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Predicting mental illness at workplace using machine learning

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KEYWORDS

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ABSTRACT

Mental illness (MI) is a leading cause of workplace absenteeism that often goes unrecognized and untreated. This paper presents a machine learning algorithm for predicting MI at workplace. The dataset consisted of responses from 1259 subjects collected through an online survey using a self-assessed questionnaire on the workplace environment. The responses were used as features for training a support vector machine to predict MI. Statistical analysis using the Guttmann correlation and the analysis of variance was done to determine feature significance. Results using 10-fold cross-validation showed that the model predicted MI with good accuracy. Findings support the feasibility of this approach for MI monitoring at the workplace as it offers an advantage over other technologies e.g., MRI scans, and EEG analysis, previously developed for the objective assessment of MI.

1. Introduction

The American Psychiatric Association defines mental illness (MI) as a health condition that changes the normal behavior and emotions of a person and causes distress and abnormality in functioning at work, family, or social activities [1]. MI is characterized by the absence of mind, loss of concentration, hyperactivity, and unexpected behaviors [2]. It can be caused by an injury to the brain, abnormal development of the brain during birth, or pressure to perform well in academic studies or at the workplace. Some studies suggest that MI is heritable and psychiatric disorders such as attention deficit hyperactivity disorder (ADHD), schizophrenia, and depression have genetic roots [3]. Other causes of MI are ill-treatment and abusive behavior during adolescence. MI affects people during their prime working years and lasts for a lifetime if untreated [4]. If left untreated, the consequences of MI can be as costly as managing AIDS or heart disease. According to a survey [5], around 43.7 billion US dollars are lost due to absenteeism from work which is equal to over 200 million days of work lost per annum. Moreover, in the USA alone, nearly 19% of adults experience MI and around 4% of adults develop serious illness. Nevertheless, MI is treatable if identified, and once treated, most individuals can function normally in their daily lives.

Several methods were introduced to automatically classify MI using neuroimaging. Qureshi et al. [6] used cortical MRI data recorded from subjects having an attention-deficit-hyperactivity MI. A support vector machine (SVM) was trained using features extracted from 159 MRI images and was able to classify MI with an accuracy of 60.78%. Another study by Du et al. [7] proposed a set of features from the same dataset. These features were trained on a binary SVM, and the model was able to classify MI with an accuracy of 84%. In another study, Mohammadi et al. [8] proposed an approach for distinguishing between 30 healthy and 30 children with attention-deficit-hyperactivity-disorder MI using EEG. EEG Signals were recorded by placing electrodes on the scalp of children during cognitive activities. Features were extracted from EEG signals and used to train an artificial neural network. It was reported that children with MI were less accurate and slower in performing cognitive tasks. The model correctly identified MI with an accuracy of 93.65%.

Krishnaveni and Radhamani [9] proposed a cost-effective machine-learning model using Naïve Bayes and J48 classifiers for MI. They designed a sample questionnaire that focused on the behavioral and medical characteristics of school children aged between 5-9 years. A MI dataset was created using 105 data samples and 30 different attributes. Their model produced an accuracy of up to 100% in classifying the MI samples using J48. Other methods [10] used wearables and smartphone sensors for characterizing mental disorders such as depression using motor activity signals. Statistical features were extracted from the signals from a total of 55 samples recorded from 23 depressed subjects and 32 healthy controls and used to train a random forest classifier. Depressive subjects were identified with a sensitivity of 0.867.

Studies to identify MI using neuroimaging reported promising results [6-8]. However, since the imaging equipment is expensive, and data acquisition requires visiting medical facilities, therefore sample sizes used in these studies tend to be small. Also, the survey-based [9] and sensor-based [10] methods to classify MI used small datasets, i.e., 105 and 55 samples respectively for model development and analysis. Hence, the validation of these methods requires a large and diverse cohort of data. Additionally, interpretations of neuroimages are performed by a clinician. These interpretations are subjective and can vary based on the knowledge and perception of the clinician.

This paper proposes a machine learning scheme that predicts MI based on a self-assessed questionnaire survey that was conducted to understand the predictors of MI at the workplace. Our study was performed on a large cohort of 1259 sample points collected from respondents around the world having diverse cultural and employment backgrounds. We demonstrated that the general attributes of the workplace affect the mental health of employees.

2. Method

2.1 Data

The survey on ‘Mental Health in Tech Workplace’ [11] was designed and conducted by Open Sourcing Mental Illness (OSMI) Corporation in 2014. The dataset consisted of survey questions given in Table 1. There were a total of 1259 respondents to the survey. Ethical consent was obtained from the respondents for data sharing and publication. For method development, first, we digitized responses to survey questions such that a Boolean response Yes / No was quantified to 1 / 0. Responses that include Yes / No / Some of them, Yes / No / Maybe, or Yes / No / Not Sure, were quantified to 1 / 0/ -1. Responses that include Do not know / Very easy / Somewhat easy / Somewhat difficult / Very difficult, or, Not Applicable / Never / Rarely / Sometimes / Often, were quantified to a rank-order Likert scale of -1 / 0 / 1 / 2 / 3, respectively.

In the absence of an expert’s opinion on the mental health of respondents, responses to questions Q7 on treatment and Q8 on work interference served as the ground truth of a respondent’s mental health (Table 1). In response to Q7 on treatment, 622 respondents answered a ‘No’, and 637 respondents answered a ‘Yes’, which implies that the dataset was well balanced for training a model to discriminate between mentally ill and healthy respondents. The questions with a nominal response such as ‘1) Age’, ‘3) Country’, and ‘4) State’ were excluded and responses of the rest of the 20 questions were used as training features. Two different SVMs were trained using responses of Q7 and Q8 respectively as targets to characterize MI. Further, a statistical analysis of features was done to identify MI predictors.

Table 1

Survey on Mental Health in Tech Workplace

Number	Question	Response Options
Q1. Age	-	Any number
Q2. Gender	-	Male / Female / Transgender
Q3. Country	-	Name of country
Q4. State	If you live in the United States, which state or territory do you live in?	Name of state
Q5. Self-employed	Are you self-employed?	Yes / No
Q6. Family history	Do you have a family history of mental illness?	Yes / No
Q7. Treatment	Have you sought treatment for a mental health condition?	Yes / No
Q8. Work interference	If you have a mental health condition, do you feel that it interferes with your work?	Not Applicable / Never / Rarely / Sometimes / Often
Q9. No. of employees	How many employees does your company or organization have?	1-5 / 6-25 / 26-100 / 100-500 / 500-1000 / >1000
Q10. Remote work	Do you work remotely (outside of an office) at least 50% of the time?	Yes / No
Q11. Tech company	Is your employer primarily a tech company/organization?	Yes / No
Q12. Benefits	Does your employer provide mental health benefits?	Yes / No / Do not know
Q13. Care options	Have you been informed of the care options for mental health that your employer provides?	Yes / No / Not sure
Q14. Wellness program	Did your employer discuss mental health as part of a wellness program?	Yes / No / Do not know
Q15. Seek help	Does your employer provide information about mental health and ways to seek help?	Yes / No / Do not know
Q16. Anonymity	Is your anonymity protected if you use treatment resources for mental health or substance abuse?	Yes / No / Do not know
Q17. Leave	Is it easy for you to take medical leave for a mental health condition?	Do not know / Very easy / Somewhat easy / Somewhat difficult / Very difficult
Q18. Mental health consequence	Do you think that discussing a mental health issue with your employer would have negative consequences?	Yes / No / Maybe
Q19. Physical health consequence	Do you think that discussing a physical health issue with your employer would have negative consequences?	Yes / No / Maybe
Q20. Co-workers	Would you be willing to discuss a mental health issue with your co-workers?	Yes / No / Some of them
Q21. Supervisor	Would you discuss a mental health issue with your supervisor(s)?	Yes / No / Some of them
Q22. Mental health interview	Would you discuss a mental health issue in an interview with a potential employer?	Yes / No / Maybe
Q23. Physical health interview	Would you discuss a physical health issue in an interview with a potential employer?	Yes / No / Maybe
Q24. Mental vs. physical	Do you feel that your employer takes mental health seriously as compared to physical health?	Yes / No
Q25. Observed consequence	Have you observed or heard negative consequences for co-workers with mental health conditions?	Yes / No

2.2 Feature selection

A feature selection algorithm was used to choose significant features for training the model. The distributions of feature values were non-gaussian. Therefore, a Kruskal-Wallis (KW) [12] median rank test was used for the nonparametric analysis of features. The KW test compares rank-order medians of two groups to reject the null hypothesis that two groups, having a continuous distribution of samples, have equal medians. The test returns a statistical significance p-value within a 95% confidence interval (CI) based on acceptance or rejection of the null hypothesis. This means that a feature producing p-value < 0.05 discriminates target groups significantly.

We divided the feature values between target groups, i.e., groups 0 and 1 for treatment, and groups -1, 0, 1, 2, and 3 for work interference. The test was performed separately for each feature against treatment and work interference, respectively. Rank order medians were compared between each group to obtain a p-value. Results are given in section 3.1.

Selected features were used to train two SVMs to classify MI based on treatment and work interference. To further optimize the model, a minimal set of features that produced the highest classification accuracy was obtained using a sequential feature elimination algorithm. This was done by keeping a p-value ≤ 0.1 as a threshold. The set of features that qualify the threshold was used for training the SVM. In each subsequent round, the threshold was divided by 10. The process was repeated until a minimum number of features is obtained for training.

2.3 Classification

SVM discriminates classes by using support vectors that lie at the edge of class domains over a feature space [13]. The benefits of using SVM over other classifiers are that 1) The SVM solution to find the optimal location of hyperplanes has a single minimum that prevents the model from producing sub-optimal solutions. 2) The SVM does not overtrain if the training compounds relate to the property of interest. In our case, the feature selection algorithm assures the selection of relevant features for training.

A binary SVM was trained to classify MI based on work interference. Responses of work interference were binarized by merging classes '-1' (Not applicable), '0' (Never), and '1' (Rarely) into a new class '0'. Also, classes '2' (Sometimes) and '3' (Often) were combined into a new class '1'. The sample size was 650 and 609 for classes '0' and '1' respectively. A matrix of 14 (features selected in the first round) x 1259 (samples) was used to train the SVM to discriminate between classes '0' and '1' using a sequential minimum optimization algorithm [13] and a radial basis function kernel. 10-fold cross-validation (CV) was used to validate the model. The sequential feature elimination algorithm was used to produce optimal results. Further, we performed SVM hyperparameter tuning using Bayesian optimization [14] to yield minimum classification error over 100 iterations and 10-fold cross-validation. The model that produced the highest classification accuracy was analyzed using the confusion matrix and area under the ROC curves. The results are discussed in section 3.2.

The second binary SVM was trained to classify MI based on treatment using a matrix of 15 (features selected in the first round) x 1259 (samples) to discriminate between classes '0' (No) and '1'(Yes) with the same configuration as in the first experiment. Bayesian optimization was used to tune SVM hyperparameters over 100 iterations and 10-fold cross-validation to obtain optimal performance. The best model was analyzed using the confusion matrix and ROC curves. Results are given in section 3.3.

2.4 Statistical analysis

Statistical surveys that are designed employing structured interviews and have items having binary responses (Yes/No) represent a Guttmann scale if the binary responses can be ranked in order so that the response pattern can be captured using a single index on that ordered scale [15]. In the OSMI dataset, the variable treatment has binary responses (Yes/No). On the other hand, the variable work interference represents an ordered Likert scale such that if an index of the MI frequency interfering work is selected by an individual between -1 and 3, for instance, 2 ('rarely'), the individual would agree that -1, 0 and 1 are the items of the lower frequency. Hence the binary responses (Yes/No) of variable treatment and rank-order responses of variable work interference can be correlated using the Guttman correlation coefficient μ2. The μ2 between treatment and work interference has a value of 0.909 (Table 3), suggesting that the two variables have a near-perfect positive correlation with a statistical significance p-value<0. This suggests that the two variables are redundant. To avoid bias, the two variables were used separately as targets for model development.

We used μ2 to correlate between feature sets that produced optimal classification performance, and MI representative variables, treatment, and work interference. Bootstrapping was used to stratify the data to generate reliable correlation estimates [16]. Further analysis of these features was performed using the analysis of variance (ANOVA) [17]. Results are presented in section 3.4.

3. Results

3.1 Feature selection

The KW test produced the lowest p-values (<0.01) for 'Family history' against treatment and work interference (Table 2). Other variables that produced significant p-values (<0.05) were 'Gender', 'Anonymity', 'Benefits', 'Care options', 'Leave', 'Mental health consequence', 'Mental health interview', 'Mental vs. physical', 'Observed consequence', 'Seek help' and 'Wellness program'

Table 2

Statistical significance of features using the Kruskal-Wallis test. Features are sorted in terms of their significance from the lowest p-value to the highest against a) Work interference and b) Treatment. Bold represents statistical significance (p-value < 0.05).

	a. Work interference		b. Treatment	
No.	Feature	p-value	Feature	p-value
1	Family history	**8.81E-32**	Family history	**5.72E-41**
2	Mental health consequence	**7.09E-13**	Care options	**2.75E-21**
3	Leave	**1.19E-12**	Benefits	**8.54E-15**
4	Observed consequence	**6.94E-11**	Gender	**5.67E-12**
5	Care options	**8.13E-11**	Observed consequence	**2.58E-08**
6	Mental vs physical	**2.76E-07**	Anonymity	**1.85E-06**
7	Gender	**3.65E-06**	Leave	**5.08E-06**
8	Benefits	**5.47E-06**	Mental health consequence	**1.43E-05**
9	Wellness program	**0.0001**	Mental vs physical	**0.0001**
10	Seek help	**0.0001**	Mental health interview	**0.0017**
11	Anonymity	**0.0016**	Wellness program	**0.0032**
12	No. of employees	**0.001**	Seek help	**0.0042**
13	Physical health consequence	**0.0035**	Coworkers	**0.0498**
14	Self-employed	**0.0043**	Physical health interview	0.1829
15	Mental health interview	**0.0086**	Physical health consequence	0.1856
16	Supervisor	**0.0114**	Tech company	0.2635
17	Remote work	0.3324	Supervisor	0.4222
18	Physical health interview	0.3449	Self-employed	0.7677
19	Tech company	0.7236	No. of employees	0.1191
20	Coworkers	0.8382	Remote work	0.91

3.2 Classification of MI based on work interference

The SVM performance to classify MI based on work interference is shown in Fig. 1. In the first round of feature elimination, a classification accuracy of 58% was produced by the SVM. As the number of features reduced in the subsequent rounds, the classification accuracy reduced until only one training feature ('Family history') was used for training. The SVM produced the highest average classification accuracy of 65% using 'Family history' and 10-fold cross-validation. The sensitivity and specificity were 75% and 54% respectively.

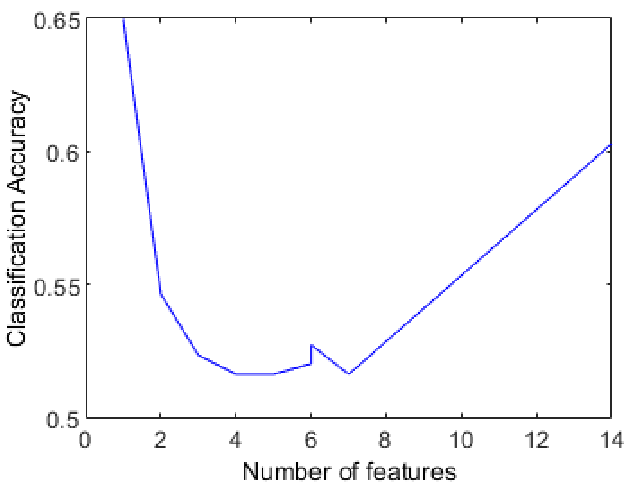
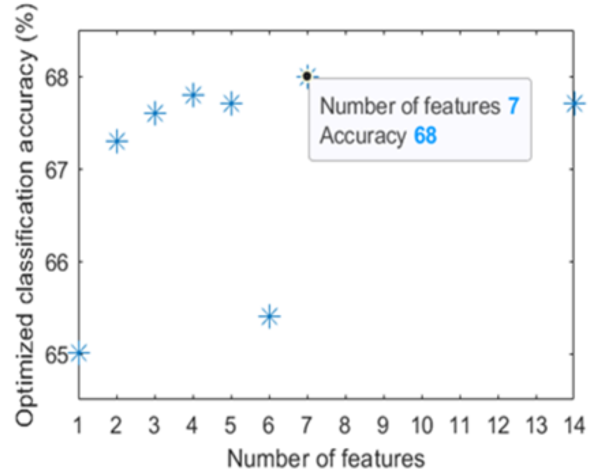
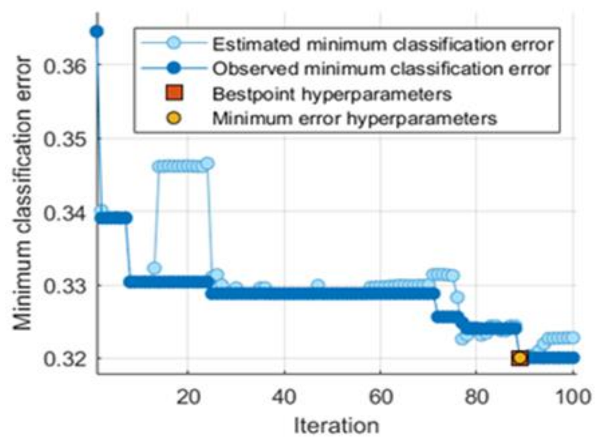


Fig. 1. SVM classification of MI based on work interference. The highest average classification accuracy of 65% with a sensitivity of 75% was produced by the feature 'Family history' in a 10-fold cross-validation

The results of the Bayesian optimization of SVM hyperparameters are shown in Fig. 2. The SVM and 'Family history' produced an optimal classification accuracy of 65%. However, accuracies improved when other feature sets were used to train SVM with an optimized setting of hyperparameters. A set of seven features produced an overall accuracy of 68% (Fig. 2a) with a minimum error of 0.32 at the 89^{th} iteration (Fig. 2b). These features were 'Gender', 'Care options', 'Family history', 'Leave', 'Mental health consequence', 'Mental vs physical', and 'Observed consequence'. The confusion matrix of this model produced a sensitivity of 67.2% and a specificity of 68.8% (Fig. 2c). Also, the AUC to classify MI was 71% (Fig. 2d).



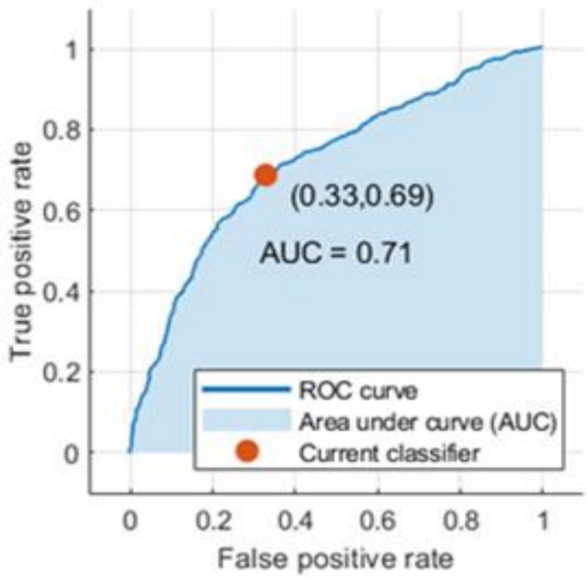
a. Optimized classification accuracies produced by selected feature sets



b. Minimum error estimation using the optimal model

		Predicted class	
		Healthy	Mentally ill
True class	Healthy	447 (68.8%)	203 (31.2%)
True class	Mentally ill	200 (32.8%)	409 (67.2%)

c. Confusion matrix



d. Receiver operating characteristic curve

Fig. 2. SVM hyperparameter tuning for classification of MI based on work interference

3.3 Classification of MI based on treatment

The SVM classification of MI based on treatment is shown in Fig. 3. The classification accuracies reduce in the subsequent feature elimination rounds until only one variable 'Family history' was used for training. The model produced an average classification accuracy of 68% with high sensitivity (80%) of characterizing MI in a 10-fold cross-validation.

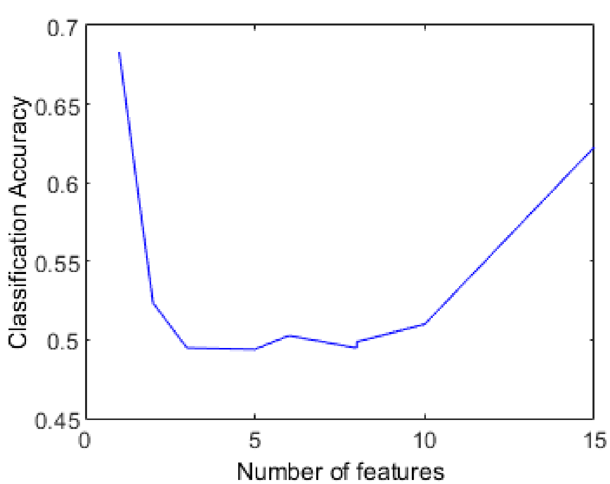
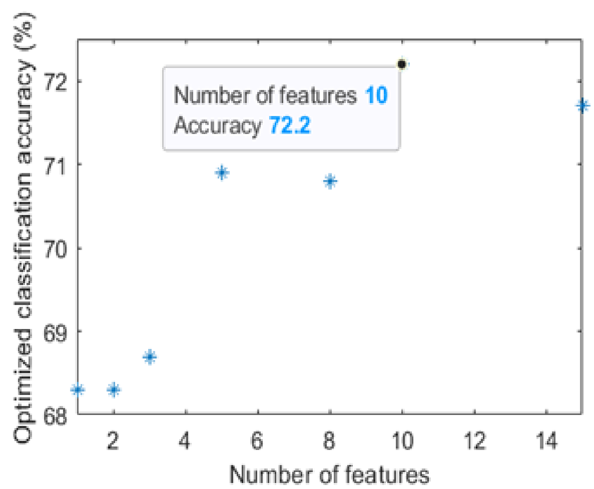
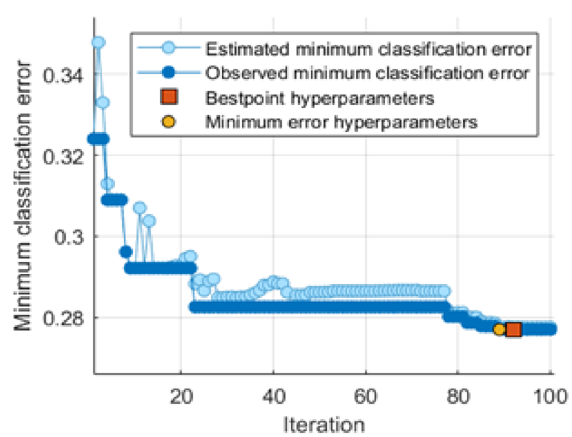


Fig. 3. SVM classification of MI based on treatment. The highest average classification accuracy of 68% with a sensitivity of 80% was produced by the feature 'Family history' in 10-fold cross-validation

The results of the Bayesian optimization of SVM hyperparameters are shown in Fig. 4. The SVM and 'Family history' produced a classification accuracy of 68%. However, accuracies improved when other feature sets were used to train SVM with an optimized setting of hyperparameters. A set of ten features produced an overall accuracy of 72.2% (Fig. 4a) with a minimum error of 0.28 at the 89th iteration (Fig. 4b). These ten features were 'Gender', 'Benefits', 'Care options', 'Family history', 'Leave', 'Mental health consequence', 'Mental vs physical', 'observed consequence', 'Seek help', and 'Wellness program'. The confusion matrix of this model produced a sensitivity of 72.7% and a specificity of 71.7% (Fig. 4c). Also, the AUC to classify MI was 77% (Fig. 4d).



a. Optimized classification accuracies produced by selected feature sets

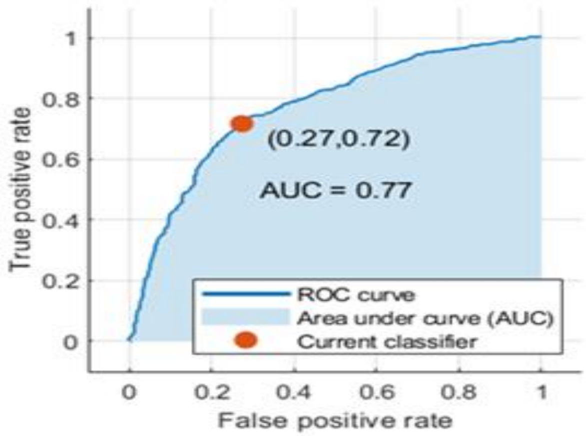


b. Minimum error estimation using the optimal model

Predicted class

True class		Healthy	Mentally ill
	Healthy	446 (71.7%)	176 (28.3%)
	Mentally ill	174 (27.3%)	463 (72.7%)

c. Confusion matrix



d. Receiver operating characteristic curve

Fig. 4. SVM hyperparameter tuning for classification of MI based on treatment

3.4 Statistical analysis

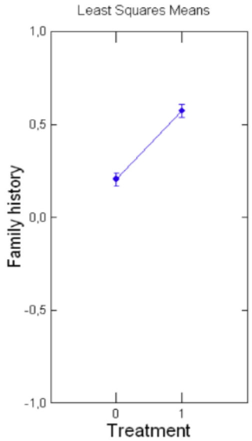
Bootstrap estimates of $\mu2$ for selected features are given in Table 3. ‘Family history’ showed the strongest correlation with MI based on treatment ($\mu2=0.631$) and work interference ($\mu2=0.528$). ‘Gender’ showed a negative moderate correlation with MI. ‘Benefits’, ‘care options’, ‘Leave’, and ‘Observed consequence’, were moderately correlated with MI.

ANOVA of selected features is shown in Fig. 5. The least-square means of features ‘Family history’, ‘Care options’, ‘Gender’, ‘observed consequence’, and ‘Leave’ were significantly different (p-value<0.05, 95% CI) across target groups both for treatment and work interference (Fig. 5a and 5b). ‘Benefits’, ‘Mental vs physical’, ‘Seek help’, and ‘Wellness program’ produced least-square means that were significantly different across treatment groups. However, the least-square means of ‘Mental health consequence’ were not significantly different across treatment groups. Similarly, the least-square means of ‘Mental vs. physical were not significantly different across work interference groups.

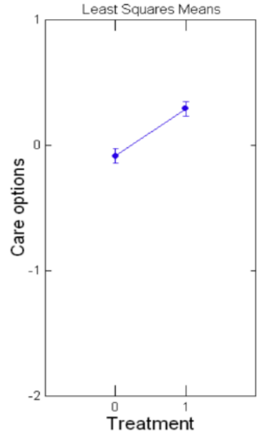
Table 3

Bootstrap estimates of Guttman correlation coefficient μ2. Bold represents moderate, and italics represent a strong correlation between a feature and MI, respectively.

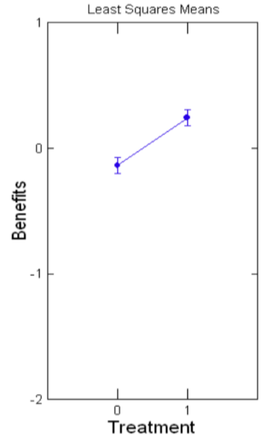
Features	Gender	Benefits	Care options	Family history	Leave	Mental health consequence	Mental vs physical	Observed consequence	Seek help	Wellness program	Treatment	Work interference
Gender	1											
Benefits	-0,13	1										
Care options	-0,032	0,67	1									
Family history	-0,202	0,233	0,236	1								
Leave	0,179	0,091	0,192	0,055	1							
Mental health consequence	0,111	-0,016	0,108	0,058	0,331	1						
Mental vs physical	0,109	0,257	0,278	0,07	0,268	0,207	1					
Observed consequence	-0,028	0,149	0,198	0,327	0,44	0,233	0,052	1				
Seek help	0,04	0,581	0,531	0,048	0,242	0,149	0,285	0,264	1			
Wellness program	0,12	0,557	0,531	0,081	0,09	0,141	0,179	0,224	0,681	1		
Treatment	**-0,353**	**0,405**	**0,383**	***0,631***	**0,327**	0,02	0,055	**0,416**	0,104	0,134	1	
Work interference	-0,21	0,212	**0,324**	***0,528***	**0,37**	0,133	0,098	**0,377**	0,123	0,147	0,909	1



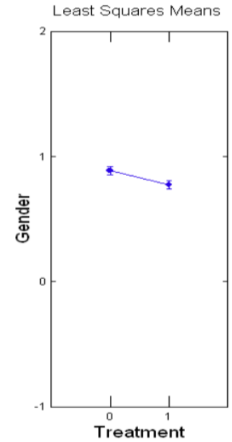
i. ‘Family history’
(**p-value = 0**)



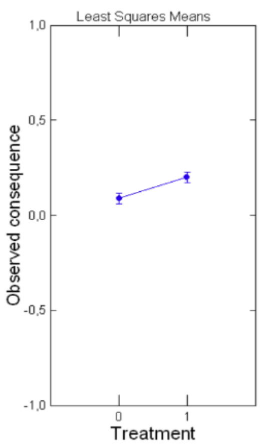
ii. ‘Care options’
(**p-value = 0**)



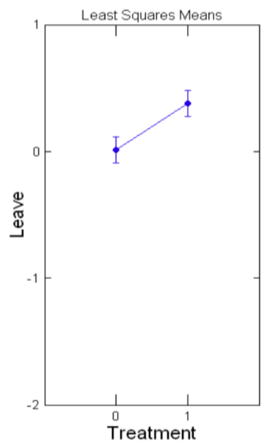
iii. ‘Benefits’
(**p-value = 0**)



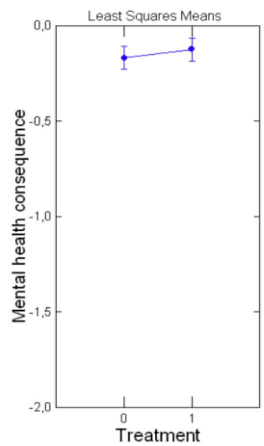
iv. ‘Gender’
(p-value = 0)



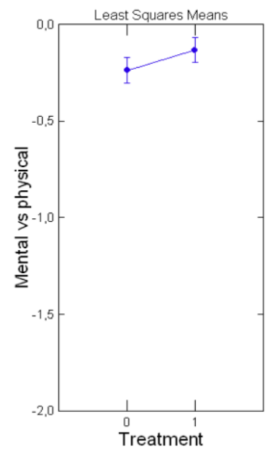
v. ‘Observed consequence’
(p-value = 0)



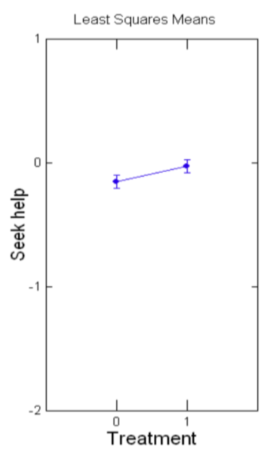
vi. ‘Leave’
(p-value = 0)



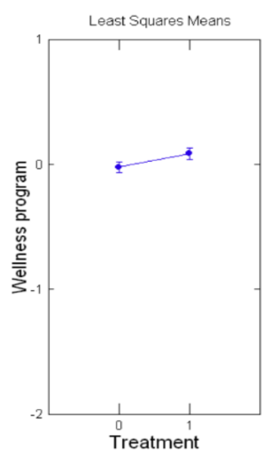
vii. ‘Mental health consequence’
(p-value = 0.28)



viii. Mental vs physical
(p-value = 0.026)

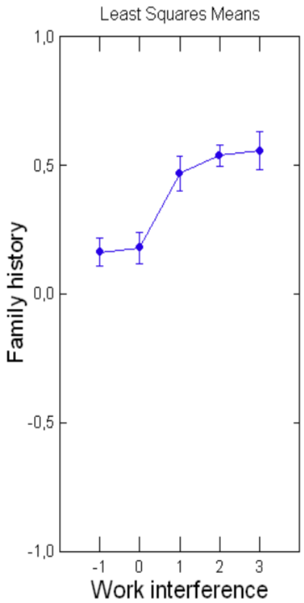


ix. ‘Seek help’
(p-value = 0.001)

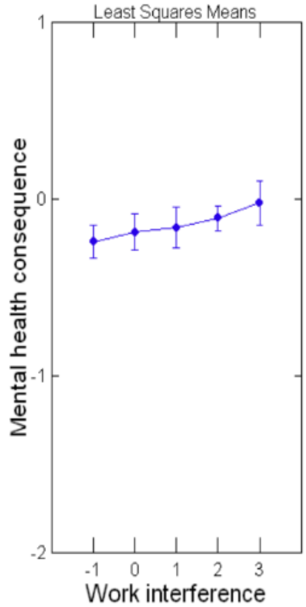


x. ‘Wellness program’
(p-value = 0.001)

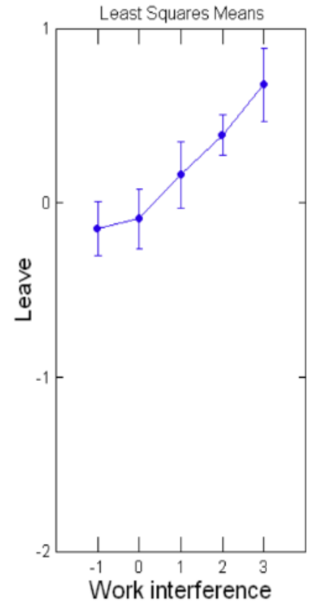
a. Least-square means of selected features across treatment groups ‘0’ (no treatment) and ‘1’ (sought treatment)



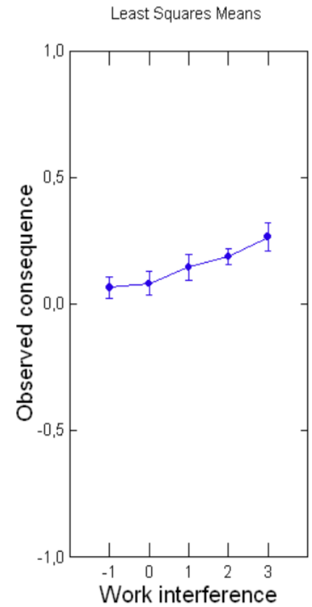
i. 'Family history' (**p-value** = **0**)



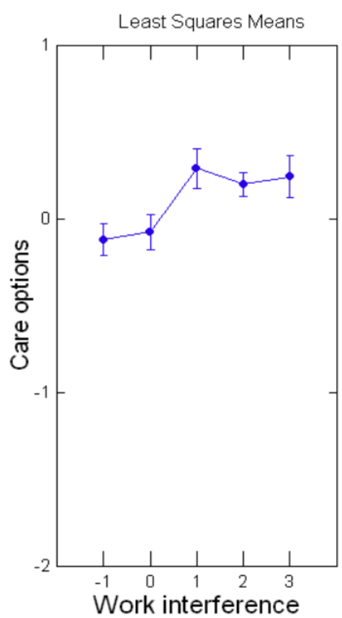
ii. 'Mental health consequence' (**p-value = 0.043**)



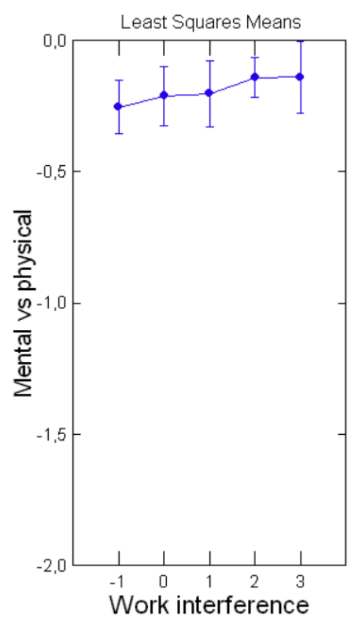
iii. 'Leave' (**p-value = 0**)



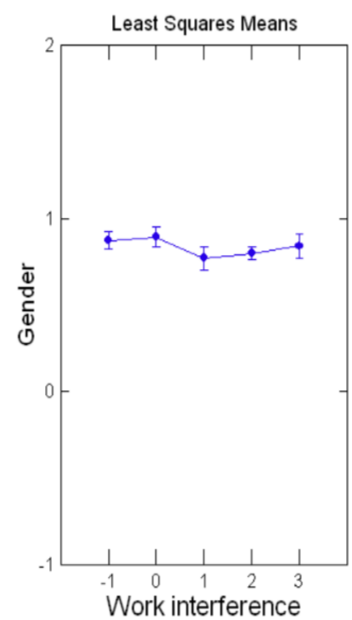
iv. 'Observed consequence' **(p-value = 0)**



vi. 'Care options' **(p-value = 0)**



vii. 'Mental vs physical' (p-value = 0.44)



viii. 'Gender' **(p-value = 0.012)**

b. Least square means of selected features across work interference groups '-1' (Not Applicable), '0' (Never), '1' (Rarely), '2' (Sometimes), and '3' (Often)

Fig. 5. ANOVA of selected features. Bold represents significantly (p-value<0.05; 95% CI) different group means

4. Discussion

This research used an online survey to investigate the predictors of MI at workplace. Survey responses were used as features to train SVMs for predicting MI using a sequential feature elimination algorithm. In the absence of an expert's opinion on the mental health of respondents, responses to Q7: if the respondent has sought medical treatment for MI, and Q8: the frequency of work interference at the workplace due to MI, were used as ground truth for method validation. Importantly, behavioral changes of an employee at the workplace can be best reported and rated by an employee himself who experiences symptoms of MI such as an absence of mind or loss of concentration, which is unnoticed by peers. Hence the two questions, Q7 and Q8, allow for gathering reliable estimates of MI that could be used as ground truth for method development and evaluation.

A comparative analysis of features and results from the sequential feature elimination algorithm revealed that 'Family history' is the most significant feature that could accurately predict MI with high sensitivity. This is in line with previous literature that established an association between the cognitive impairment of individuals and their family history of mental disorders [18]. To date, there is no evidence of how MI passes on in families. One study [19] suggested that people with MI arouse anxiety and fear among their family members. They surveyed Jaroslaw county in Poland from January and March 2019 and found that 66% of the respondents felt significant stress from having a mentally sick member in their family. According to these respondents, every psychiatric event was a traumatic experience for them.

Tools for screening family psychiatric history at the workplace can help in identifying employees who are susceptible to MI. Weissman, et al. [20] showed that a brief screening of family history that takes 5 to 20 minutes to collect psychiatric information of first-degree relatives anonymously, is a valid tool for screening for MI such as depression, anxiety, alcohol addiction, or suicidal thoughts.

Statistical analysis based on ANOVA, KW test, and Guttman correlation suggests that employers who do not provide mental health benefits (Q12), care options (Q13), wellness programs (Q14), information on seeking help (Q15), and sick leave to employees (Q17), instigate MI at the workplace. It is therefore important for employers to show flexibility in discussing mental health issues with their employees (Q18 and Q24).

Other important findings from statistical analysis were, that women have a higher tendency to develop MI at the workplace (Q2) which is in line with the World Health Organization report 2020 [21], that women predominate men in the rates of common mental disorders such as anxiety and depression. This may be due to gender bias, socioeconomic disadvantages, sexual violence, inequality of income, subordinate position, rank, etc. [22].

The KW test and ANOVA of 'Observed consequences' (Q25) revealed that group means were significantly different (p-value < 0.05) between work interference levels and treatment groups, respectively. The Guttman correlation was strong between this feature and MI. Importantly, the feature contributed to the SVM classification of MI. This suggests that the observed negative consequences of revealing MI by coworkers, and discrimination on the part of employers, have a strong impact on the mental health of employees at the workplace. Findings raise an ethical concern about whether mental health should be concealed. However, concealment is accompanied by psychological disadvantages and legal consequences [23]. According to a survey by the UK National Labor Force [24], people who developed MI were forced to resign from their jobs, restricted promotions, or be denied a job due to their psychiatric history. Also, employers showed a stigmatizing attitude towards employees with MI, such as malicious gossip and social exclusion. Hence, disclosure decisions are based on a supportive working environment that may help employees with MI to work effectively once their condition is revealed.

5. Conclusion and Future Work

In conclusion, the current framework allows the diagnosis of MI remotely and inexpensively using the proposed machine learning scheme and the response variables of the online survey. Importantly, the SVM model, optimized using a Bayesian optimization algorithm, was able to discriminate between healthy employees and employees having MI with high accuracy.

In the future, more questions relevant to MI can be explored and added to the survey for statistical analysis and model training. An expert psychiatrist's opinion is required to optimize model performance. Importantly, there is no gold standard available to date that characterizes MI. Hence, machine learning algorithms can be harnessed for an accurate prediction and assessment of MI that can be used as tools to monitor abnormal behaviors. Further, with a large data cohort, deep learning could be utilized to continue to improve the MI assessment. Moreover, longitudinal studies are needed to enable predicting MI onset and to produce a longitudinal picture of MI progression, which can be achieved at a reasonable cost using a survey-based machine learning approach. This will significantly help in identifying people with severe MI who are in danger of self-harm or suicide.

Conflict of interest

The authors declare no conflict of interest.

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