

ANALYSIS ON MENTAL HEALTH AND WELL BEING

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Abstract - In this analysis, we try to find the factors that affect mental health from the data obtained from a survey of around 1400 people from the working population aged between 20 and 70. We also analyze them to put forward a few suggestions that can be implemented in the workplace to build a healthy community. The factors considered in this analysis are age, gender, self-employed, ever diagnosed with a mental health issue, family history of illnesses, etc. The prediction is done using logistic regression, k-nearest neighbors, and random forest classifier algorithms. The available data is tested and trained and the best model that fits with maximum accuracy is taken for further predictions. The model can then be used by employers or other professionals to predict if a person is prone to be mentally affected.

Key Words s: Mental Health, Exploratory Data Analysis, Random Forest model, logistic regression, ROC curve, Confusion Matrix

1.INTRODUCTION

According to the dictionary, mental health is defined as, "a person's condition concerning their psychological and emotional well-being". It can affect a person's thinking, mood, or behavior decision-making skills. Mental health, as defined by the World Health Organization (WHO), is "a state of well-being in which the individual realizes his or her abilities, can cope with the normal stresses of life, can work productively and fruitfully, and can make a contribution to his or her community". From the perspectives of positive psychology or holism, mental health may include an individual's ability to enjoy life and to create a balance between life activities and efforts to achieve psychological resilience. Cultural differences, subjective assessments, and competing professional theories all affect how one defines "mental health".

Various trigger points can influence a person's mental health state such as work stress, financial problems, employment issues, detachment from families, age, physical ailment, loneliness to name a few. One in four people in the world will be affected by mental or neurological disorders at some point in their lives. The COVID-19 pandemic has accelerated

this problem even further. According to a few reports, 1 in 6 people would have experienced mental health problems in the past year. These issues range from common problems such as depression and anxiety to rarer problems such as schizophrenia and bipolar disorder.

Even after being such an important matter of discussion, open communication on mental health is still looked down upon. One of the reasons why mental health can be a taboo subject is the fear of appearing weak and vulnerable in front of others. Also since we don't see a physical injury or impairment, mental health issues are not considered illness.

In some parts of the world, mentally disturbed people are said to be victims of witchcraft or possessed by evil spirits and the patients are themselves blamed for their condition.

2.LITERATURE REVIEW

According to Salima Hamouche^[1], Covid 19 has made a negative impact on an individual's mental health. Stressors include perception of safety, threat and risk of contagion, infobesity versus the unknown, quarantine and confinement, stigma and social exclusion as well as financial loss and job insecurity. Furthermore, three dimensions of moderating factors have been identified: organizational, institutional and individual factors. In addition, a list of recommendations has been presented to mitigate the impact of COVID-19 on the employee's mental health, during and after the outbreak, from a human resource management perspective.

According to Jodi Oakman, Natasha Kinsman, Rwth Stuckey, Melissa Graham & Victoria Weale^[2], the findings from their review suggest the impacts of WAH on individuals' mental and physical health vary considerably. However, despite limitations with a relatively low number of studies, some consistent principles emerge which can be used to support employers in improving working conditions to mitigate the negative effects of WAH and enhance the positive effects of WAH on employees' health. At a minimum, opportunities for regular communication between managers and their team and between colleagues are important and help to reduce the negative impacts associated with feeling isolated whilst WAH.

According to Ana Lucia Teixeira Hirschler, Sônia Maria Guedes Gondim^[3], as a practical contribution, the results

they found were relevant and can help support policies and programs to improve well-being and reduce the stress of workers, from a more careful look at stressors, work resources, organizational and social support, interpersonal relationships, personal resources, and work-life balance. These factors have proven to be highly important and, if not properly treated, may constitute psychosocial risks with harmful consequences for workers' health.

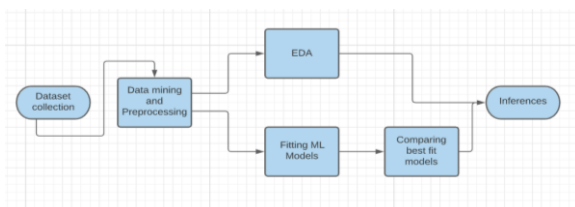
According to U M Read, V CK Doku^[4], their studies review have been small in scale and of limited generalizability. Nonetheless, they provide important insights into the development of mental health care in Ghana and suggest directions for future research.

According to Anja Thieme, Danielle Belgrave, Gavin Doherty^[5], recent years have witnessed an increase in excitement and exploratory research on potential applications of ML for mental health. Their review has offered an overview of this area of research and highlighted current trends and challenges. Aiming to shape the future direction of work, they have discussed current approaches and potential steps toward achieving ML systems that are effective and implementable for mental health care.

3. PROJECT DESCRIPTION

In today's daily hustle and bustle, most people ignore the fact that their mental health is at stake. Many are away from their loved ones not just physically but also mentally. It is very common to see mentally disturbed people being unaware of their issues until a professional diagnosis. We aim to find major factors affecting mental health. And also to find the most accurate fitting ML model from k-NN, Logistic Regression, and Random Forest classifier to predict if a person is prone to be mentally affected or not.

3.1 Architectural Diagram



3.2 Methodologies

3.2.1 Hardware Requirements

- Computer System

3.2.2 Software Requirements

- MS-Excel
- Python

3.2.3 Tools Required

- Jupyter notebook

3.2.4. Modules

- ❖ Exploratory Data Analysis
- ❖ ML models
 - Random forest classifier
 - Logistic Regression
 - KNN classification
- ❖ Comparing best fit models
 - ROC curve
 - Confusion matrix

4. DATA ANALYSIS AND INTERPRETATIONS

| | self-employed | number of employees in your company | tech company | company related to IT | employer provide mental health benefits | knowledge about mental healthcare options workplace | employer discussed mental health | employer offer resources to learn about mental health | medical leave from work | comfortable discussing with coworkers | feel that treatment interferes with your work | feel that treatment does not interfere with your work | age | gender |
|---|---------------|-------------------------------------|--------------|-----------------------|---|---|----------------------------------|---|-------------------------|---------------------------------------|---|---|-----|--------|
| 0 | 0 | 1 to 5 | 1.0 | NaN | Yes | Yes | No | No | Somewhat difficult | Maybe | Sometimes | Often | 33 | Male |
| 1 | 0 | 1 to 5 | 1.0 | NaN | No | No | No | I don't know | Very easy | Yes | Not applicable to me | Not applicable to me | 40 | male |
| 2 | 0 | 1 to 5 | 1.0 | NaN | Yes | Yes | No | I don't know | I don't know | Maybe | Not applicable to me | Not applicable to me | 21 | male |
| 3 | 0 | 1 to 5 | 1.0 | NaN | No | No | No | No | Very difficult | No | Often | Often | 36 | Male |
| 4 | 0 | 1 to 5 | 0.0 | 1.0 | I don't know | No | Yes | No | Very difficult | Yes | Not applicable to me | Often | 36 | F |

Figure 1: survey results of working population

The above figure contains all the results of the survey including the employment details, and personal details. This dataset is cleaned, encoded, trained and tested, and then fitted to determine the best ML model.

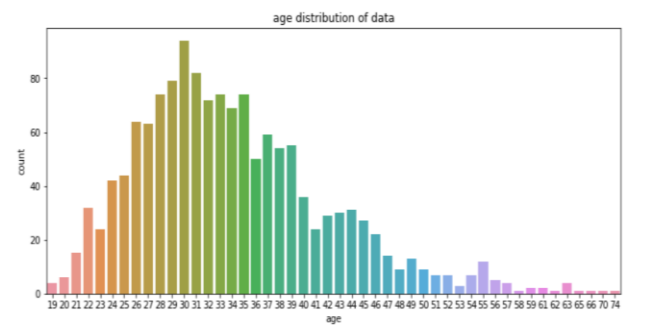


Figure 2.1: Age distribution of the data

From the above figure, it can be seen that the majority of the working population lies between the age of 25 to 40.

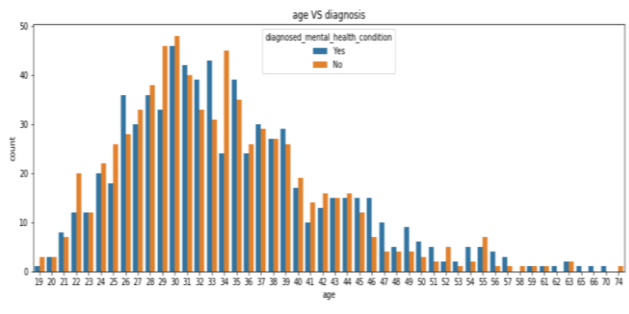


Figure 2.2: Age vs Mental health diagnosis

It is seen that positive diagnosis takes a higher toll in the older working population.

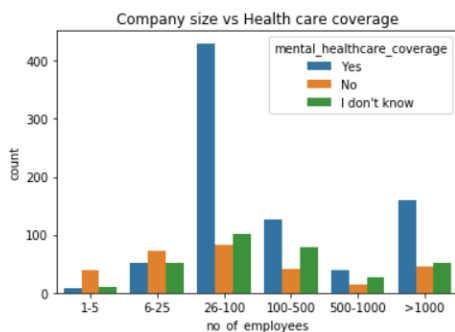


Figure 3: Companies providing health care coverage

From the figure, it is seen that smaller companies are reluctant to include mental health in their health care coverage.

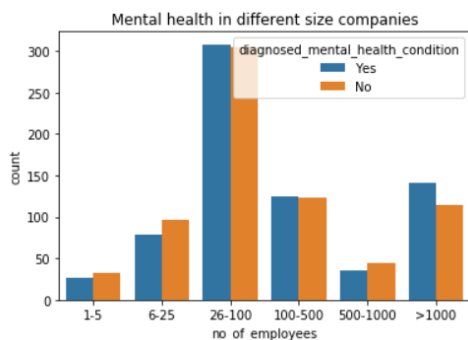


Figure 4: mental health diagnosis in different companies.

From the above figure, regardless of company size, around 50% of the employees are diagnosed positive with mental health issues.

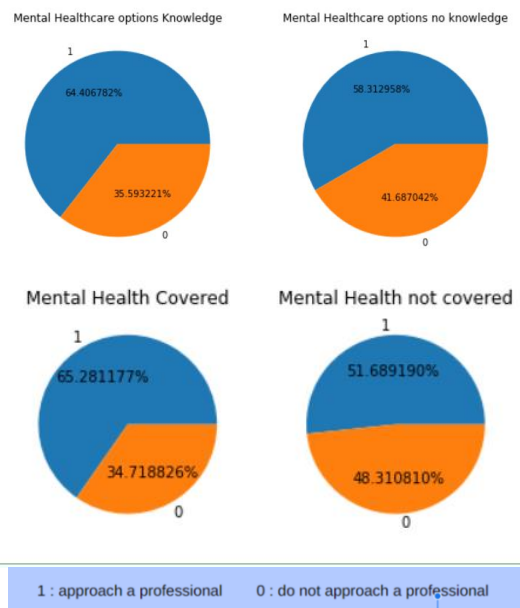


Figure 5: Employers take on mental health

When mental healthcare knowledge and medical benefits are covered by employers, employees are more confident to acknowledge mental health problems.

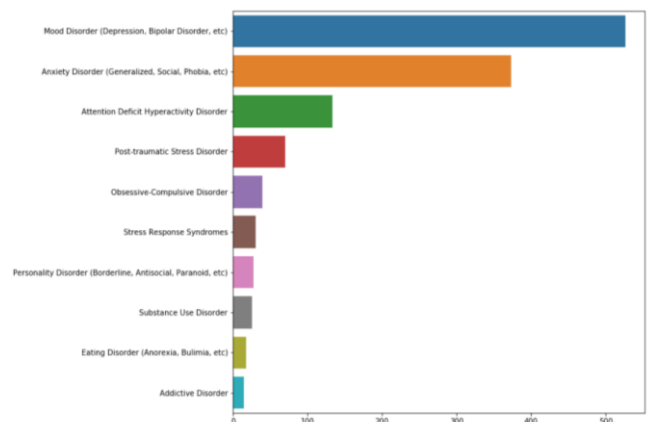


Figure 6: Diagnosed Disorders

The most commonly diagnosed disorders are Mood disorders (Depression, Bipolar Disorder, etc) and Anxiety disorder (social, phobia, etc).

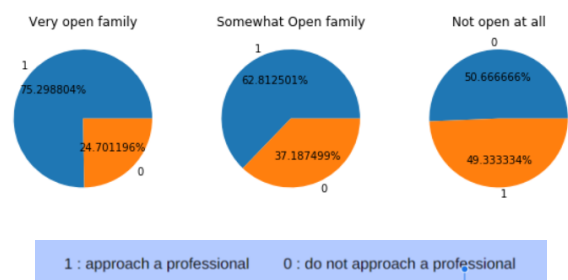


Figure 7.1: Family openness and help-seeking mentality

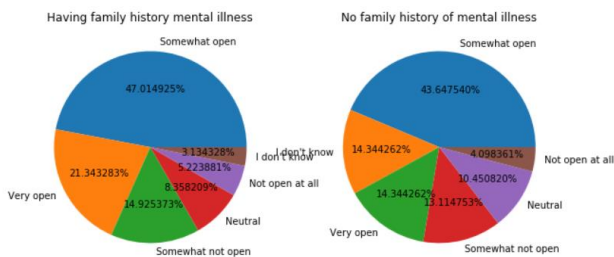


Figure 7.2: Openness among family and diagnosis

It's clearly evident from Figure 7.1 that individuals from open-minded families tend to be more comfortable in approaching professionals for diagnosis. From figure 7.2, the other categories outnumber very open families to a great extent stating there are still many households where open discussions on mental health are not entertained.

Discussions for topics like mental health may still be considered taboo according to the above graph.

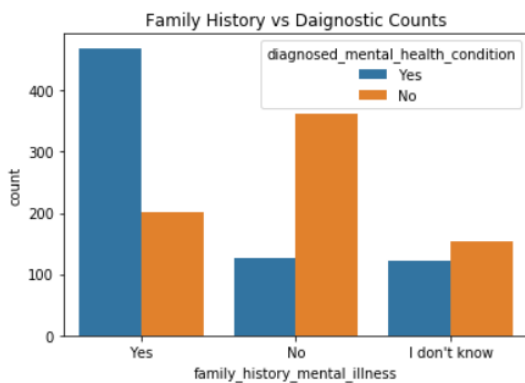


Figure 8: Influence of family history in diagnosis

From the above Family history of an individual influences positive diagnosis to a great extent. It thus shows the necessity of knowing family health history and having communications regarding the same.

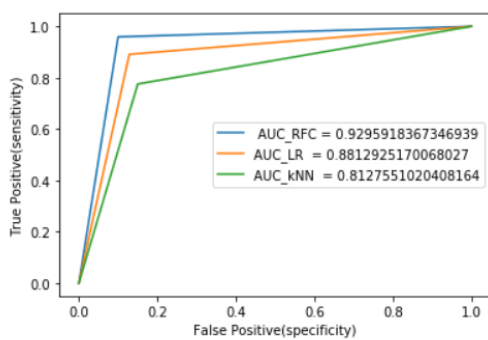


Figure 9: ROC Curve

After selecting the best variables to fit in the ML models, an ROC Curve is plotted to find the best fit ML model.

The more the graph points to the left top corner, the better the model.

Thus, in this case, Random Forest Classifier is better than the Logistic regression classifier and k-NN classifier model.

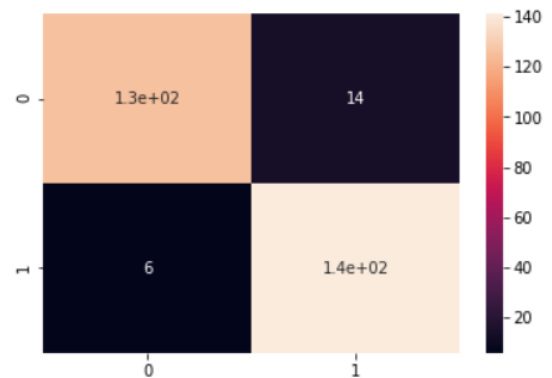


Figure 10.1: Confusion matrix of Random forest classifier

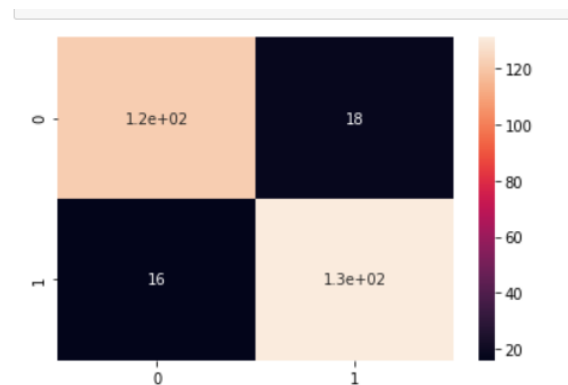


Figure 10.2: Confusion matrix of Logistic Regression classifier

From the above confusion matrices in figures 10.1 and 10.2, it can be concluded that the Random Forest classifier is the best fit among the ML models to predict the expected diagnosis of mental health issues.

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.95 | 0.90 | 0.93 | 140 |
| 1 | 0.91 | 0.96 | 0.93 | 147 |
| accuracy | | | 0.93 | 287 |
| macro avg | 0.93 | 0.93 | 0.93 | 287 |
| weighted avg | 0.93 | 0.93 | 0.93 | 287 |

Figure 11: The accuracy and scores of the Random Forest model

Random Forest Model classifier provides an accuracy of 93% in predicting the proper results than the other two models.

CONCLUSIONS

Regardless of company size, around 50% of the employees are diagnosed with mental health issues. It is also found that the employer's part in discussion and involvement in providing necessary information on the topic has a positive impact in helping the employees seek medical help and communicate about it.

Irrespective of age or gender, anyone is prone to mental health problems, but the risk is a little higher in people aged above 45.

An open-minded family plays an integral part in the early diagnosis of mental health issues and helps in speedy recovery. If there is a family history of such problems, there is a higher risk of being affected mentally. Discussion and conversations on mental health are still discouraged in many households even now.

Individuals who were affected previously are at higher risk than people who haven't been affected.

The best-fitted ML model to predict possible Diagnosis is the Random Forest model with an accuracy of 93%.

Suggestions

- ★ Every employee should be informed about the beneficiaries they can avail from their employers
- ★ Every employer should conduct regular discussions on mental health and stress management
- ★ Medical coverage should also cover visits to counseling centers or psychologists
- ★ Once diagnosed, pay regular visits to the consultant and keep track of your progress.
- ★ Keeping oneself surrounded with Open-minded people is necessary

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