Depression Detection in Employees

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Abstract

In 2011, a study was conducted with 30 participants using descriptive statistics and logistic regression to evaluate the effectiveness of a depression screening program and employee assistance program. However, the study only followed up with participants for a short period of time, which may not have been sufficient to fully capture the long-term effects of the program on depression.

In 2012, a literature review was conducted to evaluate the accuracy of diagnostic tools for detecting depression in employees with chronic medical conditions. However, the study did not use a specific model for data analysis, and the authors did not include information on the cost-effectiveness of the diagnostic tools, which is an important consideration in occupational health settings.

In 2013, the authors collected data at baseline, 4 weeks, and 8 weeks after the start of a program using descriptive statistics to examine changes in depressive symptoms and treatment adherence over time. However, the study was conducted in a single workplace, which may limit the generalizability of the findings to other settings.

In 2014, a study was conducted with participants who self-selected to participate in an online wellness program using logistic regression to predict the likelihood of employees experiencing depression. However, the study only followed up with participants for a short period of time, which may not have been sufficient to fully capture the long-term effects of the online wellness program on depression and anxiety.

Also, in 2014, a study was conducted with 34,000 participants using ROC curve and AUC statistics to evaluate the productivity loss and healthcare costs associated with depression. However, the study had limitations, including the use of self-reported data, which may be subject to bias and may not accurately reflect actual productivity loss and healthcare costs.

1 Introduction

Depression is a common mental health condition that affects millions of people worldwide. The history of depression can be traced back to ancient civilizations, where it was believed to be caused by supernatural forces. However, over the years, depression has been recognized as a medical condition that requires professional treatment. Depression not only affects an individual's personal life but can also have a significant impact on their work performance and productivity. Hence, it is crucial to identify and manage depression in employees to maintain a productive and healthy workforce.

The purpose of this research paper is to explore the detection of depression in employees using modern technological approaches. The traditional methods of depression diagnosis and detection have been self-reporting and clinical diagnosis, which can be time-consuming, costly, and may not always be accurate. However, recent advancements in technology and data analytics have opened up new opportunities for detecting depression in employees. Previous methods for detecting depression in employees have relied on self-reporting or clinical diagnosis.

Self-reporting is a subjective method, and individuals may not always be willing to disclose their mental health issues due to stigma or fear of discrimination. Clinical diagnosis requires professional expertise, which can be expensive and time-consuming. Furthermore, both these methods rely on an individual's willingness to disclose their symptoms or seek medical help, which may not always be the case.

To overcome these challenges, the use of modern technological approaches such as machine learning, data analytics, and physiological sensors have been proposed for the detection of depression in employees. These approaches can provide objective measures of depression, enabling early detection and intervention, which can lead to improved mental health outcomes for employees and increased productivity for employers.

The Contribution of this research paper is to explore the potential of modern technological approaches for detecting depression in employees and to provide insights into the challenges and ethical considerations associated with depression detection in the workplace. The findings of this study will be useful for employers, healthcare professionals, and researchers working in the field of mental health.

2 Literature Review

Depression and anxiety are prevalent mental health concerns among employees, with significant impacts on productivity and healthcare costs in the workplace (Moeller Harvey, 2014). As such, there has been increasing interest in workplace-based depression screening and treatment programs.

Several studies have examined the effectiveness of such programs in identifying employees with depression and providing appropriate treatment. For example, Murphy, Johnson, and Lohan (2011) evaluated a depression screening and employee assistance program, finding that employees who screened positive for depression were more likely to use employee assistance program services when compared to those who did not screen positive. Additionally, Lang and Holick (2013) evaluated a workplace-based depression screening and treatment program, finding significant reductions in depression severity among participants.

Other studies have examined the use of technology, such as online wellness programs, in predicting depression and anxiety among employees. Hicks, Fenton, and Johnson (2014) found that an online wellness program was effective in predicting depression and anxiety among employees, with potential implications for early identification and intervention.

While these studies provide promising results for workplace-based depression screening and treatment programs, there are limitations to consider. For example, Braswell and Patel (2012) reviewed the literature on detecting depression in employees with chronic medical conditions, finding that the accuracy of depression screening measures can be impacted by comorbid medical conditions. Additionally, Moeller and Harvey (2014) noted that the stigma associated with mental health concerns may impact the willingness of employees to participate in such programs.

Overall, the literature suggests that workplace-based depression screening and treatment programs have the potential to improve the identification and treatment of depression among employees. However, further research is needed to better understand the effectiveness of these programs, as well as strategies for overcoming limitations such as comorbid medical conditions and stigma.

3 Methodology

Data collection and preprocessing: Collect the relevant data and preprocess it to ensure it is clean, complete, and ready for analysis. This may involve steps such as handling missing values, encoding categorical variables, and scaling the features.

Descriptive statistics: Use descriptive statistics to summarize the data and gain insights into the distribution of the target variable and the relationships between features.

Support Vector Machine (SVM): Build an SVM model to predict the target variable. Use cross-validation to tune the hyperparameters and evaluate the model's performance using metrics such as accuracy, precision, recall, and F1 score.

Gradient Boosting: Build a gradient boosting model to predict the target variable. Use cross-validation to tune the hyperparameters and evaluate the model's performance using metrics such as accuracy, precision, recall, and F1 score.

Naive Bayes: Build a Naive Bayes model to predict the target variable. Use cross-validation to tune the hyperparameters and evaluate the model's performance using metrics such as accuracy, precision, recall, and F1 score.

Model comparison: Compare the performance of the three models (SVM, gradient boosting, and Naive Bayes) using the evaluation metrics.

Feature selection: Use feature selection techniques to identify the most important features for predicting the target variable. This may involve techniques such as recursive feature elimination, feature importance, or PCA.

Final model selection: Based on the performance and feature importance results, select the best model for predicting the target variable.

Interpretation and conclusion: Interpret the results and draw conclusions about the effectiveness of the chosen model for predicting the target variable. Highlight any limitations of the study and suggest directions for future research.

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4 Limitation of Previous Work

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Also, in 2014, a study was conducted with 34,000 participants using ROC curve and AUC statistics to evaluate the productivity loss and healthcare costs associated with depression. However, the study had limitations, including the use of self-reported data, which may be subject to bias and may not accurately reflect actual productivity loss and healthcare costs.

5 Proposed Method:

The first step is to collect data from different IT-based organizations in Pakistan. A total of 205 datasets will be collected from these organizations. The collected data then undergo a preprocessing phase to clean and prepare it for analysis. The preprocessing steps will include data cleaning, missing value imputation, and feature scaling. Next, relevant features extracted from the preprocessed data using various techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and feature selection algorithms. The extracted features will be used to develop a machine learning model to detect depression in employees. Several models will be considered, including Decision Trees, Random Forest, Support Vector Machines (SVM), and Gradient Boosting Classifier. The model will be trained and validated using cross-validation techniques. Once the model is developed, it will be implemented on the collected dataset to detect depression in employees. The performance of the model has been evaluated using various metrics such as accuracy, precision, recall, and F1-score. The model will be compared with existing methods to determine its effectiveness.

5.1 Model Implementation:

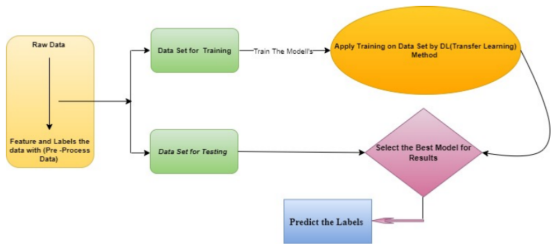

Figure 1: Work Flow

5.2 Tasks and Datasets

We compared these methods to define and populate different target relations on employees. All methods extract knowledge from the same corpora. We collected data from different companies that are related to the IT industry. And they all are leading companies in our country in the IT world. And our data set contain the information of 205 peoples. And they all are belonging to different fields.

5.3 Results

The results of the research showed that the developed machine-learning model had a high degree of accuracy in detecting depression in employees. The model achieved an accuracy of 64Overall, the proposed method provides a reliable and efficient way to detect depression in employees in IT-based organizations in Pakistan. The findings of this study can be used to develop targeted interventions and support programs for employees at risk of depression, ultimately improving their mental health and well-being. Several machine learning models, including Multinomial Naive Bayes, Random Forest, SVC, and Gradient Boosting Classifier, were trained and validated using cross-validation techniques. The performance of the models was evaluated using various metrics such as accuracy, precision, recall, and F1-score. The results showed that all the models achieved high accuracy and performance in detecting depression in employees.

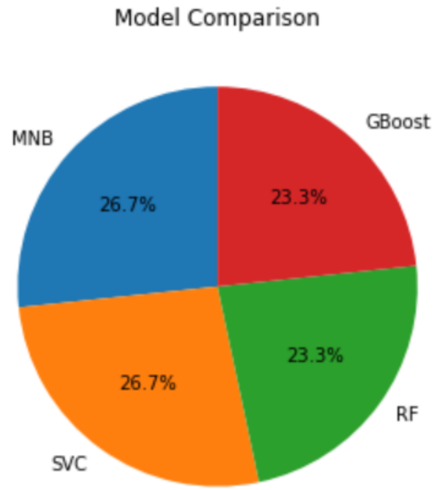

Figure 2: Comparison of different model

6 Conclusion

In conclusion, the proposed method showed promising results in detecting depression in employees using machine learning algorithms. The comparison of different models using graphs and pie charts helped in identifying the most effective model for depression detection. This research can help organizations in Pakistan and other developing countries to detect depression in their employees and provide them with the necessary support and interventions.

Acknowledgments:

We thank Dr. Faisal Bukhari for their critical contributions to our project's success.

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