

Identifying psychological health status of employees of an organization by using feature selection and Machine learning techniques

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Submitted By:

Saurav Maan

(2K19/SWE/14)

Under the supervision of

Prof. Rahul Katarya

Department of Computer Science & Engineering



DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

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I, Saurav Maan, Roll No. 2K19/SWE/14 student of MTech Software Engineering, hereby declare that the project Dissertation titled "Identifying psychological health status of employees of an organization by using feature selection and Machine learning techniques". Which is submitted by me to the Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any degree, Diploma Associateship, Fellowship, or other similar title or recognition.

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Prof. Rahul Katarya

SUPERVISOR

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Saurav Maan

Saurav Maan

Roll No. 2K19/SWE/22

M.Tech (Software Engineering)

E-mail: sauravmaan67@gmail.com

ABSTRACT

Mental health has always been a major concern across the globe, but when it comes to the mental health of employees one way or another it is somehow neglected. Due to workload and short deadlines employees have always been under a great burden and thus more prone to mental health disorders. Poor mental health leads to degradation in employees performance and productivity. So in this project, we proposed a model to detect the mental health state of organization employees, and determine the key features affecting the mental health of employees using feature selection. We used randomized Hyperopt in conjunction with Xgboost to predict the mental health state of employees. Data used belongs to the year 2019 and 2020, where the year 2020 refers to the mental health state of employees during the coronavirus pandemic. A total of three datasets has been used to determine the mental health state of employees before and during novel coronavirus and a comparison is made to check the increase in the number of employees with mental health disorders during coronavirus. Feature selection is performed to determine the features affecting the mental health of employees during coronavirus. Randomized Hyperopt and Xgboost were found more effective in predicting the mental health state of employees than traditional machine learning algorithms during coronavirus. It was found to have an accuracy of 91% when predicting mental health disorders. In the 2019 dataset mental disorders are used to determine the mental health state of employees, where having a mental disorder refers to bad mental health. Whereas in the 2020 dataset or during covid-19 lockdown mental health fatigue rate of employees is used as a baseline to predict the mental health state of employees. A comparison with some machine learning techniques to determine how effectively the mental health state of employees is predicted.

Keywords: Hyperopt, Xgboost, Machine learning, MH, covid-19, and Roc.

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List of Abbreviations

MH: Mental health

WHO: World Health Organization

AUC: Area under the curve

GAD: General Anxiety Disorder

TPE: Tree structured parzen estimators

EI: Estimated improvement

CHAPTER 1

INTRODUCTION

Mental health has always been a challenging issue, especially for working professionals. Working under peer pressure, short deadlines are a few of the things contributing to the mental health of employees. According to a survey 40 million people which is 18% of the working population in the US suffers from mental health disorders. Neglecting the mental health of employees may cause industries to lose a fortune if not handled properly. In the year 2020 or during the coronavirus pandemic whole world population was under great panic and pressure over a long duration of time (months), which lead to a huge increase in the number of people with mental health disorders. When talking with or dealing with the aftermath of coronavirus mostly physical damage done by coronavirus has been taken into account whereas psychological impact caused by covid-19 is mostly neglected. It is to be noted that humans are social animals and need to communicate with others for a healthy lifestyle. But during covid-19 the harsh measures to deal with the spreading of covid-19 like lockdown and social distancing made it hard for people to communicate. Lockdown also leads to the loss of jobs for a large group of employees. Unemployment caused a lot of impact on the mental health of people, but we will only talk about employees still working during the covid-19 lockdown. Work from home has become the mainstay for employees during covid-19 also the working conditions have changed due to this, but one thing which remains the same is mental fatigue. We used mental fatigue as the baseline to determine the mental health state of employees during the covid-19 lockdown.

1.1 Mental health

Mental health refers to the psychological, social, and emotional well-being of a person. It affects in many ways and up to a certain extent determines how we think, act, and feel. Mental health does not simply mean being free from mental disorders or illness, it also means how we deal with daily life tasks and how we handle stress. Of course, someone faces a mental illness it affects how we thinking, mood. If a person is mentally healthy he can realize his full potential, deal with daily life stress, and contribute to society. Some simple ways to maintain mental health are keeping a positive attitude, remain physically active, communicating with others, getting enough sleep, not taking too much sleep, taking medical health in case necessary.

1.1.1. Mood disorder:

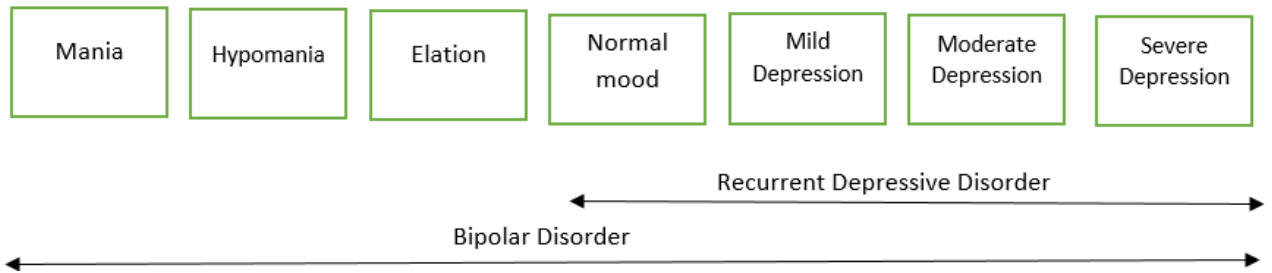


Fig.1.1. Mood disorder

A mood disorder is serious changes in mood in the form of emotional inconsistency or abrupt changes/ amplification of certain specific emotions, which can be feeling extremely sad or feeling irritable. When these mood changes start affecting our daily life performance we call them mood disorders. We can further classify them into mania, hypomania, depression disorder, and bipolar disorder as shown in the figure above. Depression after reaching a certain level start affecting our daily life like lack of interest in daily life, lack of motivation, not being able to meet goals, losing appetite. Suicidal tendencies are also normal if depression reaches a severe level, all this collectively is known as depressive disorder.

Mania is a form of overexcited or hyperactive state in which people are prone to taking risks due to bloated self-confidence or overconfidence. They get easily distracted and cannot sit still, have a hard time sleeping, and talk too much. One of these cases is talking about too many projects within a short deadline without thinking about the consequences. Whereas hypomania is like a milder version of mania and is less severe.

Bipolar disorder is the transition between mania and depression and is usually detected using mania and hypomania symptoms.

1.1.2. Anxiety disorder:

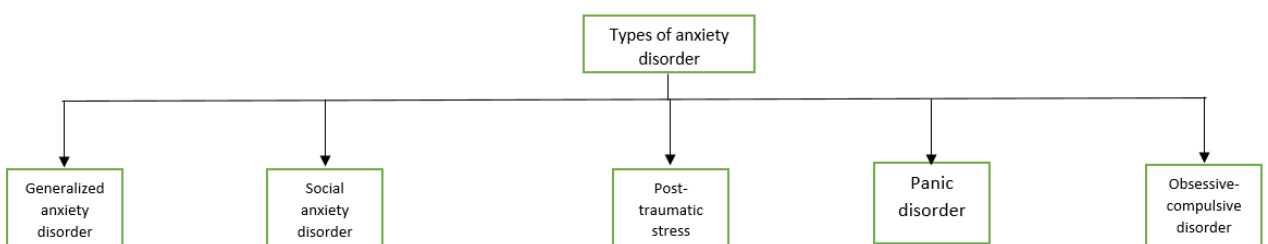


Fig.1.2. Anxiety disorder

Facing occasional anxiety during daily life is a common thing and it is helpful up to some

extent. Facing anxiety during some important events can help us perform better thus improving productivity. We don't have any control over these simple bursts of fear, but anxiety disorders are a different case. People with anxiety disorder shows severe signs of anxiety over simple day to day life events like exams, presentation, meeting with people are some events over which they can overact and show a higher degree of fear and tension. We can further classify anxiety disorders as shown in the diagram:

- **Generalized anxiety disorder**

It occurs when a person shows out of proportion worry about daily life events which does not demand that much attention. The person in question shows excessive anxiety even when not needed and cannot control his physical reactions. It generally occurs with other anxiety or expression disorders.

- **Panic disorder**

When a person repeatedly feels intense anxiety or terror/ fear which reaches to peak in few minutes also known as panic attacks. Shortness of breath, feeling of impending and heart palpitation are some symptoms of panic disorder. These are usually due to some events which happened in the past so to avoid the same kind of event happening again.

- **Social anxiety disorder (social phobia)**

Usually due to a persons lack of confidence in himself in which he or she feels embarrassed during social meetings and is afraid of how people see him or afraid of being judged by people. Introversion can be counted as the initial phase for social phobia.

- **Substance-induced anxiety disorder**

Usually caused by misuse of drugs or during withdrawal of drugs. The user faces intense anxiety or panic, which is the result of using drugs or toxic substances. Marijuana, caffeine, and some other hallucinogens like cocaine can cause anxiety disorders. Withdrawal from these sedatives, alcohol, and hypnotics can also lead to the development of different symptoms of anxiety disorder. All these are a part of substance substance-induced anxiety disorder.

- **Post-traumatic stress disorder**

Usually seen after a certain traumatic event encountered by a person, the event can be child abuse, warfare, sexual assault, traffic collision, domestic violence etc. Symptoms of PTSD include disturbing thoughts, dreams related to trauma, and trauma-related cues.

A person with PTSD has a higher tendency to suicide or self-harm and shows alteration in their behaviour.

1.1.3. Mental Fatigue:

As the name suggests it represents a lack of mental energy and makes people unusually tired and lethargic. Similar to physical fatigue in the early stages mental fatigue usually makes the employees lazy or tired but in later stages, it can cause some serious repercussions like stress, anxiety, depression, and even mental disorders becomes a possibility. Working over long hours and under short deadlines already makes employees more prone to mental health issues like stress, anxiety, and depression. The mental health of employees has always been a major concern for companies as it affects the productivity of employees. During lockdown due to indoor confinement and social distancing, we witnessed an increase in depression and suicidal tendencies. It is noted that loss of employment or financial burden is a bigger contributor to causing widespread panic and anxiety among people. Those still employed have to work under the extra pressure of facing sudden unemployment. Mental fatigue score is rated between 0-10, where 0 means no stress/fatigue and 10 means maximum fatigue or we can say on the verge of a breakdown. An employee with mental fatigue of equal or greater than 7 starts showing symptoms of general anxiety disorder.

CHAPTER 2

RELATED WORK

In this section, we have discussed some work that has already been done in this domain. Through analysis, we have found the key areas that are still lacking and have tried to overcome those shortcomings with our proposed model.

In [1] the author used HRV (Heart rate variability) to predict Bipolar disorders and used wearable sensors to take the input. In [2] the author used the random forest to predict the stress in employees and predicted stress with an accuracy of 75.13%. In [3] the author used ML algorithms and heart rate data to detect stress. He proposed taking heart rate data input after 5 minutes instead of continuous heart rate input to better predict the stress. In [4] the author predicted Generalized anxiety disorder among women using random forest. The author proposed that women are more prone to anxiety disorder than almost two times more prone. The author got an accuracy of 89% when predicting GAD. In [5] author developed an early warning system for bipolar disorder patients and used a smartphone-based system to measure the changes in bipolar disorder patients and provide timely assistance in case of emergency. In paper [6] author used a hybrid model of the logistic tree which is a combination of logistic regression and decision tree to predict Anxiety disorder. The author also proposed rules based on the personal life of participants to better predict the anxiety disorder, rules include working conditions (work from home or not), gym or not, and some other personal factors.

In [7] the author took stress, anxiety, and depression as factors in determining the mental health of people during covid-19. And conducted a cross-sectional survey on mental health during COVID. The author took people with different age groups into account and found that people with ages less than 35 are more prone to the psychological health impact of covid-19. Also, there is a huge increase in the number of people taking mental health treatment, which shows how severe is the impact of covid-19 psychological health of people.

In [8] the author analyzed how mental health affects the mortality rate of covid-19 patients. The author used 16 studies containing more than 600,000 responses to determine the mortality rate of covid-19 patients who have mental health disorders. The author proposed two models to determine the severity of impact mental disorders has on the mortality rate of covid-19 patients and found that patients with mental health disorders

have a higher mortality rate and severity than covid-19. It was proposed that people with mental disorders should be given priority during vaccination. In [9] author surveyed 600 college students to determine the behavioural and mood change of students due to novel coronavirus. The survey consists of three assessments which were used to determine the impact of coronavirus based on the completion rate of assessments.

In [10] the author addressed the issue of mental health deterioration during coronavirus in low-income countries. The author proposed two cheap methods to deal with the mental health impact of coronavirus. Which are task shifting and digital technologies, where digital technologies refer to the internet which is a lifesaver in such situations as it provides the option of free online self-guided behavioural therapy, also therapies can be conducted online (telehealth).

In [11] the author conducted a study on children and adolescents and their mental health during covid-19. Factors such as age, sex, school closing, covid-19 infection, and domestic violence are taken into account. Stress, anxiety, and depression symptoms are used to determine the mental health status of children (age 6-15) and adolescent(age 16-21).

In [12] the author conducted a study on the impact COVID-19 has on small and medium-sized enterprises. The author found that 80% of small-sized enterprises and 19% of medium-sized enterprises are closed, and 25% of self-employed businesses are shut down. Mostly due to lack of labour force or no demand of goods, thus affecting the economy.

In [13] author took 19 studies, which span across 8 countries are taken into account, which uses different factors to determine the mental health of people covid-19. Which takes into account both PTSD, stress, and anxiety. WHO – Five wellbeing index, beck anxiety inventory, and self-rating anxiety scale are the mainstream measures used to assess anxiety and depression levels. There was heterogeneity among studies making it hard for the author to make inferences also there was a certain gender bias present in some studies.

To determine the anxiety, stress, and depression during COVID-19 lockdown by monitoring the behavioural changes in people during the lockdown. The author used the data collected by research electronic data capture software from Ontario Canada. People above 16 years of age are taken into account. Past MH levels and MH treatments if any ongoing and dosages are taken into account. Adults with age group < 35 years are more prone to MH problems in comparison to older adults > 60 years age group. In addition, the female sex is more prone to MH problems. Factors taken into account are not comprehensive enough [14].

In [15] author did survey literature to find and minimize the economic impact of covid-19. The author proposed a few policies to minimize the impact based on 80 papers that shows the economic activity during the pandemic. The author took the stock market into account and found a global GDP decline of 4.9%. A combination of monetary policy, macroprudential policies, and fiscal policies are proposed to better mitigate the impact of COVID. In [16] author checks the MH of college students in China during covid-19, by correlating various factors such as economic status, daily life and academic activities. It was found that anxiety symptoms and academic activities are positively correlated. The author proposed the monitoring of college students mental health.

In [17] in order better facilitate the diagnosis of covid-19 author used both structured and unstructured data. From user-friendly AI platforms for physicians and researchers. A neural network is created using these inputs to better detection of covid-19 and thus helping in the treatment of covid-19. Deep learning techniques such as RNN, GAN, and ELM are used with some clinical and non-clinical datasets.

CHAPTER 3

Method Used

This section discusses the model as well as the implementation of our proposed model.

3.1 Architecture:

Figure 3.1 shows the architecture of randomized Hyperopt with xgboost.

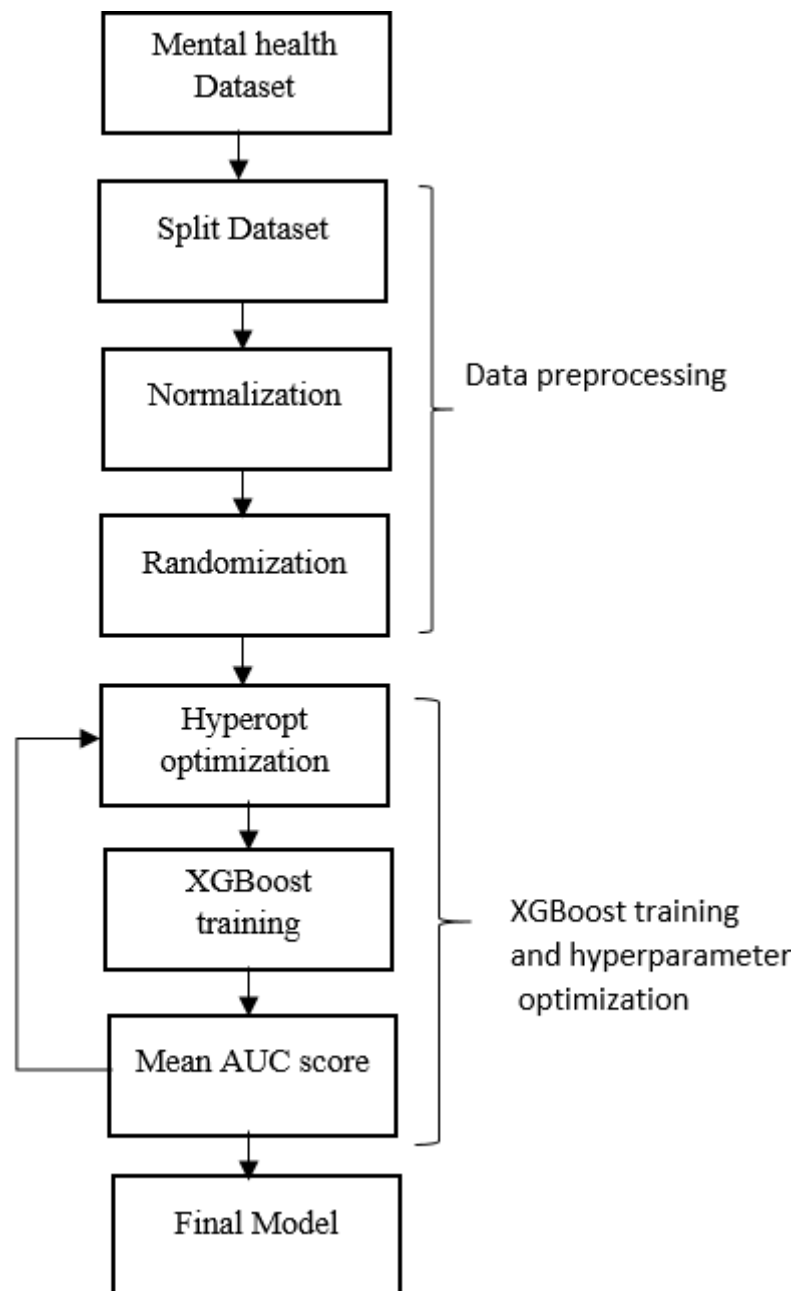


Fig. 3.1. Architecture

As shown in figure 3.1 the first step is to split the data into training data and testing data in a ratio of 7:3. Followed by training dataset and feature encoding which is part of data preprocessing. Training data is randomized before applying Hyperopt followed by Xgboost. All these will be explained next.

3.2 Xgboost

Xgboost also known as extreme gradient boosting is one of the best gradient boosting algorithms. It is a tree-based (sequential decision tree) algorithm and provides enhanced performance and speed. It was created by Chen and Guestrin in the year 2016, it is an open-source software initially it was only available in R and python now it is available in Java, Scala and other languages also. Xgboost is a combination of decision trees and ensemble learners. So let's start with the decision tree first:

Decision trees are a supervised learning technique that can be used for regression as well as classification.

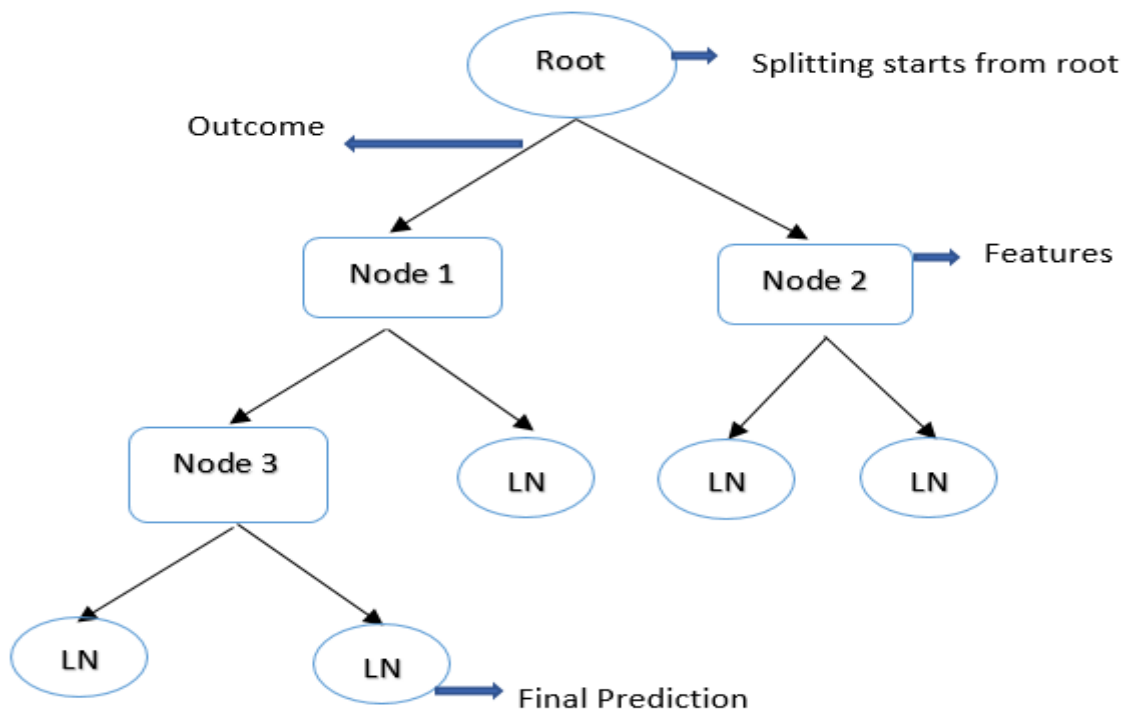


Fig.3.2 Decision tree structure

Splitting starts from the root node and a tree structure is created in which internal nodes of the tree represent the features in our dataset and the branches represent the possible values of these features. For example, if the feature in question is age and we have to

classify based on age less than 30 and greater or equal to 30. Then left branch will have values less than 30 and right values greater than and equal to 30. When splitting we try to maximize the information gain and keep we keep on splitting recursively until splitting no longer provides any information i.e. adding any value to prediction. The final value or prediction is provided by the leaf node. The time of computation keeps on increasing with the depth of the tree also decision tree is prone to error when classification is done on more than 2 classes and a small dataset.

3.3 Ensemble Learning

Ensemble learner as the name suggests it is a learner and the goal of learning is previous predictions. There are two types of ensemble learner bagging and boosting, as xgboost uses boosting we will only talk about the boosting. A general boosting technique increases the weight of the incorrectly classified predictions to reduce the bias error and get a better predictive model. However xgboost is a gradient boosting algorithms, and in gradient boosting algorithms instead of increasing the weight of wrongly predicted value we try to minimize the loss function.

Xgboost uses regression trees also known as weak learners to create a sequential learning process. Where the prediction of the last iteration is used to improve the current iteration our motive being the minimization of the loss function. Where loss function tells us how far is the difference between the predicted value and true value. All these are combined to get the final prediction such that bad predictions cancel out and better predictions sum up to form the final prediction.

3.4 Hyperopt

Hyperopt is a machine a Scikit machine learning library used for automation [12]. It performs an automatic search to find hyperparameters and its main task is to optimize the hyperparameter tuning process [13]. There are various methods for hyperparameter tuning like

- Manual search

The user sets the value of hyperparameters based on his or her domain knowledge.

- Grid search

A grid of values possible for hyperparameters are defined and each possible grid value is tested to determine the best combination of hyperparameter values.

- Random search

We select samples out of the distribution of values available for hyperparameters and check the performance of the model on that value to determine the most optimal hyperparameter values.

➤ Bayesian search

In this, we create a probabilistic model also known as the surrogate model represented by $P(y|x)$.

x = hyperparameter value

y = performance metrics

past iterations are used to improve the surrogate model until the maximum number of iterations is reached.

Hyperopt uses a modified version of Bayesian search. It builds the surrogate model using tree-structured parzen estimators (TPE) and expected improvement (EI) to improve the model.

Where,

➤ TPE (tree structured parzen estimators)

In TPE we use $P(x|y)$ instead of $P(y|x)$

$$P(x|y) = \begin{cases} f(x), & y < y' \\ n(x), & y \geq y' \end{cases} \quad (1)$$

Where y' is the threshold of y in performance metrics and $f(x)$ is the response after using x_i and $n(x)$ is the response when we use the rest of the observations. Here our main motive is to minimize the performance metrics. In our case, we are using confusion metrics and want to maximize the performance such as accuracy, precision, and recall. For that, we take the negative of the performance and then maximize it.

➤ EI (Expected Improvement)

It refers to the response of a model and for this response we expect it to exceed a certain threshold which is denoted y' negatively.

$$EI(x) = \left[\int_{-\infty}^{\infty} \max(y' - y, 0) pm(y|x) dy \right] \quad (2)$$

Here we try to maximize the response at x_i which is $f(x)$ and minimize the responses for the rest of the responses $n(x)$.

CHAPTER 4

EXPERIMENT AND RESULTS

4.1. Simulation Setup

Intel(R) Core i7 5th gen CPU@4.2 GHz, 8 GB RAM, 64-bit OS, and X64-based Processor are the requirements for the implementation configuration. The language of programming in python. Anaconda 3 is used.

4.2 Results for Kaggle dataset

The results for the proposed model, when applied to the Kaggle dataset (covid-19), are shown in figure 4.1. We found that KNN has the worst performance with 79% accuracy and randomized Hyperopt with xgboost has the best performance when predicting the mental health of employees during the covid-19 lockdown.

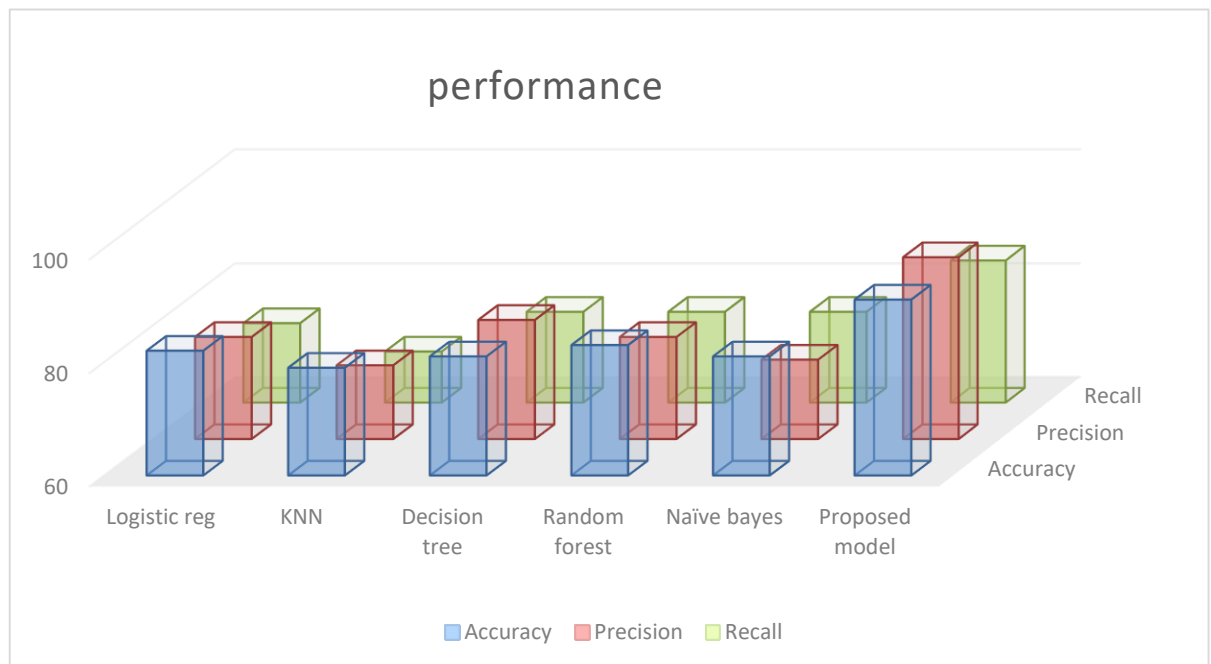


Fig.4.1 performance on Kaggle dataset

Figure 4.2 shows the AUC curve for the proposed model, and we can see the model has done a great job in predicting the mental health of employees during the covid-19 lockdown.

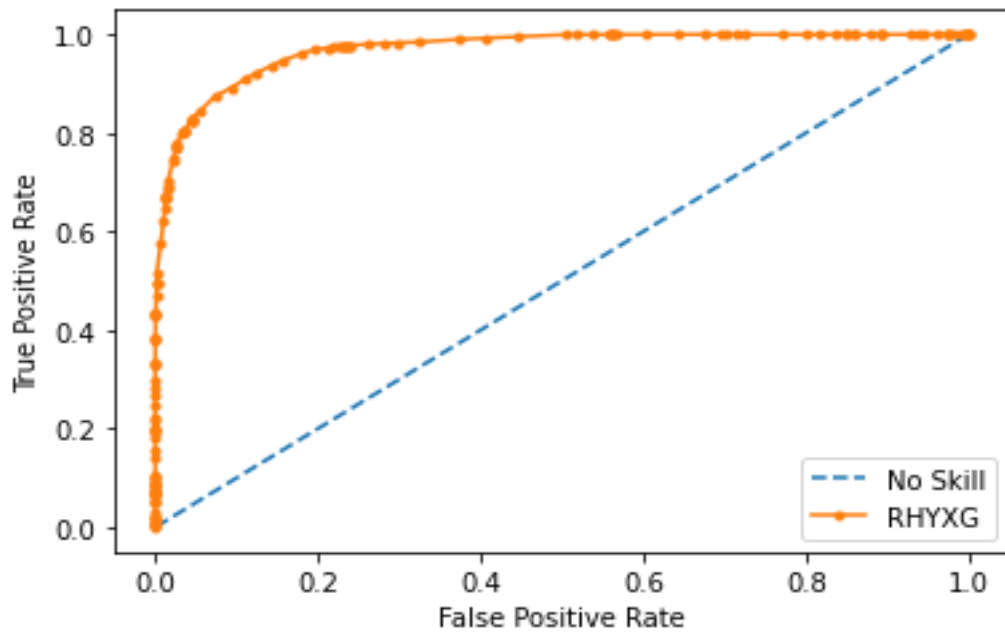


Fig. 4.2 AUC curve for Kaggle dataset

Figure 4.3 shows how much individual features are contributing to the prediction of the mental health state of employees during the covid-19 lockdown. And as we can see resources allocation contributes the most when predicting mental health state and company type has the least influence on MH state of the employees that is both employees from tech and non-tech companies are under great mental fatigue during covid-19. The designation is the second most important feature after resources and unlike the stereotype, the lowest designation means most mental fatigue it was found that employees with the medium designation are under the highest amount of stress during covid-19. The same was the case for resources allocated. For gender, it was found that men are under more mental stress during covid-19 lockdown

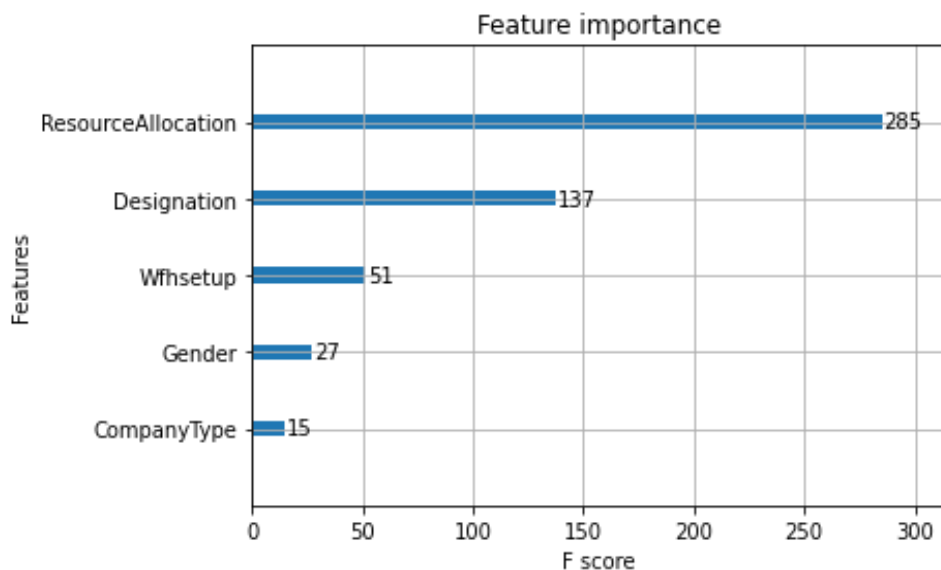


Fig. 4.3 Feature importance for Kaggle dataset

4.3 Results of OSMI dataset

Where OSMI means Open source mental illness which is a non-profit organization that contributes to the tech community by raising awareness about mental illness/ disorders. The motive of the organization is to create a better working environment for employees with mental disorders. Applying the proposed model to OSMI 2020 dataset we got the following results. Figure 7 shows the comparison of the Proposed model with different ML algorithms using confusion metric as the measure. We used precision and recall to check the performance of models.

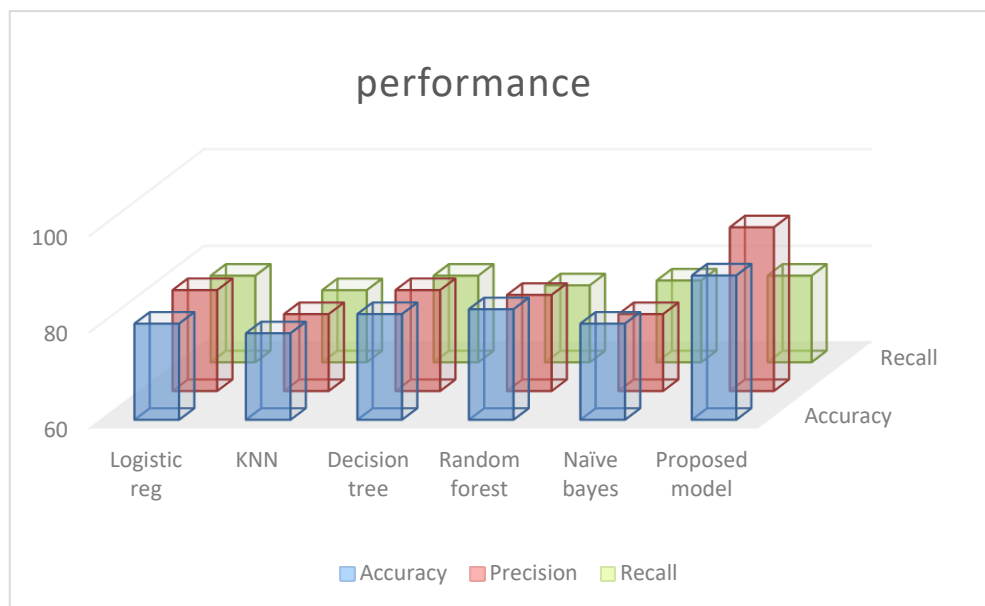


Fig. 4.4 performance on OSMI dataset 2020

We found that KNN has the worst performance with 78% accuracy and the proposed model has the highest accuracy of 90%.

Figure 4.5 shows the feature importance for the OSMI dataset. And as shown in figure 8 age contributes the most when predicting the mental health state of employees during the covid-19 lockdown. Followed by past which represents the history of mental illness if there is any for the employee in question. On third place is discuss which refers to discussion and support from the superiors in the organization (mental health benefits). Fourth is family, which refers to the mental illness in the family if there is any. On fifth is company type whether the company is tech or non-tech. The least contributing attribute was gender means both male and female employees are under pressure or stress during covid-19.

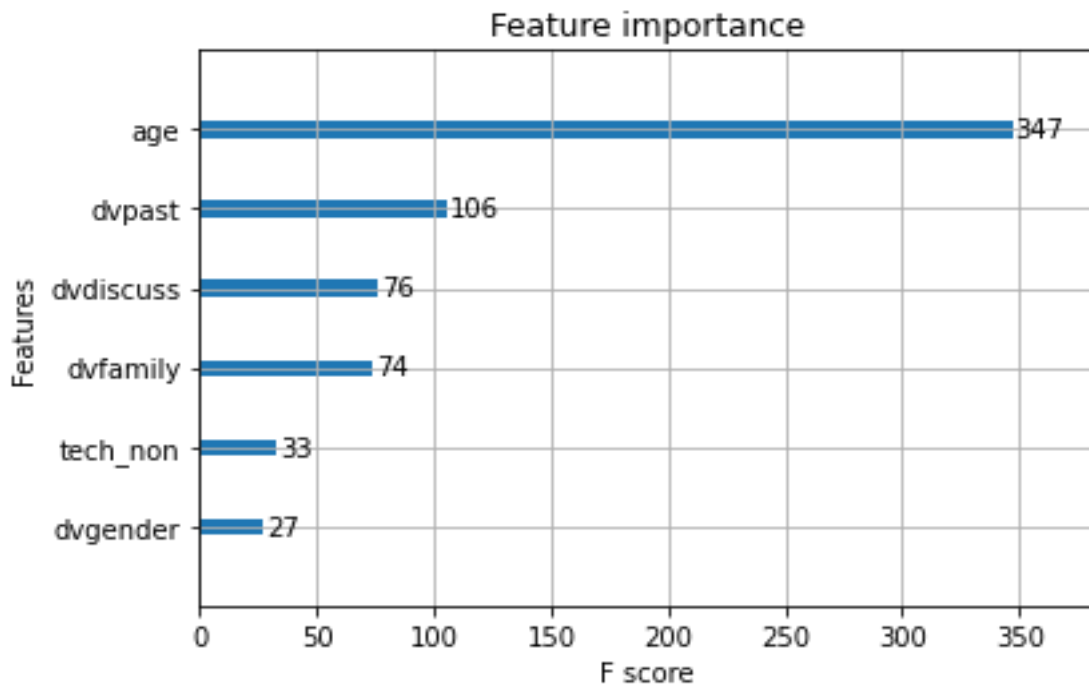


Fig. 4.5 Feature importance for OSMI dataset

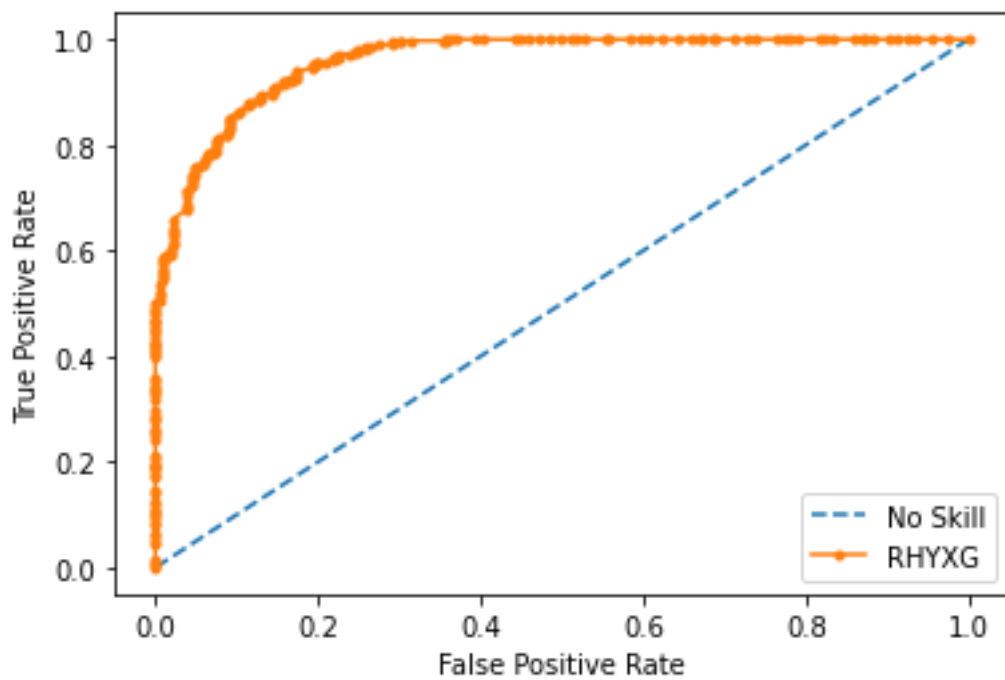


Fig. 4.6. AUC curve for OSMI2020 dataset for the proposed model

Figure 4.6 shows the AUC curve of the proposed model on the OSMI dataset and tells how well the model is working in predicting the mental health of employees.

4.4 Comparing the results with the year 2019:

By comparing the results during covid-19 with the year 2019 we analyzed how severe is the impact of covid-19 on the psychological health of employees. During the year 2019 employees with mental disorders accounted for 34.6% which has shown a steep increase during covid-19. According to OSMI 2020 dataset employees with mental disorder, cases has increased to 53%, and according to the Kaggle dataset, 62.3% of employees are suffering from mental disorders during covid-19. Which is nearly double the number of the year 2019.

CHAPTER 5

CONCLUSION AND FUTURE WORK

In this, we have discussed the major issue of mental health, which has been neglected by people during the novel coronavirus. Employees are only part of the population, which has suffered from coronavirus. Using randomized Hyperopt with XGBoost we were able to predict the mental health state of employees during covid-19 lockdown with an accuracy of 91% for kaggle dataset and 90% for OSMI dataset. By comparing the results with OSMI 2019 dataset we found that number of employees suffering from mental disorders/ illness has increased from 34.6 during 2019 to 62.3% during covid-19. Which shows how huge the impact coronavirus has on the psychological health of people. This study can be used as the reference for mental health state during pandemic and in case similar situation reoccurs in future, we can use this as the reference to take better actions when dealing with mental health. Similarly, mental health care can be provided to the employees using mental fatigue as a measure to detect mental health state of employees.

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LIST OF PUBLICATIONS OF THE CANDIDATE'S WORK

1. R. Katarya and S. Maan, "Predicting Mental health disorders using Machine Learning for employees in technical and non-technical companies," 2020 IEEE International Conference on Advances and Developments in Electrical and Electronics Engineering (ICADEE), 2020, pp. 1-5, doi: 10.1109/ICADEE51157.2020.9368923.
2. R. Katarya and S. Maan, "Stress Detection using Smartwatches with Machine Learning: A Survey," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 306-310, doi: 10.1109/ICESC48915.2020.9155568.



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