Result

3.1. Baseline characteristics of the study populations

The present study has been carried out among 470 sailors working at Haldia Dock Complex. All the sailors working there were male. Different socio demographic characteristics and occupational profiles and disease condition are summarised in Fig. 4 (Plot A to D), Fig. 5 (Plot E to H) and Fig. 6 (Plot I and Plot J). The figures are self-explanatory. Distribution of the continuous type of features have been plotted in Fig. 7 (Plot K to Plot N) and values with in the plot are median of the respective group. Status of anxiety and depression among the sailors

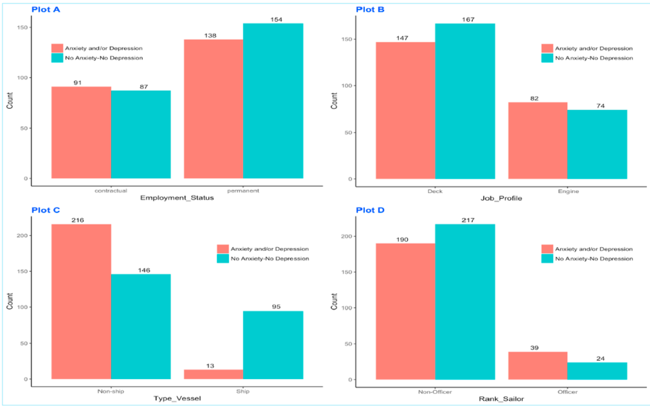

Fig. 4. Distribution of the categorical features (Employment status, job profile, type of vessel where posted, rank) according to Anxiety-Depression status.

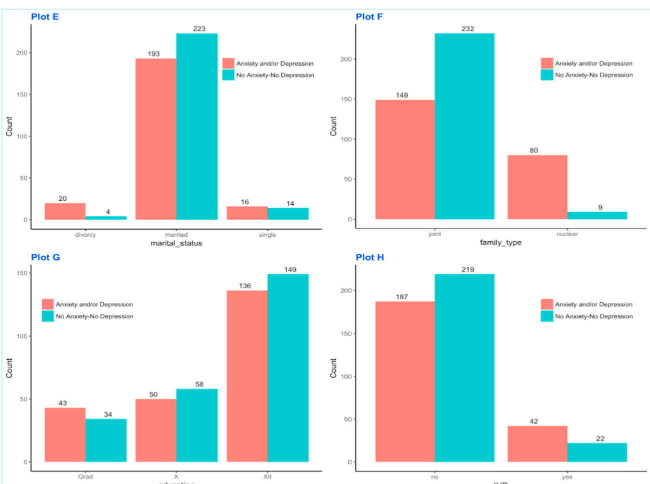

Fig. 5. Distribution of the categorical features (Marital status, family type, education and IHD i.e. ischemic heart disease) according to Anxiety-Depression status.

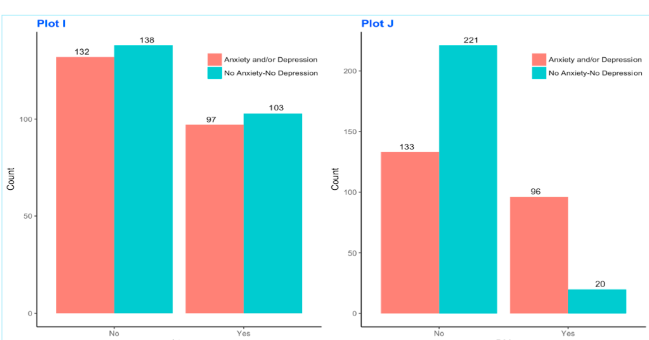

Fig. 6. Distribution of Hypertension (htn) and Diabetes Mellitus (DM) according to Anxiety-Depression status among the sailors.

were assessed by Hamilton Anxiety and Depression rating scale respectively. According to score every sailor were classified into one out of two categories viz. No anxiety-No depression and Anxiety and/or Depression. There were 51.3% sailors, who were not suffering from any anxiety or depression but remaining 48.7% were suffering from either anxiety, or depression or both (Fig. 8).

3.2. Comparison between different machine learning classifier

In this study, 14 features/predictor attributes, namely age,

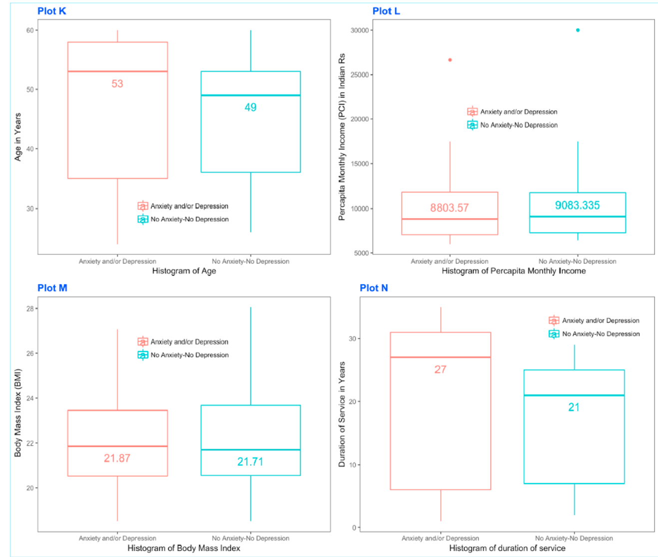

Fig. 7. Distribution of continuous features (Age, Per Capita Income, BMI and Service duration).

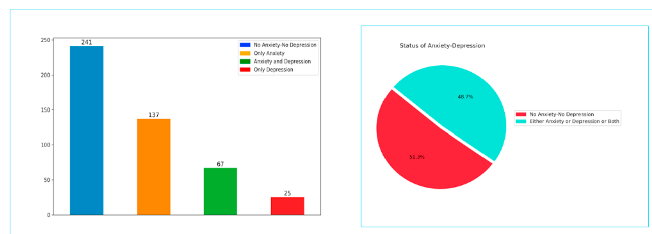

Fig. 8. Prevalence of Anxiety-Depression among the sailors (n = 470).

educational qualification, type of family (nuclear/joint), marital status (married/divorced/single), per capital monthly family income, employment status (permanent/contractual), job profile (deck worker/engine worker), rank in the organization (officer/non officer), type of vessels where posted (ship/other than ship), duration of service as a sailor, presence or absence of hypertension, diabetes, ischemic heart disease, and Body Mass Index (BMI) were used to predict the one target/outcome label i.e. presence or absence anxiety and/or depression among them. The final data set were analysed in Python (Jupyter Notebook) [29] for evaluation of five different machine learning classifiers. Those classifiers are compared with respect to three different metrics (Table 1), namely accuracy, precision and area under the curve (AUC) of ROC. Values of those metrics for 5 different classifiers were summarised in Table 2. Fig. 9 is showing ROC curves of the five classifiers on training dataset after 10 fold cross validation. The learning process of the Catboost algorithm using training dataset with 10 fold cross validation is represented in Fig. 10. From the values in Table 2 and Fig. 9, it has been observed that 'Catboost' classifier yields best result for this training data set.

To assess the robustness of the machine learning algorithms, the test dataset with 56 instances (Section-2.4.) are deployed on the trained

Table 1
Evaluation metrics.

Metrics	Formula
Accuracy	$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative}$
Precision	$Precision = \frac{True\ Positive}{False\ Positive + True\ Positive}$
ROC area	Area under the curve of ROC i.e. True Positive vs False Positive

Table 2
Evaluation of 5 Classifier on training set with 10 fold cross validation.

Classifier	Accuracy	Precision	ROC Area
Catboost	82.6%	84.1%	0.882
Random Forest	81.2%	81.2%	0.868
Logistic Regression	77.8%	78.0%	0.855
Naïve Bayes	75.8%	76.1%	0.847
SVM	76.1%	76.9%	0.759

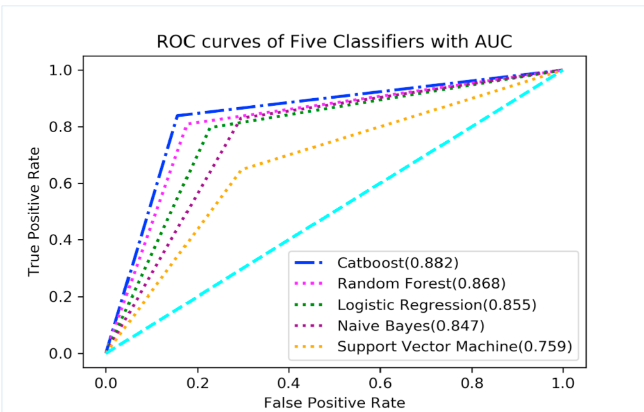

Fig. 9. ROC curves of 5 classifiers on training set with 10 fold cross validation.

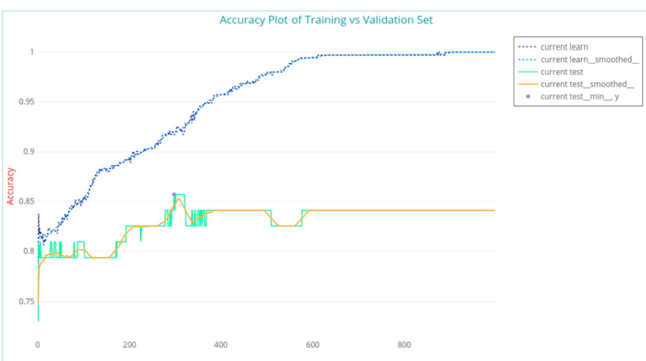

Fig. 10. Accuracy Plot of the Catboost algorithm on training dataset.

Table 3
Evaluation of 5 Classifier on test dataset.

Classifier	Accuracy	Precision
Catboost	89.3%	89.0%
Logistic Regression	87.5%	84%
SVM	82.1%	80.7%
Naïve Bayes	82.1%	76.9%
Random Forest	78.6%	80.7%

model in Python (Jupyter Notebook). Predictive accuracy and precision of the 5 classifiers ate tabulated in Table 3. The Catboost algorithm outperforms the other machine learning algorithms on test dataset also with predictive accuracy of 89.3% and precision of 89.0%. Accuracy Plot of the Catboost algorithm on test dataset is represented in Fig. 11. Logistic regress provides predictive accuracy of 87.5 and precision of 84.0% on test dataset. The accuracy and precision of other classifiers ranges between 75 and 85% with test dataset.

4. Discussion

Machine learning technology is a state of the art concept in the field of predictive modelling in health science. In the present article, 5 different machine learning classifiers were evaluated for their effectiveness and efficacy to screen those sailors who were probably suffering of any mental health disorder, particularly anxiety and/or depression. Researcher from various disciplines are doing research to find out the best classifiers for predicting or classifying different medical problems. Lahmiri et al. applied a new approach to classify Alzheimer's disease, mild cognitive impairment and healthy brain magnetic resonance images using support vector machine [30]. The proposed system was applied on magnetic resonance imaging, positron emission tomography scan and Cerebrospinal fluid data obtained from 45 Alzheimer's disease patients, 91 mild cognitive impairment patients and 50 healthy controls. They applied support vector machine for classification purpose and achieved more than 95% classification accuracy. A. Sau et al. compared different machine learning classifiers with respect to predicting anxiety and depression among geriatric population [18]. More than 500 hundred older person above 60 yrs of age were screened for anxiety and depression using hospital anxiety and depression scale. That data set was used as a training data set and then 110 geriatric population were screened for anxiety and depression both by gold standard method and machine learning method. In that article, Random Forest algorithm provided the best result with predictive accuracy of 90%. Kessler et al. tested a machine learning algorithm to predict the persistence and severity of major depressive disorder [31]. They applied machine learning technology in the 1065 respondent with history of major depressive episode in lifetime. Result showed that major depressive disorder risk stratification can be generated by machine learning technology from self-reporting data of the patients. Austin et al. tried to predict and classify heart failure using data mining approach [32]. Another study, conducted by A. Sau and I. Bhakta, on applicability of Artificial Neural Network (ANN) model to predict depression among the geriatric population living at slum area, found the predictive accuracy more than 90% [33]. In that study, ANN model had been applied to predict depression among 105 geriatric person using geriatric depression scale (GDS). Study conducted by Ahmed Husseini Orabi et al. applied deep learning architecture to detect depression and post-traumatic stress disorder from tweets of twitter users and achieve more than 80% accuracy level [34]. So, screening for mental health disorders by machine learning technology is an evolving concept. Its applicability among the different population has not been firmly established yet. Seafarers are one of the vulnerable group of population for mental health disorders. Different electronic databases of scientific literature were extensively searched, but no article was found to be published on screening for anxiety and depression among the sailors using machine learning technology. In this perspective, the present article is first of its kind. It was found that Catboost algorithm can efficient enough to screen those sailors who are probably suffering from anxiety and or depression with a high accuracy and precision of more than 80%. Consistently it provided best result on training, validation and testing phase. Based on the finding, a computerized automated

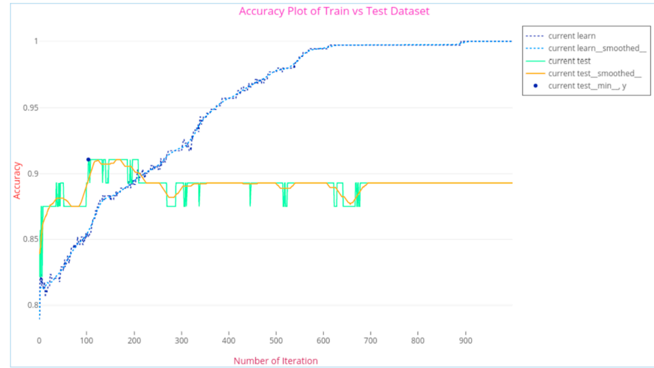

Fig. 11. Accuracy Plot of the Catboost algorithm on test dataset.

anxiety and depression screening system can be developed and this system can be linked with the treating psychiatrist for feedback and subsequent iterations to increase the predictive accuracy of the system. Though external validation of all the classifiers were made using 10-fold cross validation method, still extensive multi-centric research is necessary to find out appropriate feature set to develop a more efficient and effective model which can be applied to seafarers from all over the world.

5. Conclusion and future scope

This research emphasizes the application of machine learning technology in the field of automated screening for mental health illnesses. Using this technology, time consuming, manual, anxiety and depression screening procedure by various rating scales, can be replaced by an automated computer based technique with reasonable amount of accuracy. This will be beneficial both for the employees and the employers. In the current study, the predictive model based on this research is restricted to the specific group of working population but its robustness can be tested by prospective evaluation on seafarers from different cultural and geographical background in future studies. But the success of machine learning technology in mental health screening among them, can be widened to encompass the others working population in the country. Even, this technology can be used for population screening for mental health illnesses as well as other non-communicable diseases. State of the art machine learning algorithm like deep learning can be tested for its applicability in this perspective. Deep learning architecture in image processing can be applied to detect mental health problems from facial expressions also. Socio demographic, occupational profile, medical records and facial expression of the sailors over the period captured by photography can be coupled with magnetic resonance imaging of brain can be used for development of a more accurate screening tool. In that case, the volume of data will be quite voluminous and it may be applied in deep learning algorithms. For that, intense research is necessary in the field of digital health technologies for mental health screening. So, researcher from medical and computer engineering filed needs to put their hand together to achieve the targets set by SDGs #3 with respect to non-communicable diseases and mental health disorders.

Conflicts of interest

Authors declare that, there is no potential Conflict of Interest relating to this article. The authors received no external funding for this research work.

Authors contributions

Dr. A. Sau formulated the concept, designed the research framework and interviewed the seafarers. Dr. A. Sau and I. Bhakta analysed the data, compared different machine learning algorithms in Python (Jupyter Notebook) and write up the manuscript. Both authors approved the manuscript before submission.

Ethical statement

Informed consent had been obtained from every study participant before being interviewed. Necessary permission was taken from the port authority for the study and ethical clearance was obtained from the institutional ethics committee of R G Kar Medical College and Hospital, 1 Khudiram Bose Sarani, West Bengal, Kolkata 70004, India.

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Screening of anxiety and depression among seafarers using machine learning technology

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ABSTRACT

BACKGROUND: Seafarers are vulnerable to suffering from various mental health disorders, most commonly anxiety and depression. Therefore, periodic screening for anxiety and depression is necessary for their health and well-being. Machine learning technology may be useful as a rapid, automated screening procedure to identify at risk seafarers for early referral to psychological counselling and treatment.
Objectives: To compare the performance of machine learning algorithms for screening of anxiety and depression among seafarers.
Methods: A total 470 seafarers were interviewed at Haldia Dock Complex, India, after obtaining necessary permissions and ethical clearance. Various socio-demographic, occupational, and health-related information were collected. Then presence of anxiety and depression was assessed by the Hospital Anxiety and Depression Scale. Five machine learning classifiers i.e., CatBoost, Logistic Regression, Naïve Bayes, Random Forest, and Support Vector Machine, were evaluated using the Python programming language.
Result: CatBoost appeared to be the most satisfactory measure for this purpose, with an accuracy and precision 82.6% and 84.1%, respectively.
Conclusion: This study emphasizes the application of machine learning technology in the field of automated screening for mental health illness. Using this technology, a manually derived and time consuming screening procedure for anxiety and depression can be replaced by an automated computer based analysis technique with a degree of accuracy sufficient for screening purposes.

1. Introduction

The World Health Organization (WHO) defines health as “a state of complete physical, mental and social well-being, and not merely an absence of disease or infirmity”, and also included is the ability to lead a “socially and economically productive life” [1,2]. The WHO, further clarifies mental health as “a state of well-being in which every individual realizes his or her own potential, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to her or his community” [1]. Thus, mental conditions have been recognised as one of the most important dimensions of health and well-being of every individual. Depression and anxiety are two important states in the wide spectrum of mental health disorders. Disability due to those mental health problems are gradually increasing worldwide. It was estimated that lifetime prevalence of depression among high and low-middle income countries are 14.6% and 11.1% respectively [3]. On the other hand, a systematic review and meta regression found that, global current prevalence of anxiety disorders is 7.3% (4.8–10.9%), and ranges from 10.4% (7.0–15.5%) in high income countries to 5.3% (3.5–8.1%) in low-middle income countries [4]. It is estimated by WHO that globally 23% of Disability Adjusted Life Years (DALY), are lost due to mental health disorders, especially anxiety and depression [5].

Anxiety and depression are major public health problems worldwide [5]. They affect all age groups, from paediatrics to geriatrics, and both women and men [5]. Effects of anxiety and depressive disorders on health and well-being are multidimensional. On one hand, they are responsible for multiple somatic symptoms such as acid reflux, gastritis,

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Employment_Status	Job_Profile	Type_Vessel	Rank_Sailor	age	marital_status	family_type	education	PCI	duration_service	htn	DM	IHD	BMI	Anxiety_Depression
contractual	Engine	Non-ship	Non-Officer	36	married	joint	X	7200.00	8	Yes	No	no	18.83	No Anxiety-No Depression
contractual	Engine	Non-ship	Non-Officer	33	single	joint	XII	7666.67	4	No	No	no	19.60	No Anxiety-No Depression
permanent	Deck	Ship	Non-Officer	46	married	nuclear	XII	10000.00	20	No	No	no	18.83	Only Depression
permanent	Deck	Ship	Non-Officer	48	married	joint	Grad	12400.00	19	No	No	no	19.15	No Anxiety-No Depression
contractual	Deck	Non-ship	Non-Officer	40	married	nuclear	XII	7000.00	10	Yes	Yes	no	25.40	Only Anxiety
contractual	Deck	Non-ship	Non-Officer	44	married	joint	XII	6400.00	9	Yes	Yes	yes	25.22	Anxiety and Depression
permanent	Engine	Non-ship	Non-Officer	48	married	nuclear	XII	15000.00	20	No	Yes	yes	18.51	No Anxiety-No Depression
permanent	Deck	Non-ship	Non-Officer	34	married	joint	X	16000.00	9	No	No	no	18.59	No Anxiety-No Depression

Fig. 1. Sample Data Set with features and label.

palpitation, tremor, insomnia or hypersomnia, significant weight loss or gain, and on the other hand, different psycho social manifestations such as social withdrawal, depressed mood, suicidal ideation or attempt suicide, decrease productivity in the workplace, and lack of concentration [6]. Anxiety and depression are the important risk factors for other lifestyle diseases including hypertension, ischemic heart diseases, diabetes, as well as intentional and unintentional injuries [5,7,8]. Depression and suicidal ideation are closely interrelated, and depression can lead to suicide. These are also adversely associated by different communicable diseases including HIV and Tuberculosis [9]. People suffering from anxiety and depression are often stigmatised by society and excluded by family. They may underperform in educational institutes and workplaces. As a consequence, they become increasingly deprived of economic and social opportunities, leading to a poor quality of life [9]. Economic burden is an enormous and often unmeasured manifestation, and contributes to a cycle of poor health and poverty. Poor and middle income families are mostly affected. With this perspective, to give due importance to the increasing problems of mental health disorders, WHO has declared the theme for the year 2017 as "Depression: Let's Talk" [10].

The causes of anxiety and depression are multifactorial, including biological, economic, social, environmental and cultural. Diagnosis is made by psychiatrists or psychologists according to the Diagnostic and Statistical Manual of Mental Disorders (DSM)-5 [11] or the International Classification of Diseases (ICD) 10 [12]. Shortages of psychiatrists and psychologists are the most important barriers to identifying patients and providing treatment and care in low- and middle-income countries [5]. There are only 5 psychiatrists per 10 million people in low and middle income countries [5]. Sometimes social stigma acts as a hurdle between patients and psychiatrists [9]. Often, illness remains undiagnosed, suffering continues, and the disease became more severe. There are some questionnaire type screening tools including the Hospital anxiety and depression scale (HADS), and Hamilton Anxiety and Depression Rating scale, which is assistive to identify patients suffering from anxiety and depression [13]. The screening tools are most effective when applied by trained health professionals. Predictive accuracy depends upon individual insight and depth of understanding of the questions [14]. Due to those limitations, screening tools are mostly applied for research purposes only, and to some extent in hospital settings. There is no such mechanism to detect individuals suffering from anxiety and depression from the apparently healthy general population. Hence, it is of utmost importance to develop a system to screen the at risk population who are more likely suffering from anxiety and/or depression. To address the limitations of existing questionnaire based screening tools, the new system should be predicated upon clearly defined objective criteria. In general, different socio-demographic variables and co-morbid conditions such as gender, age, marital status, educational status, occupation, hypertension, diabetes, insomnia, and palpitation, are significantly associated with anxiety and depression, and have also been proposed as important predictors for the development of anxiety and depression [15–17]. Machine learning technology can be applied to formulate an effective and efficient model to predict anxiety and depression from predictor variables and subsequently to provide a quick, reliable, automated screening methodology that can be designed to identify the at risk individual and refer them to psychiatrists or psychologists for further diagnostic evaluation and management [18].

The shipping industry is indispensable for economic growth and sustainable development of the society, and therefore indirectly plays an important role in all of the sustainable development goals (SDGs) set by the United Nations [19]. Seafarers are the most important member of that industry. A sailor, mariner, seaman, or seafarer is a person who navigates or assists as a crew member in the operation and maintenance of waterborne vessels. Due to their work schedule, life style, job profile, and other factors, they are more vulnerable to suffer from various mental health disorders, most commonly anxiety and depression [20,21]. Moreover, mental health and well-being of everyone should be given a priority as evident from the target 3.4 of SDG-3 [19]. Therefore, periodic screening, followed by necessary treatment for anxiety and depression, is necessary for physical and mental health and wellbeing, as well as to increase performance at the workplace. Occupational health specialists implement this work by interviewing seafarers with a gold standard such as the Hamilton anxiety and depression rating scales (HAM A and HAM D) of Hospital Anxiety and Depression Scale (HADS). It requires approximately 20–30 minutes to complete an interview for this purpose only. Most of the time, mental health screening procedures for seafarers have been ignored by their employers, especially in developing countries, due to shortage of expert manpower and time. As an alternative, machine learning technology can be used as a quick and automated screening procedure to identify at risk seafarers for early referral to psychological counselling and treatment centers. This digital health technology could lead to creation of a mentally healthy workforce for industry, and enables them to lead socially and economically productive lives.

2. Materials and methods

2.1. Study population

The seafarers working at Haldia Dock Complex, a riverine major port in India, under Kolkata Port Trust, were interviewed, using a predesigned and pretested questionnaire, between January 2016 and August 2016. A total of 470 seafarers, both permanent and contractual, were interviewed within that period. Those seafarers were doing all kinds of shipping related activities in the port. Some helped to navigate

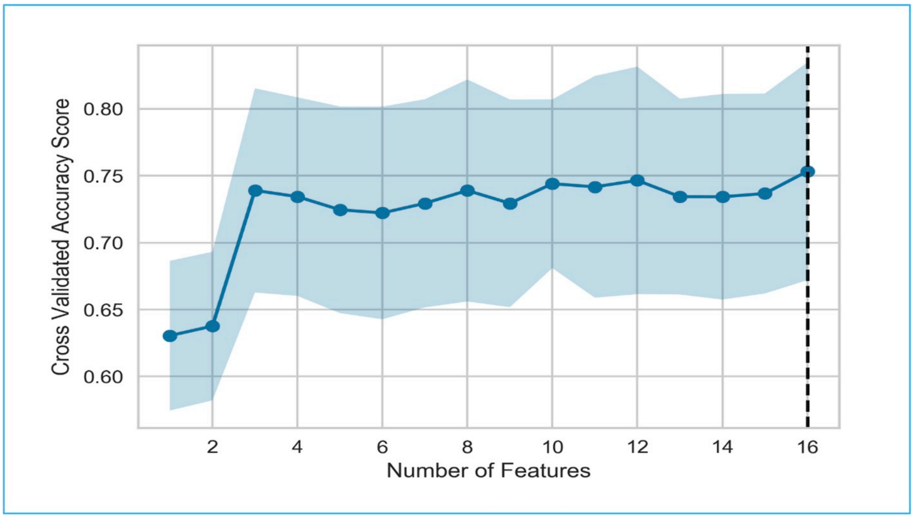

Fig. 2. Recursive feature elimination with accuracy score.

waterborne vessels in and out from the deep sea to river port. They do their job in a shift duty manner. According to their working pattern, the job profile of sailors can be grouped mainly into two categories. One category is sailors working in the Deck Department. They do the job of sailing, piloting the vessel, and loading and unloading the cargo, preparing and serving foods, cleaning, maintaining cabin and receiving, issuing, and inventorying supplies, and management of passengers during voyages. Another category is seafarers who labor in the Engine Department. They do the job of maintaining propulsion and other kinds of mechanical systems on board the vessel. From all categories of sailors working together in a waterborne vessel, there may be some common health problems according to their job profile, duration of service, and different working conditions in the vessel. For this study, informed consent was obtained from every participant prior to interview. Sailors already suffering from any mental health disorder, as diagnosed by a qualified doctor, or who had history of drug addiction, were excluded from the study. Necessary permission was obtained from the port authority for the study, and ethical clearance was granted from the institutional ethics committee at R. G. Kar Medical College and Hospital, Kolkata.

2.2. Study variables

Based on a literature review [15–17,20,21] several socio-demographic and occupational factors and co-morbid conditions were included in the interview questionnaire and considered as predictor/independent variables/features (Sample dataset is in Fig. 1.). Those variables are age, educational qualification (X/XII/Graduate level), type of family (nuclear/joint), marital status (married/divorced/single), per capita monthly family income in Indian Rupees, employment status (permanent/contractual), job profile (deck worker/engine worker), rank in the organization (officer/non officer), type of vessel where posted (ship/other than ship), duration of service as a sailor in years, presence or absence of hypertension, diabetes, ischemic heart disease, and Body Mass Index(BMI). The status of anxiety and depression during the interview were assessed by HAM-A and HAM-D [22,23]. Those two scale are considered as valid and reliable screening tools for anxiety and depression among adult individuals [22,23]. The HAM-A was one of the first rating scales designed to measure severity of anxiety, and is still widely used in both research and clinical practice. The scale consists of 14 domains to measure both psychic and somatic anxiety. The sum of the score from all parameters ranges between 0 and 56. Score less than 14 was considered as not significant anxious (labelled as “No Anxiety”); otherwise the subject was considered to be suffering from a significant anxiety disorder (labelled as “Anxiety”) [23]. The HAM D scale was used to measure the level of depression. The scoring is based on the first 17 items on the scale. A HAM D score between 0 and 7 was conceded to be normal (labelled as “No Depression”); or otherwise the subject was labelled as having “Depression” [22]. As per the HAM A and HAM D score, a person could be labelled either “No Anxiety-No Depression” or “No Anxiety-Depression” or “Anxiety-No Depression” or “Anxiety-Depression”. Except for the “No Anxiety-No Depression” group, all others required psychiatric treatment for mental health disorder. The basis of any medical screening technique is to detect the affected individual followed by necessary referral to medical doctors for confirmation of the diagnosis and management. As this research work was designed to test the applicability and suitability of machine learning technology as a medical screening tool, outcomes were grouped into two labels, “No Anxiety-No Depression” and “Anxiety and/or Depression”. The “Anxiety and/or Depression” group would be said to be suffering from either anxiety or depression or both, and they were to be referred to a psychiatrist for diagnostic evaluation and proper management. Another advantage of this binarification is that solving a binary classification problem is less complex than solving a multiclass problem.

2.3. Feature selection

Feature selection is one of the most important steps in the machine learning framework. It eliminates irrelevant and redundant features from the set of original predictor variables. In this research work, among the 14 predictors, 4 features were in ratio scale (age, per capita monthly income, BMI, duration of service) and 10 other features (educational qualification, type of family, marital status, employment status, job profile, rank in the organization, type of vessels where posted, presence or absence of hypertension, diabetes, ischemic heart disease) were categorical in nature. Dummy variables were created for the categorical features. Thus, there were 16 features with in the final data set (one extra dummy variable is for education qualification and another from marital status, as both the features have three classes). In this study the recursive feature elimination (RFE) method was applied to identify the optimal number of features. To find the optimal number of features, cross-validation is used with RFE to obtain the accuracy score of different feature subsets, and to select the best scoring collection of features. The result (see Fig. 2.) shows that all features are important to obtain the highest level of accuracy. Hence, we decided not to drop any predictor from the original feature set.

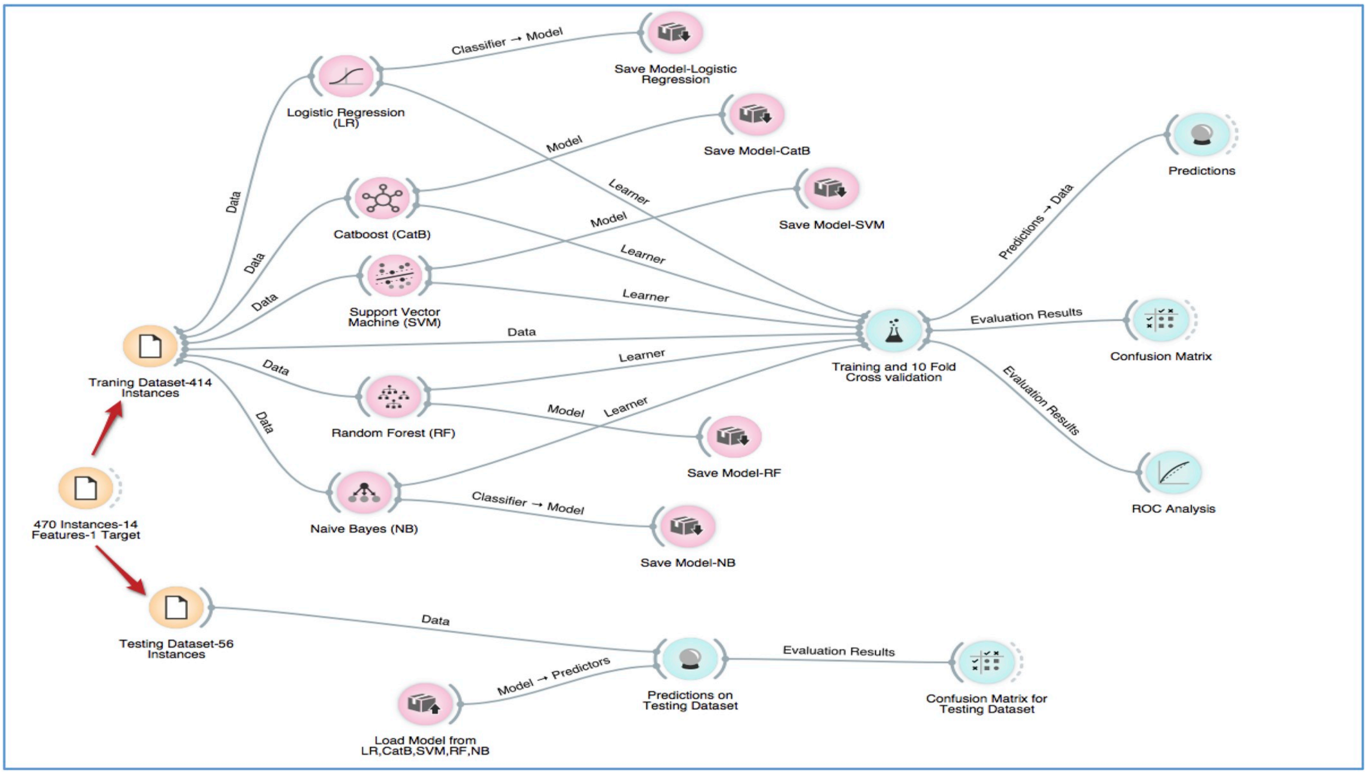

Fig. 3. Workflow of the Data mining Task.

2.4. Machine learning classifiers and training and testing dataset

A final dataset with all 14 features and 1 target and 470 instances were prepared for classification. This was divided into 2 groups based on period of data collection. Data collected between January 2016 to July 2016 i.e. 414 instances was used for training and validating the machine learning classifiers/models. Data collected during the month of August 2016 i.e. 56 instances was used to test the previously trained model for validity. A pictorial view of the classification methodology for screening of anxiety and depression among seafarers is provided in Fig. 3.

In data mining, classification requires mapping of input instance to a decision class variable. The classifier performs this task by learning from a dataset of input and class variables. Hence classifier is a function that can be defined by Equation (1).

$$f_c : I \rightarrow D \tag{1}$$

where I represents a set of attribute variables, and D represents a set of the decision class. Thus: $I = \{i_1, i_2, \ldots, i_n\}$ and $D = \{d_1, d_2, \ldots, d_n\}$, and f_c represents the classification function which maps an input attribute instance (I) to a decision class (D).

The network for the system was trained with the 10-fold cross validation method. In this method a dataset is randomly divided into 10 equally sized parts. One of these parts is used as a test set, and remaining 9 sets are used for training. In the next iteration, from the 9 sets, 1 is selected as test data and the former data set is included in training set. In this way, variability is reduced using a different partition. At the end, all the results, collected from different iterations, are averaged and the final result is shown.

Five machine learning classifiers (Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machine and CatBoost) can handle binary outcome variables (labels) with a mixture of categorical and continuous features, and are selected for comparison purpose. Among them 'CatBoost' is a state-of-the-art algorithm which uses gradient boosting in the decision tree.

A brief description of these five machine learning classifiers are given in this section.

2.4.1. Logistic regression (LR)

The logistic classifier is based on a multinomial logistic regression model, where parameters are estimated using the ridge estimator [24]. Statistically, the logistic function (F(x)) is defined by Equation (2):

$$F(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{e^x + 1} \tag{2}$$

let there be n_1 number of classes, n_2 number of observations, and n_3 number of features. Then parameter matrix (β) for each feature with each class will be a $\{n_3 \times (n_1 - 1)\}$ matrix, calculated from Equation (3).

$$P_j(X_i) = e^{X_i\beta_j} \Big/ \sum_{j=1}^{n_1-1} e^{X_i\beta_j} + 1 \tag{3}$$

here, $P_j(X_i)$ = the probability for class j except the last class, $j = 1 \ldots n_1$, $i = 1 \ldots n_2$, X_{ij} = feature set for observation i with respect to class j. The probability of the last class is calculated with Equation (4).

$$1 - \sum_{j=1}^{n_1-1} P_j(X_i) = 1 \Big/ \sum_{j=1}^{n_1-1} e^{X_i\beta_j} + 1 \tag{4}$$

the negative multinomial log-likelihood of the model is calculated with Equation (5).

$$L = -\sum_{i=1}^{n_2-1}\left\{\left(\sum_{j=1}^{n_1-1} Y_{ij} * \ln P_j(X_i)\right) + \left(\left(1 - \sum_{j=1}^{n_1-1} Y_{ij}\right) * \ln\left(1 - \sum_{j=1}^{n_1-1} P_j(X_i)\right)\right)\right\} + r_v * (\beta^2) \tag{5}$$

here, Y_{ij} = represents the matrix for the decision class variable and r_v = ridge factor.

After that matrix β is found for which the L value is minimum using Quasi Newton method. With these values of parameters in matrix β, classification can be made. In this research work, the logistic regression model with default parameter values in "scikit learn" python library

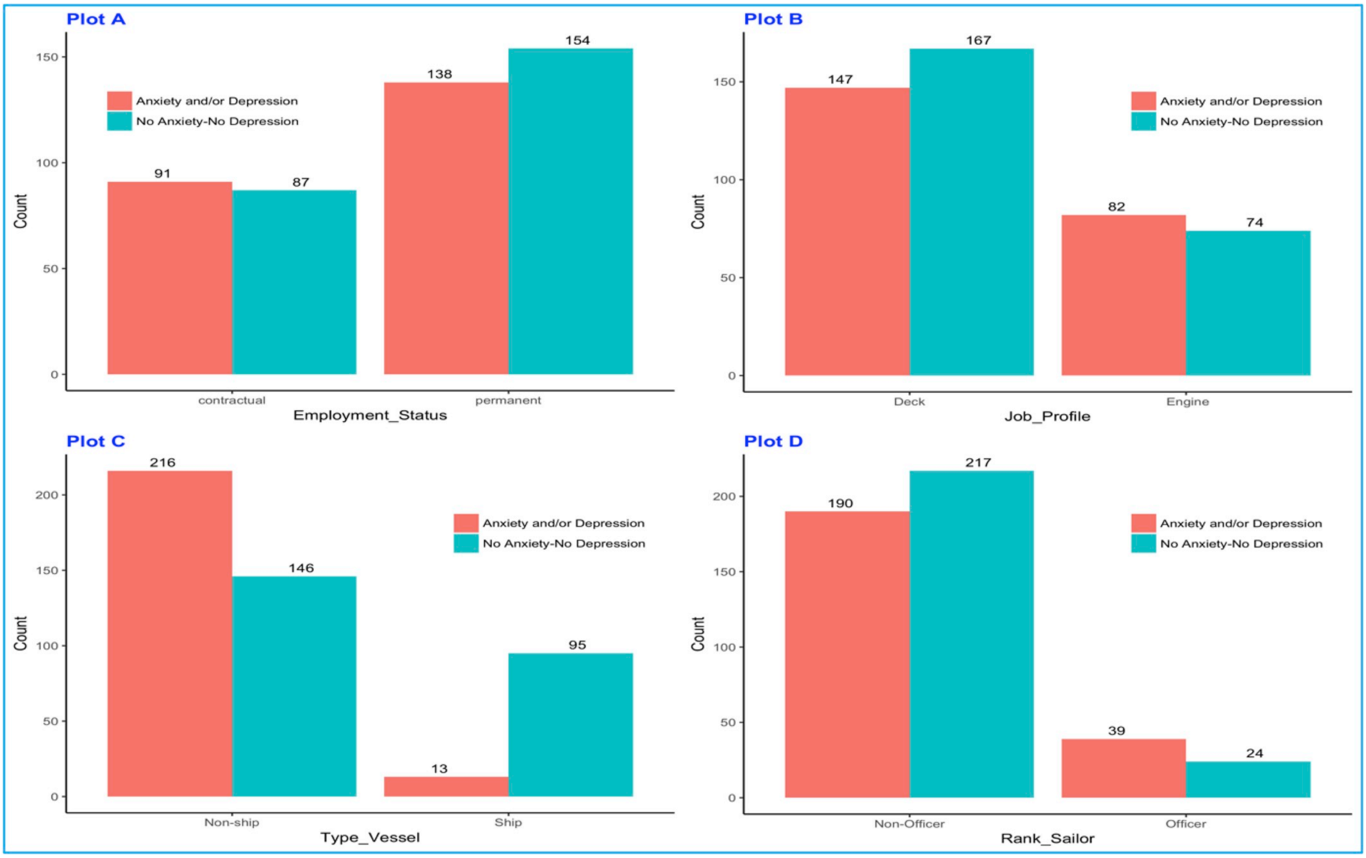

Fig. 4. Distribution of the categorical features (Employment status, job profile, type of vessel where posted, rank) according to Anxiety-Depression status.

were applied. For optimization the "lbfgs" solver algorithms are used, which supports only an L2 penalty. A maximum number of iterations 100 is taken for the solvers to converge.

2.4.2. Naïve Bayes classifier (NB)

Naïve Bayes is a classifier based on the theory of the Bayes Network with independent prediction assumptions [25]. It assumes that presence of a feature in a decision class is not dependent on the presence of another feature in that class. For this strong assumption of feature independence, it is called Naïve. Suppose $X = \{x_1, x_2, \ldots, x_n\}$ is a set of features and $C = \{c_1, c_2, \ldots, c_m\}$ is a set of classes. From the Bayes theorem, the posterior probability of each class variable with a given feature can be calculated using Equation (6).

$$P(C_i|X_j) = \frac{P(X_j|C_i)\ P(C_i)}{P(X_j)} \tag{6}$$

where, $i = 1,2, \ldots m$ and $j = 1,2, \ldots, n$, $P(X_j|C_i)$ = Probability of feature X_j with given class C_i, $P(C_i)$ = Prior probability of class C_i and $P(X_j)$ = Prior probability of feature X_j.

Thereafter, the classifier determines the maximum probability for class variables. The class with the highest posterior probability value will be the result of the classification. In this study, parameters of prior probabilities was set to 0 and the variance was set to $1e^{-9}$.

2.4.3. Random forest (RF)

Random Forest is an ensemble learning method which selects features randomly with bagging [26,27]. It was first proposed by Ho. Let there be n number of features ($F_1, F_2 \ldots F_n$). Using the bagging procedure, m number of features are randomly selected from the feature set, where $m < n$ always. With these m feature set, a decision tree is generated. On the following iteration, another m number of features are selected randomly with replacement. With each selected feature, a decision tree is generated. The final decision is obtained by a majority voting or averaging method. If the decision class set for n number of feature sets is $\{C_1, C_2 \ldots C_n\}$, bagging selects t times m number of samples randomly with replacement. Then an unknown sample S will be predicted with Equation (7).

$$\bar{f} = \frac{1}{t}\sum_{p=1}^{t} f_p(S') \tag{7}$$

where p is the count of trees generated by bagging. f_p is a function of F and C, which represents the decision tree of F and C. This equation represents the average of all decisions taken on t number of classes. This final decision also can be chosen by voting with a maximum number of occurring classes. The parameters set for the random forest ensemble learning method are number of estimator 100, minimum sample split 2, minimum sample leaf 1 and minimum impurity split to $1e^{-7}$ as threshold for early stopping of the tree growth. The "Gini" impurity function is applied to measure the quality of split.

2.4.4. Support vector machine (SVM)

The Support Vector Machine [26] is a supervised machine-learning algorithm used in classification and regression problems. With a given training set, it tries to find an optimal hyperplane in multidimensional space, which can readily classify the test data set. The overlapping and dispersed data points in real world applications hinders hyperplane creation. To overcome the problems in real world applications, some tuning parameters such as kernel, margin, regularization, and gamma are used in the SVM classifier. Based on the aforementioned parameters, SVM can be trained for linear and non-linear classification problems. In this study, the SVM classifier is trained with a non-linear Radial Basis Function (RBF) kernel (Equation (8)).

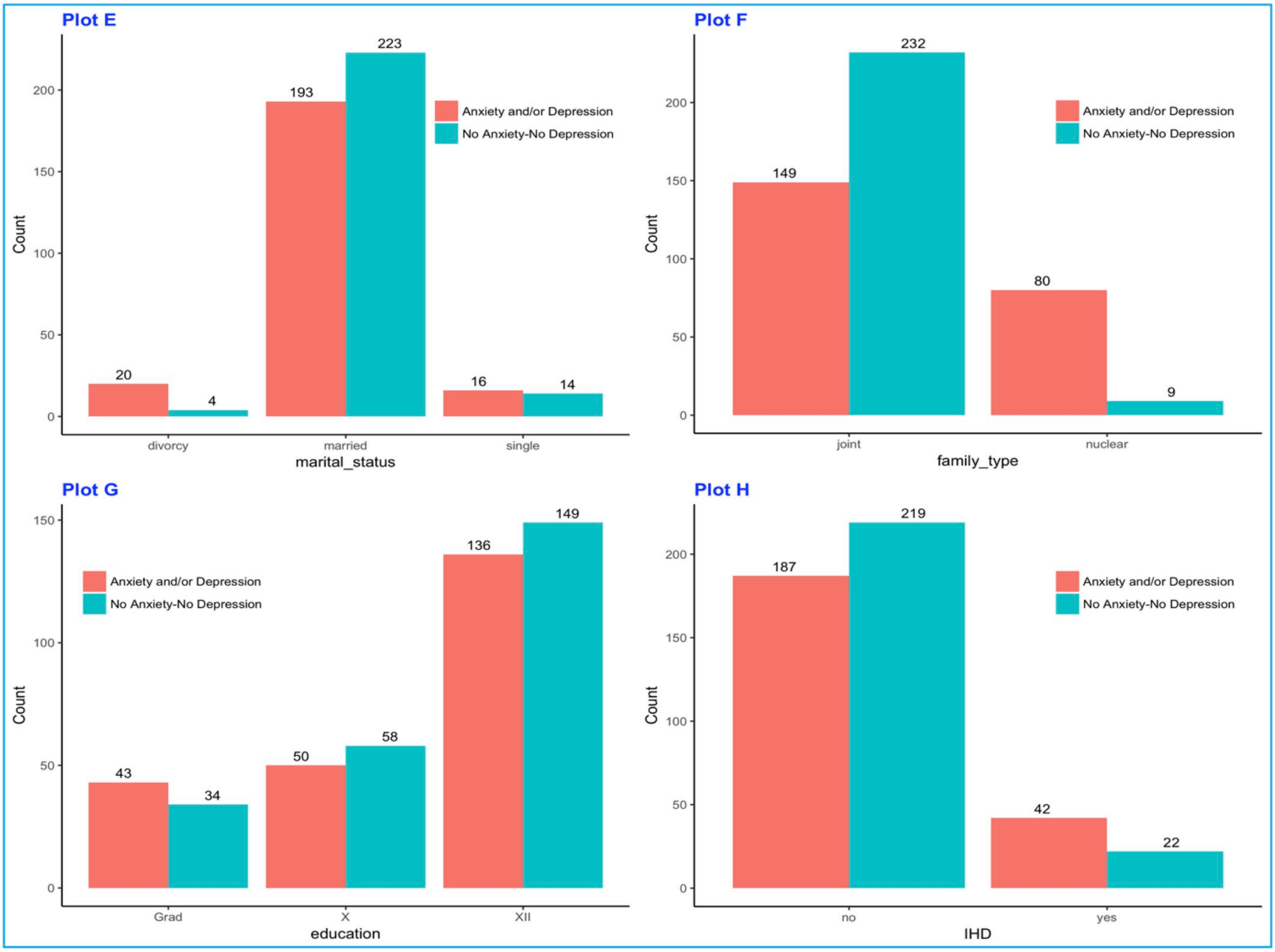

Fig. 5. Distribution of the categorical features (Marital status, family type, education and IHD i.e. ischemic heart disease) according to Anxiety-Depression status.

$$\kappa(x, x') = \exp\left(-g * |x - x'|^2 \right) \tag{8}$$

The parameters of SVM for this study were the radial bias function kernel with gamma coefficient to 1/number of features, tolerance for stopping criteria $1e^{-3}$, and “one over rest” (ovr) strategy for decision function shaping.

2.4.5. CatBoost (cat)

CatBoost [28] is a supervised machine-learning algorithm to classify categorical data using gradient boosting on decision trees. At first a series of underfitted shallow decision tree models are built up on the sampled training data set. The decision tree is created in a top-down approach by dividing the training dataset into similar instances. The homogeneity among the instances is measured with entropy. The decision trees act as weak learners in this ensemble learning method. After creating the decision trees, each tree model tries to reduce the residual error in prediction with a Log loss function. The weighted cumulative sum of these predictions produces a final predicted value in the classifier. For this purpose,different training parameters were set accordingly, including Root Mean Squared Error (RMSE) as loss function, number of iteration 1000, learning rate 0.03, L2 regularization coefficient 3, and evaluation by area under the curve (AUC) estimation.

3. Result

3.1. Baseline characteristics of the study populations

The present study has been carried out among 470 sailors working at Haldia Dock Complex. All the sailors working there were male. Different sociodemographic characteristics and occupational profiles and disease conditions are summarised in Fig. 4 (Plot A to D), Fig. 5 (Plot E to H) and Fig. 6 (Plot I and Plot J). Distribution of the continuous type of features have been plotted in Fig. 6 (Plot K to Plot N) and values within the plot are medians of the respective group. Status of anxiety and depression among the sailors was assessed by the Hamilton Anxiety and Depression rating scale. According to score every sailor was classified into one out of two categories: No anxiety-No depression or Anxiety and/or Depression. There were 51.3% sailors who were not suffering from any anxiety or depression, but the remaining 48.7% were suffering from either anxiety, depression, or both (Fig. 7).

3.2. Comparison between different machine learning classifier

In this study, 14 features/predictor attributes, namely age, educational qualification, type of family (nuclear/joint), marital status (married/divorced/single), per capita monthly family income, employment status (permanent/contractual), job profile (deck worker/engine worker), rank in the organization (officer/non officer), type of vessels where posted (ship/other than ship), duration of service as a sailor,

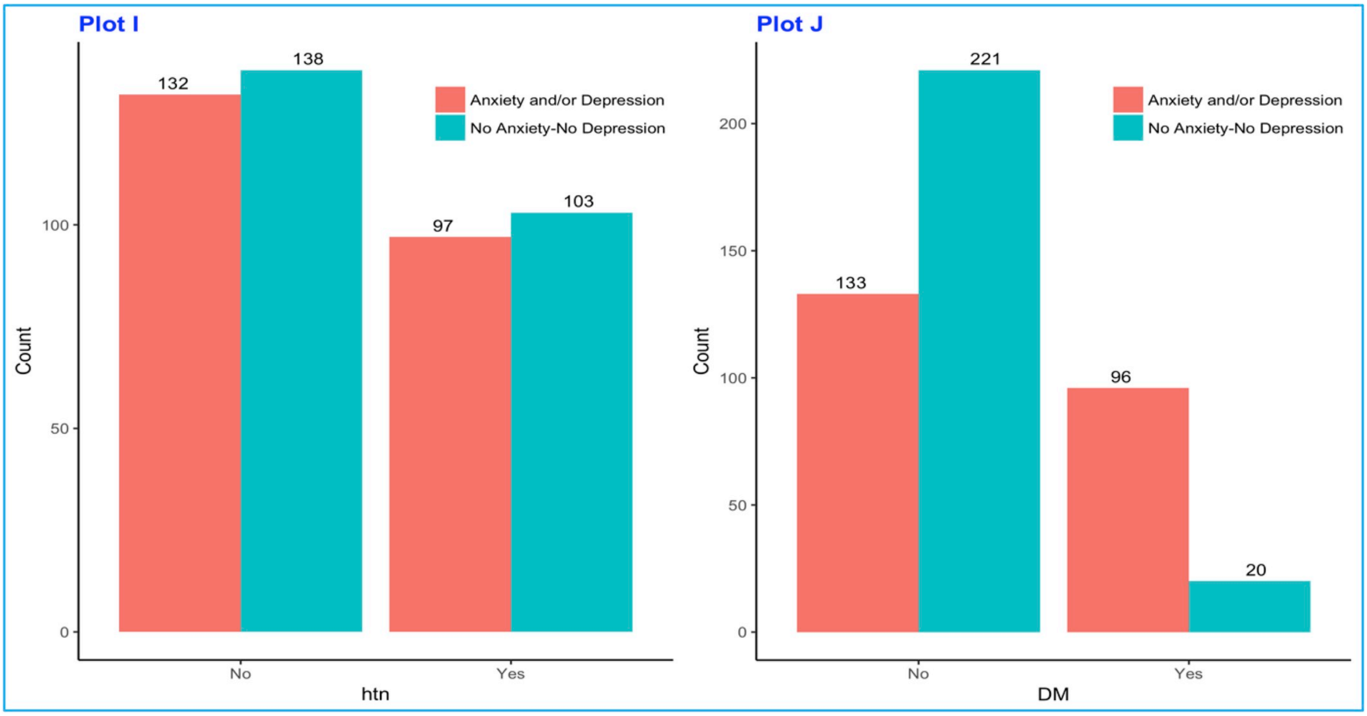

Fig. 6a. Distribution of Hypertension(htn) and Diabetes Mellitus (DM) according to Anxiety-Depression status among the sailors.

presence or absence of hypertension, diabetes, ischemic heart disease, and Body Mass Index(BMI), were used to predict the one target/outcome label i.e., presence or absence of anxiety and/or depression among them. The final dataset was analysed in Python (Jupyter Notebook) [29] for evaluation of five different machine learning classifiers. Those classifiers were compared with respect to three different metrics (Table 1), namely accuracy, precision, and area under the curve (AUC) of ROC. Values of those metrics for 5 different classifiers were summarised in Table 2. Fig. 8 exhibits ROC curves of the five classifiers on the training dataset after 10-fold cross validation. The learning process of the CatBoost algorithm using the training dataset with 10-fold cross validation is represented in Fig. 9. From the values in Table- 2 and Fig. 8, it was observed that the 'CatBoost' classifier yielded the best result for this training dataset.

Table 1
Evaluation metrics.

Metrics	Formula
Accuracy	$Accuracy = \dfrac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negetive}$
Precision	$Precision = \dfrac{True\ Positive}{False\ Positive + True\ Positive}$
ROC area	Area under the curve of ROC i.e. True Positive vs False Positive

Table 2
Evaluation of 5 Classifier on training set with 10 fold cross validation.

Classifier	Accuracy	Precision	ROC Area
CatBoost	82.6%	84.1%	0.882
Random Forest	81.2%	81.2%	0.868
Logistic Regression	77.8%	78.0%	0.855
Naïve Bayes	75.8%	76.1%	0.847
SVM	76.1%	76.9%	0.759

To assess the robustness of the machine learning algorithms, the test dataset with 56 instances (Section-2.4.) were deployed on the trained model in Python (Jupyter Notebook). Predictive accuracy and precision of the 5 classifiers are tabulated in Table 3. The CatBoost algorithm outperformed the other machine learning algorithms on the test dataset also, with a predictive accuracy of 89.3% and precision of 89.0%. The Accuracy Plot of the CatBoost algorithm on the test dataset is represented in Fig. 10. Logistic regression provides a predictive accuracy of 87.5% and precision of 84.0% on the test dataset. The accuracy and precision of other classifiers ranged between 75 and 85% with the test dataset.

Table 3
Evaluation of 5 Classifier on test dataset.

Classifier	Accuracy	Precision
CatBoost	89.3%	89.0%
Logistic Regression	87.5%	84%
SVM	82.1%	80.7%
Naïve Bayes	82.1%	76.9%
Random Forest	78.6%	80.7%

4. Discussion

Machine learning technology is a state-of-the-art concept in the field of predictive modelling in health science. In the present article, 5 different machine learning classifiers were evaluated for their effectiveness and efficacy, to screen those sailors who were likely suffering from any mental health disorder, particularly anxiety and/or depression. Investigators from various disciplines are working to determine the best classifiers for predicting or classifying different medical problems. Lahmiri et al. applied a new approach to classify Alzheimer's disease, mild cognitive impairment, and healthy brain magnetic resonance images using a support vector machine [30]. The proposed system was applied to magnetic resonance imaging, positron emission tomography scans, and cerebrospinal fluid data obtained from 45 Alzheimer's disease patients, 91 mild cognitive impairment patients, and 50 healthy controls. They applied the support vector machine for classification

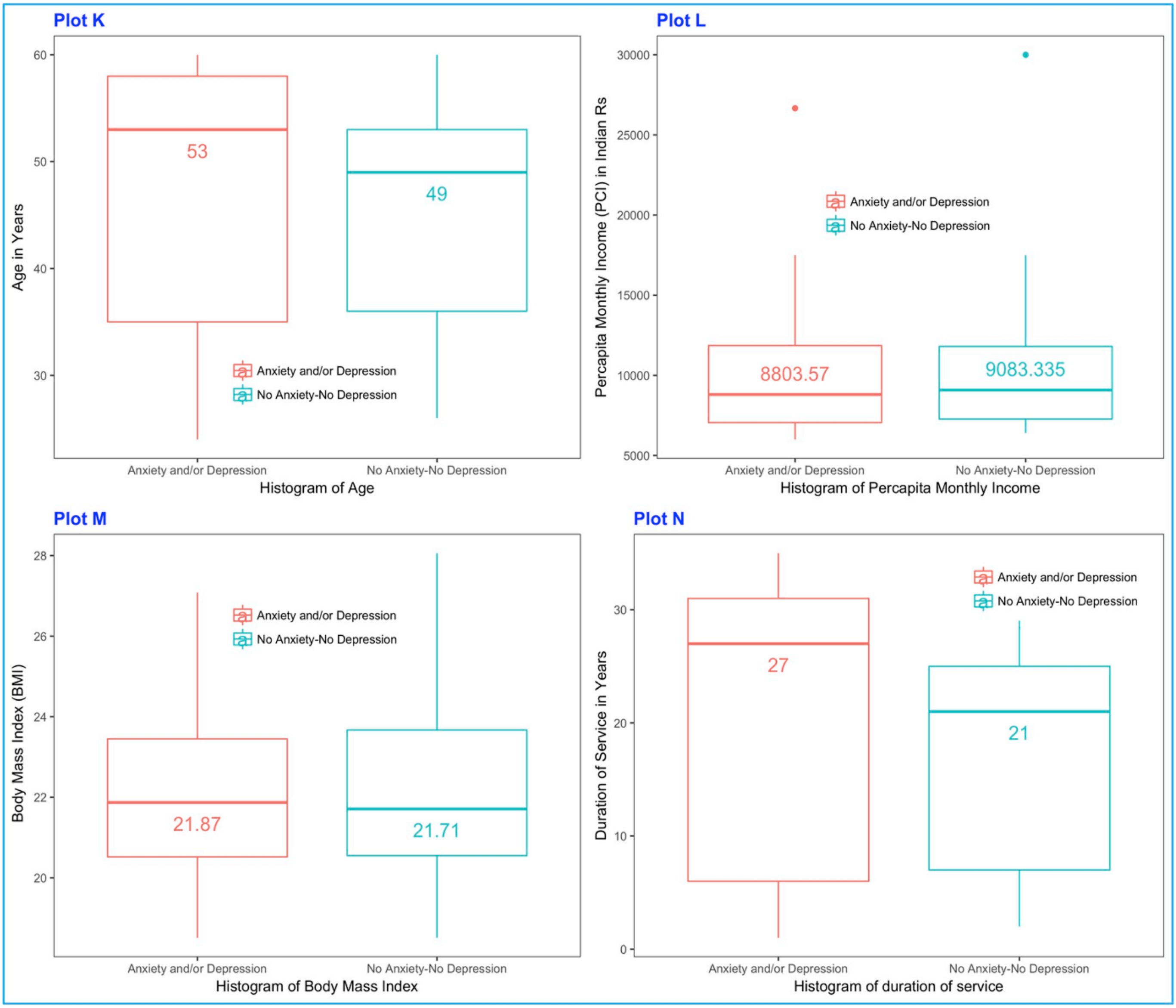

Fig. 6b. Distribution of continuous features (Age, Per Capita Income, BMI and Service duration)

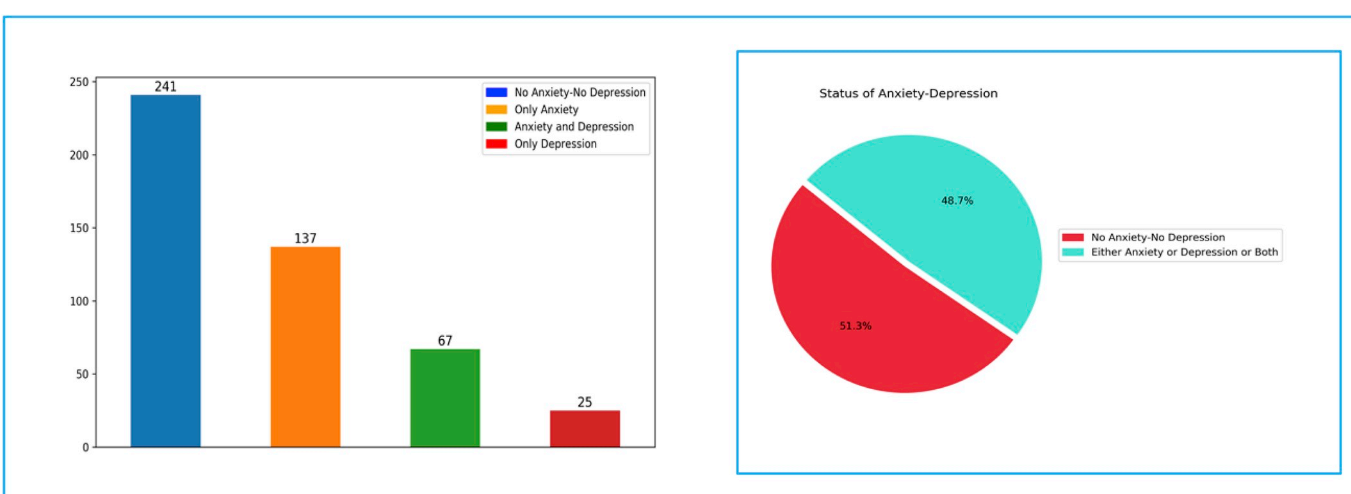

Fig. 7. Prevalence of Anxiety-Depression among the sailors (n = 470).

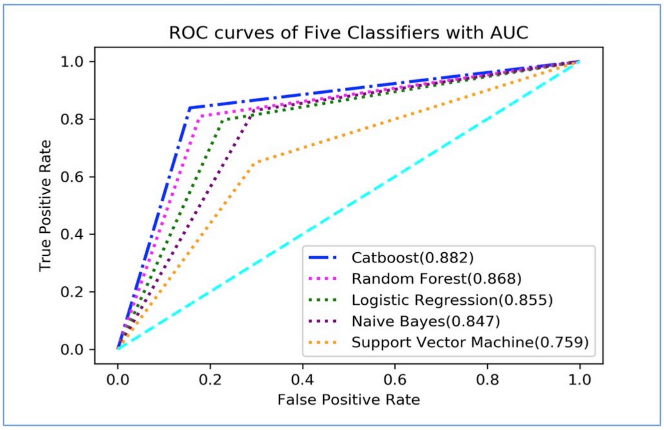

Fig. 8. ROC curves of 5 classifiers on training set with 10 fold cross validation

purposes, and achieved greater than 95% classification accuracy. A. Sau et al. compared different machine learning classifiers with respect to predicting anxiety and depression among the geriatric population [18]. More than 500 older persons above 60 years of age were screened for anxiety and depression using the hospital anxiety and depression scale. That dataset was used as a training dataset and then 110 members of the geriatric population were screened for anxiety and depression both by the gold standard method and machine learning. In that article, the Random Forest algorithm provided the best result, with predictive accuracy of 90%. Kessler et al. tested a machine learning algorithm to predict the persistence and severity of major depressive disorder [31]. They applied machine learning technology in the 1065 respondents with a history of a major depressive episode in their lifetime. Results showed that major depressive disorder risk stratification can be generated by machine learning technology from self-reporting data of the patients. Austin et al. tried to predict and classify heart failure using a data mining approach [32]. In another study, conducted by A. Sau and I. Bhakta, on the applicability of the Artificial Neural Network (ANN) model to predict depression among the geriatric population living in a slum area, they found a predictive accuracy more than 90% [33]. In that study, the ANN model was applied to predict depression among 105 geriatric persons using the geriatric depression scale(GDS). A study conducted by Ahmed Husseini Orabi et al. applied a deep learning architecture to detect depression and post-traumatic stress disorder from tweets of twitter users, and achieve a greater than 80% accuracy level [34]. Thus, screening for mental health disorders by machine learning technology is an evolving concept. Its applicability among the different populations has not yet been firmly established. Seafarers are a vulnerable group for mental health disorder. Different electronic databases of scientific literature were extensively searched, but no article was found on screening for anxiety and depression among the sailors using machine learning technology. In this perspective, the present article is novel. It was found that the CatBoost algorithm can efficiently screen those sailors who are likely suffering from anxiety and or depression, with a high accuracy and precision of more than 80%. Consistently it provided the best result on training, validation, and testing phases. Based on the finding, a computerized automated anxiety and depression screening system could be developed in future work, and this system could be linked with the treating psychiatrist for feedback and subsequent iteration to increase the predictive accuracy of the system. Although external validation of all classifiers were made using the 10-fold cross validation method, yet, extensive multicentric research is necessary to determine the most appropriate feature set to develop a more efficient and effective model, which can be applied to seafarers from all over the world.

5. Conclusion and future scope

This research emphasizes the application of machine learning technology in the field of automated screening for mental health illness. Using this technology, time consuming and manual anxiety and depression screening procedures by various rating scales, can be replaced by an automated computer-based technique with reasonable accuracy. This will be beneficial both for the employees and the employers of this occupation. In the current study, the predictive model based on this research is restricted to the specific group of working population, but its robustness can be tested by prospective evaluation on seafarers from different cultural and geographical background in future

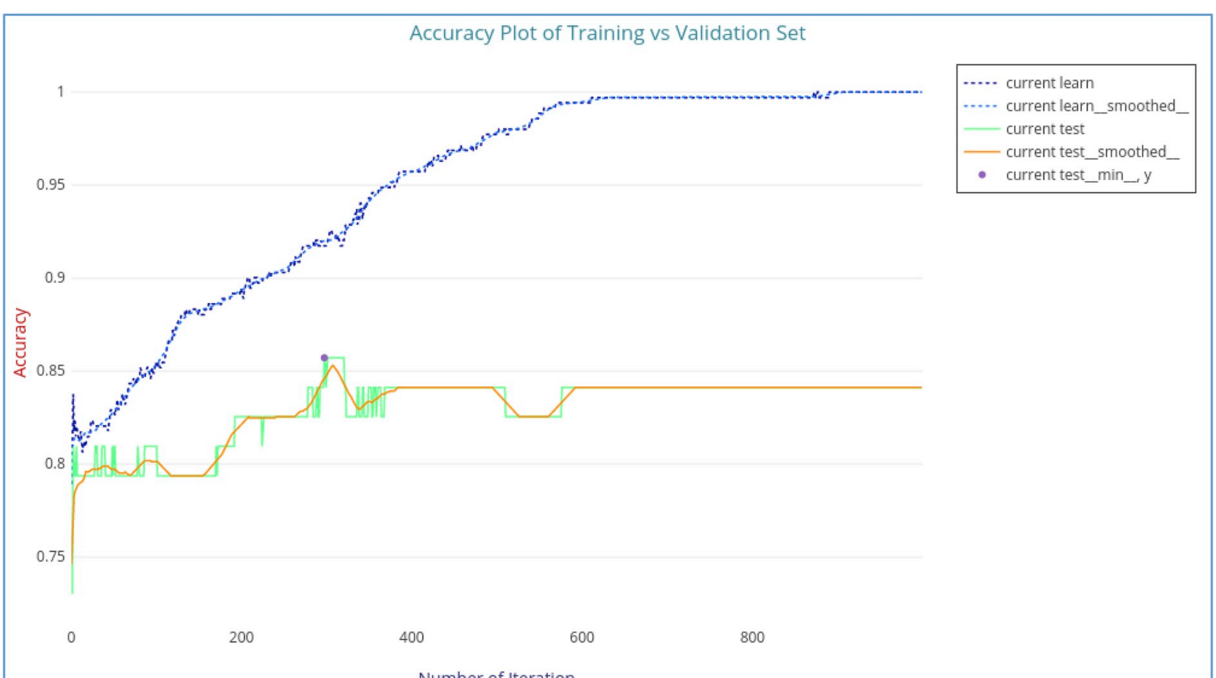

Fig. 9. Accuracy Plot of the CatBoost algorithm on training dataset.

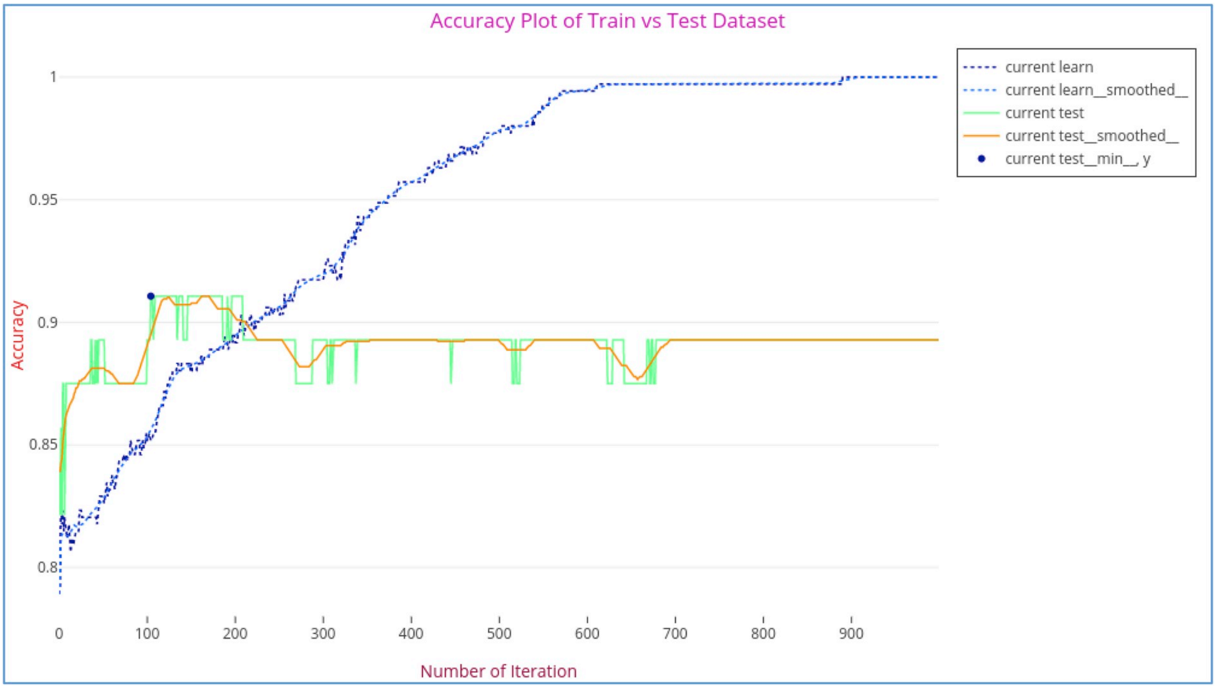

Fig. 10. Accuracy Plot of the CatBoost algorithm on the test dataset.

studies. The success of machine learning technology in mental health screening among them can be widened to encompass other working populations in the country. This technology might be useful for other population screening of mental health illness, as well as screening of other non-communicable diseases. State-of-the-art machine learning algorithms like deep learning can be tested for applicability in this perspective. Deep learning architectures in image processing can be applied to detect mental health problems from facial expressions also. Sociodemographic, occupational profile, medical records and facial expression of sailors over the period captured by photography can be coupled with magnetic resonance imaging of the brain, and used for development of a more accurate screening tool. In that case, the volume of data will be quite large, and it may be applied in deep learning algorithms. For that purpose, research is necessary in the field of digital health technologies for mental health screening. Thus, investigators from both medical and computer engineering fields are needed to collaborate in order to achieve the targets set by SDGs #3 with respect to non-communicable diseases and mental health disorders.

Conflicts of interest

Authors declare that, there is no potential Conflict of Interest relating to this article. The authors received no external funding for this research work.

Authors contributions

Dr. A. Sau formulated the concept, designed the research framework and interviewed the seafarers. Dr. A. Sau and I. Bhakta analysed the data, compared different machine learning algorithms in Python (Jupyter Notebook), and wrote the manuscript. Both authors approved the manuscript prior to submission.

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