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Predicting Anxiety Among Technical Employees: A Machine Learning Approach

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Abstract
Amidst the ever-evolving technology landscape, the concerns of technical personnel have taken the forefront, extending their ramifications to job satisfaction and productivity. Anxiety disorder, characterized by feelings of fear and stress, is a prevalent mental health condition among technical employees. In light of this, the presented study in this paper delves into enhancing the accuracy of anxiety prediction. Utilizing proficient machine learning algorithms encompassing Random Forest (RF), Decision Tree (DT), AdaBoost, bagging, Bernoulli Naive Bayes (BNB), Logistic Regression (LR), and Support Vector Machine (SVM), a predictive model is proposed to gauge anxiety levels. The study unveils an impressive accuracy pinnacle of 96.23%, particularly with the implementation of AdaBoost. These findings shed light on the substantive symbiotic relationship between machine learning and anxiety prediction. Ultimately, this study holds pragmatic implications for organizations aiming to fortify employee mental well-being, thereby elevating job satisfaction and productivity within this dynamic technological epoch.

Keywords: Anxiety; Prediction; Machine Learning; Random Forest Boosting; AdaBoost; bagging; Logistic Regression; Decision Tree; Bernoulli Naive Bayes; SVM

1. Introduction

Anxiety disorders represent a significant and serious global health issue, exerting a widespread impact on a substantial number of individuals around the globe. According to the World Health Organization, an estimated 264 million individuals are affected by anxiety [1]. Anxiety and depression are prevalent mental disorders, impacting approximately 12.5% of the global population [2]. Anxiety is a highly frequent concern in Saudi Arabia, as indicated by a prevalence rate of 71% among those who have Saudi nationality [3]. Anxiety is characterized as a discernible manifestation of contemporary society, arising from the societal demands stemming from the swift progressions in scientific and technological domains [4]. According to the definition presented by [5], anxiety is defined as a stress response that exhibits a negative tone and encompasses three fundamental components: affect, an inclination to engage in action, and physiological alterations. Moreover, anxiety is an affective state distinguished by sensations of unease, apprehensive cognitions, and somatic manifestations, like heightened blood pressure, perspiration, tremors, vertigo, or tachycardia [6].

The Fourth Industrial Revolution is distinguished by the incorporation of cutting-edge technologies into industrial applications [7]. Nevertheless, the ongoing technological revolution, characterized by the substitution of human labor with automation in diverse jobs and processes, has resulted in heightened employment instability and elevated levels of apprehension among technical profess-sionals. According to recent projections [8], it is anticipated that this particular trend will have an impact on around 30% of employment opportunities by the mid-2030s. Furthermore, the ongoing worldwide COVID-19 pandemic has intensified levels of employee fear, resulting in job losses and heightened uncertainty regarding future prospects [9].

The importance of addressing anxiety among technical professionals cannot be overstated in the context of Saudi Arabia's Vision 2030 [10]. This strategic plan seeks to improve employee well-being, job satisfaction, and productivity, making it imperative to tackle anxiety issues within this specific workforce. The correlation between the quality of job and mental health is intricately interconnected [11]. Hence, it is imperative for the organization to give precedence to the alignment of its goals with the mental well-being of all employees, with a specific emphasis on technical personnel who make substantial contributions to the economy. This method can potentially facilitate organizational performance and make a positive contribution to broader societal progress. Furthermore, it is imperative to acknowledge the detrimental impact of prolonged working hours on the overall well-being and quality of life of employees [12]. Extended working hours are a significant source of work-related stress that has a negative impact on persons' mental well-being and productivity, specifically in terms of heightened levels of anxiety and depression. According to empirical research, a significant majority of respondents, namely over 75%, who acknowledged that stress had a detrimental effect on their professional performance, also reported experiencing its repercussions in their personal lives [13]. Therefore, the accurate prediction of anxiety levels among employees is of utmost significance in order to effectively execute preventive measures and offer timely support to mitigate feelings of concern. This phenomenon, in turn, contributes to the enhancement of employees' general well-being, job satisfaction, and productivity. In recent times, there has been an increasing emphasis on the importance of psychological well-being in the pursuit of global sustainable development goals.

There are multiple factors that can impact an individual's mental well-being, leading to conditions that can alter their emotional state, cognitive processes, attitudes, and decision-making abilities. The incidence of mental health disorders among employees has risen as a result of stress experienced in the workplace. The aforementioned conditions include personality disorders, anxiety disorders, phobias, psychotic disorders, depression, mood disorders, and eating disorders, among other others [14]. Machine learning algorithms have become widely recognized as helpful tools for the analysis of large medical information. The performance of these tools has shown a steady improvement, rendering them more dependable, and they are now commonly employed to aid in medical diagnostics [15]. Prior research has demonstrated the effectiveness of machine learning in accurately predicting mental health disorders among employees, including those working in technical positions. In their study, the authors conducted an investigation into stress patterns among employed individuals, aiming to identify the significant stress variables. To achieve this, they utilized ensemble methods including logistic regression, boosting, K-NN, decision trees, random forests (RF), and bagging [16]. The authors utilized the OSMI 2017 dataset [17] to train their models. Based on their findings, they determined that Boosting exhibited the highest level of proficiency as a classifier, achieving an accuracy rate of 75%, precision rate of 84%, and a cross-validated area under the curve (AUC) of 75%.

In a similar vein, the authors of reference [17] explored the utilization of machine learning methodologies to predict stress levels and mental health conditions, achieving a notable accuracy rate of 75.13%. In the study, five machine learning algorithms were examined, namely logistic regression (LR), K-nearest neighbor (K-NN), decision tree (DT), random forest (RF), and stacking. Among these methods, stacking shown remarkable performance, obtaining a notable accuracy of 81.75% in predicting mental health illnesses. Based on these initial principles, the study conducted predictive analysis using several machine learning methods such as decision trees (DT), logistic regression (LR), naive Bayes, random forest (RF), support vector machine (SVM), and k-nearest neighbors (K-NN). The objective was to forecast mental health illnesses in both technological and non-technical enterprises. The focus was directed towards the decision tree (DT), which demonstrated notable performance with accuracies of 84% and 83% correspondingly.

Concurrently, the researchers pursued a comparable approach by utilizing a range of approaches such as Random Forest (RF), Decision Trees (DT), Support Vector Machines (SVM), AdaBoost, CatBoost, and extreme gradient boosting. Their objective was to forecast levels of depression, anxiety, and stress. Among the several models considered, the support vector machine (SVM) had the highest F1 measure, with notable accuracy rates of 94% for depression, 95% for anxiety, and 91% for stress prediction. Based on a comprehensive analysis of existing literature, the present study aims to enhance the prediction of anxiety levels among technical staff by employing sophisticated machine learning approaches that offer enhanced accuracy. This study utilizes the dataset from the OSMI Mental Health in Tech Survey 2016, which is publicly accessible through Open Sourcing Mental Illness and can be found on Kaggle [18].

This study aims to investigate various techniques and methodologies that can improve the accuracy and performance of machine learning algorithms in predicting anxiety levels among technical staff. The objective is to contribute to the resolution of this concern by exploring several approaches. In addition, this paper aims to foster the development of a more reliable and accurate machine learning model. The research involves the utilization of diverse machine learning methods for the purpose of training, employing data derived from the OSMI Mental Health in Tech Survey 2016 [19]. By employing these useful qualities, the models are positioned to attain a sophisticated understanding of stress levels and identify relevant causes that contribute to workplace stress. Furthermore, the study explores a comprehensive assessment of the effectiveness of various machine learning methodologies, such as logistic regression (LR), decision tree (DT), Bernoulli naive Bayes (BNB), random forest boosting (RF boosting), and support vector machine (SVM), within the context of stress level prediction. Through conducting this extensive investigation, the research endeavors to establish a foundation for the advancement of a more precise and resilient predictive framework for forecasting anxiety levels among technical personnel.

The rest of this paper is organized into five segments. Section 2, offers an exposition of the dataset and methodologies employed within this study. Section 3, delves into an in-depth exploration of the methodology utilized. Section 4 encompasses the presentation and discussion of the results obtained. Finally, Section 5 encapsulates the essence of the study through a concise summary and conclusion.

2. Materials and methods

This section discusses the materials including the adopted dataset, and then we illustrate a set of methods that need to be carried out in order to recover the missing and incorrect data. In addition, we discuss the machine learning models that have been employed and finally, the evaluation metrics are discussed.

2.1 Dataset

The dataset used in this study was obtained from the OSMI Mental Health in Tech Survey 2016 and is publicly available via Kaggle [19]. The dataset offered a comprehensive compilation of responses from 1,434 persons employed in the technology industry. It offers valuable insights into the complex array of mental health issues that are prevalent in the technology workplace. The poll, which was done in 2016 by the reputable nonprofit Open Sourcing Mental Illness (OSMI), aims to comprehensively investigate mental health topics within the technology industry. Consisting of 63 meticulously formulated inquiries, the survey covers a diverse range of significant aspects, such as individuals' attitudes towards mental health, their utilization of resources provided by employers, their experiences in disclosing mental health concerns, and the extensive influence of these concerns on personal productivity. The research project undertaken by OSMI is characterized by its strong dedication to advancing mental well-being through the utilization of open data, which serves as a fundamental aspect of its importance. This commitment highlights the altruistic principles that form the foundation of OSMI's work. The presented dataset serves as a testament to the convergence of technology, data-driven analysis, and activism for mental health.

1. Data Preprocessing

Before performing the analysis, a thorough data pretreatment procedure was implemented to ensure the integrity and dependability of the dataset [20]. In order to address the issue of missing data, which varied from 0% to 81.6% across different columns, with an average of 20%, a systematic approach was implemented. By utilizing uniform mode imputation, the process of replacing missing values was conducted in a careful manner, resulting in the establishment of a dataset that is both comprehensive and representative.
It is worth mentioning that a significant portion of the dataset comprised categorical variables. The use of one-hot encoding resulted in the expansion of the categorical variables into a comprehensive set of 3,209 dummy variables, encompassing 15 out of the total 63 columns. The aforementioned modification not only improves the ability of machine learning algorithms to utilize nominal data but also retains the intricate insights inherent in categorical responses.

2. Target Variable

The binary target variable is a central focus within the dataset. The variable in question, which represents individuals who have disclosed an anxiety diagnosis, encompasses a significant aspect of the overall mental health landscape. Significantly, a noteworthy proportion of 26% of the participants

in the survey reported experiencing difficulties associated with anxiety, thus emphasizing the widespread nature and immediate need for treating mental health matters within the technology sector.
In conclusion, the information from the OSMI Mental Health in Tech Survey 2016 is a valuable resource that demonstrates a diligent attempt to understand the intricacies of mental health in the field of technology. The dataset's robustness, meticulous preprocessing, and focus on a crucial objective variable collectively enhance its significance as a fundamental component of our research undertaking.

2.2 Machine Learning Models

Machine learning has emerged as a crucial instrument in diverse fields of research [21, 22]. Knowledge acquisition and performance enhancement in computer systems without explicit instructions is facilitated by a field within artificial intelligence (AI) and computer science. The capacity to acquire knowledge from data, without the need for explicit programming, renders machine learning a compelling instrument for addressing intricate challenges. This study utilizes supervised machine learning methods to forecast anxiety levels among technical personnel [23].

The dataset utilized in this research was appropriately annotated, leading us to employ supervised learning techniques in order to attain accurate and dependable predictions. Five machine learning methods were chosen based on their suitability for handling the specific characteristics of the dataset and their ubiquity in academic research. The techniques under consideration include LR (Logistic Regression), DT (Decision Tree), Bernoulli Naive Bayes (BNB), RF Boosting (Random Forest Boosting), and SVM (Support Vector Machine).
A. Supervised machine learning models

1) The LR algorithm was selected as an appropriate method for modeling binary outcomes using independent variables due to its extensive application in classification problems. This study examined a total of 63 features as independent factors in order to assess their predictive capacity for determining the probability of anxiety among technical employees.

2) The DT technique was chosen based on its simplicity and interpretability, rendering it highly suitable for a wide range of research topics. The process involves iteratively dividing the data into smaller subsets by considering attribute values, and afterwards creating a hierarchical model resembling a tree structure. This model is capable of making predictions regarding target variables. The Gini impurity criteria was employed to assess the effectiveness of the splits, while a maximum depth hyper parameter of 5, which is considered a modest number, was chosen to mitigate the risk of overfitting.

3) The BNB algorithm was selected based on its appropriateness for handling discrete data and independent features, which aligned with the characteristics of the dataset employed in this research. The algorithm utilizes Bayes' theorem to estimate class probabilities and offers efficient predictions for tasks involving binary attribute categorization.

4) RF boosting is a technique that leverages the capabilities of random forests (RFs) and boosting algorithms to enhance the accuracy of predictions. This process involves the iterative training of numerous decision trees, where each subsequent tree is trained to rectify the errors generated by the preceding trees. The collective of trees within the ensemble generates forecasts by combining aggregated outcomes, resulting in outcomes that are both robust and accurate. The aforementioned characteristic renders RF boosting very suitable for a wide range of study topics. In order to optimize the performance of the RF boosting model, the hyperparameters related to the number of estimators were adjusted to a value of 250. The hyperparameter in question governs the quantity of decision trees inside the ensemble and was fine-tuned via grid search to enhance the model's intricacy and enhance its accuracy.

5) The Support Vector Machine (SVM) algorithm was selected due to its capability to effectively handle intricate and high-dimensional datasets. This is achieved by identifying an ideal boundary that effectively separates different classes, hence maximizing the margin between them. The utilization of higher-dimensional data mapping by Support Vector Machines (SVM) resulted in the development of a precise model that proved to be valuable across multiple study disciplines. The data was mapped to a higher dimension using the linear kernel, while the hyper parameter "C" was assigned a value of 0.1, which is considered quite small. This choice was made in order to strike a compromise between the margin and classification error.

6) AdaBoost, also known as Adaptive Boosting, is a machine learning method that uses an ensemble approach to iteratively build a series of weak learners in order to generate a robust prediction model. Every individual weak learner directs its attention towards the instances that were previously categorized incorrectly, and their individual predictions are aggregated to generate a final prediction that is more precise and accurate. The AdaBoost algorithm modifies the weights assigned to incorrectly categorized examples, so enabling following weak learners to focus on

challenging situations. The aforementioned iterative approach results in the development of a resilient ensemble that demonstrates exceptional proficiency in managing intricate datasets. The given code employs the AdaBoost Classifier with 300 estimators, emphasizing the importance of ensemble size in attaining enhanced model performance.

Bagging:

Bagging, also known as Bootstrap Aggregating, is an ensemble technique that utilizes several iterations of a base model in order to get a more precise collective forecast. Bagging is a technique that aims to reduce variation and improve stability by generating several subsets of the training data through the process of bootstrapping. Each subset is then used to train a base model. The final forecast is obtained by averaging or aggregating the individual predictions from these base models. Bagging has significant efficacy when employed on algorithms that are characterized by instability or high variance. This technique effectively mitigates the issue of overfitting and consequently produces a model that is more universal in nature. The provided code snippet demonstrates the instantiation of the Bagging Classifier with a specified number of estimators, indicating the quantity of base models incorporated inside the ensemble.

The algorithms were chosen based on their appropriateness for the specific characteristics of the dataset and the objectives of the research. The hyperparameters were adjusted in order to maximize the performance of the models and mitigate the risk of overfitting.

B. Performance measurement indicators

In order to assess the performance of the trained model, several metrics were taken into account, such as the confusion matrix, accuracy, precision, recall, and F1 score.

1) The confusion matrix is described in Figure 1, where TP stands for true positive, and TN stands for true negative. TN means the output was zero or negative and was predicted correctly. TP means the output was positive or 1 and was predicted correctly. FP means the output was negative or 0 but was predicted as 1 or positive. FN means the output was positive or 1 but was predicted as 0 or negative. These values were used to check the performance of the classifier by calculating its precision and recall.

	Positive(1)	Negative(0)
Positive (1)	TP	FP
Negative (0)	FN	TN

Figure 1. Confusion matrix for the trained model.

2) The confusion matrix is depicted in Figure 1, wherein TP represents true positive, and TN represents genuine negative. The abbreviation "TN" refers to instances where the output value is zero or negative and has been accurately predicted. In the context of classification models, TP refers to instances where the predicted output is positive (denoted as 1) and aligns with the actual outcome. False positive (FP) refers to a situation in which the projected outcome is positive or 1, despite the actual output being negative or 0. The term "FN" refers to a situation in which the output of a prediction model is positive or 1, but it is incorrectly classified as 0 or negative. The aforementioned values were employed to evaluate the efficacy of the classifier through the computation of accuracy and recall metrics.

c) The evaluation of classification models in this proposed machine learning model heavily relied on the metric of precision, which was deemed to be of utmost importance. The accuracy of positive predictions was assessed by determining the ratio of genuine positive instances to the total number of instances anticipated as positive. The evaluation criterion employed to assess the model's classification abilities and its capacity to generate accurate positive predictions was precision. The analysis yielded significant findings on the model's accuracy in detecting positive instances, hence enhancing the overall assessment of its performance within the scope of this study.

d) Recall is an evaluation metric in the field of machine learning that quantifies the ratio of properly detected true positives by the model. The inclusion of this variable was imperative within the scope of this research endeavor, since it aimed to ascertain the prevalence of anxiety disorders among individuals employed in technical occupations. The utilization of accuracy and recall indicators facilitated a comprehensive assessment of the model's performance.

e) The F1 score is a commonly employed evaluation metric in the field of machine learning, which offers a well-balanced assessment of the performance of a classification model. The metric integrates precision and recall into a unified measure, encompassing both the accuracy of positive predictions and the capability to correctly recognize all positive cases. The F1 score was employed to evaluate the efficacy of the classification model in the research investigation.

3. Methodology

This section presents a comprehensive overview of the suggested model, which is an intelligent machine learning model designed to analyze the dataset pertaining to mental health in the technology industry.

The dataset was partitioned into training and validation sets via a five-fold K-fold cross-validation technique. The described approach involves the division of data into K subsets of equal size. Each subset, referred to as a fold, is utilized as the validation set, while the remaining K-1 folds are employed for training purposes. The training phase was primarily dependent on the careful selection of training data. In each iteration, the training set was chosen randomly from the pool of available data. This methodology reduced the impact of arbitrary divisions on the model's performance and guaranteed that the model's capacity to generalize was evaluated using several training and validation sets. Figures 2 and 3 depict the suggested model workflow, which encompasses K-fold cross-validation and the utilization of five supervised machine learning algorithms. The hyper parameters utilized for each algorithm are presented in Table 1. The models underwent training and optimization procedures utilizing the training set, while their performance was assessed by employing the validation set. The selection of the optimal model was based on the performance measures with the highest values on the validation set.

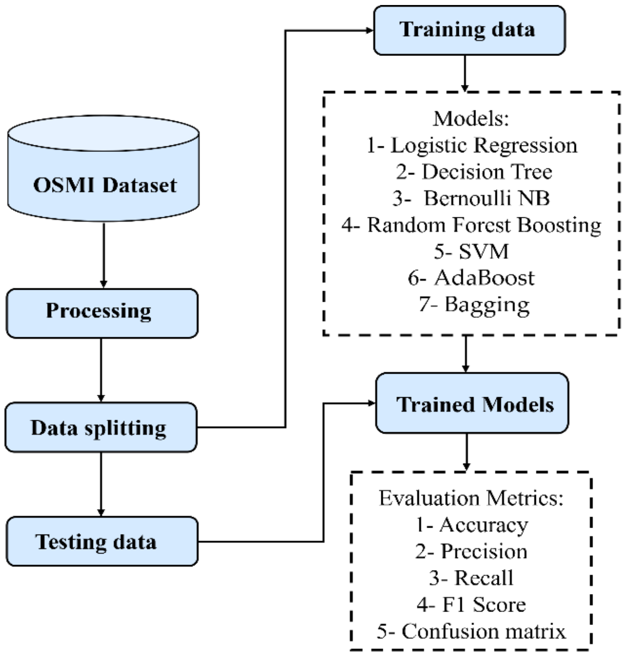

Figure 2. Proposed model workflow.

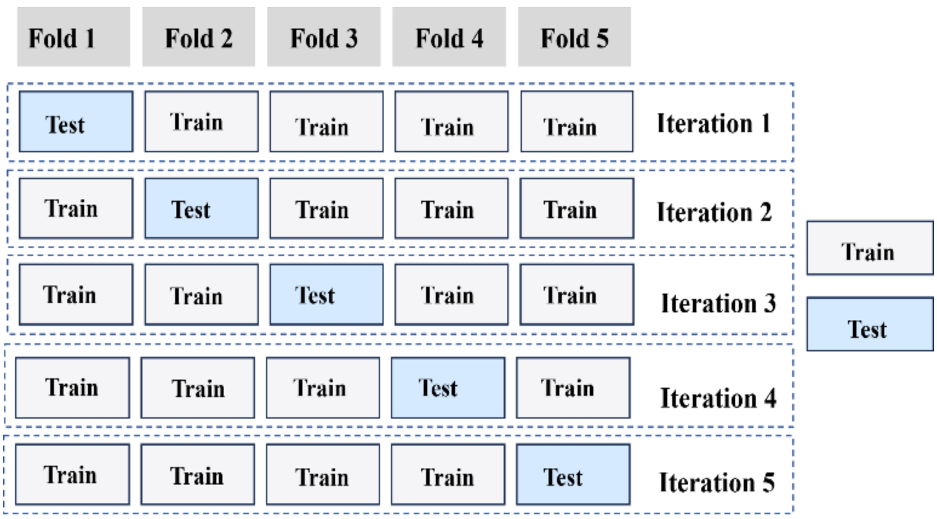

Figure 3. K-fold cross-validation.

Table 1. Algorithms hyperparameters.

Algorithms		Hyperparameters	Default Value	Tuned Value
1	**Logistic Regression**	Regularization strength 'C' (L2 regularization)	1.0	1.0
2	**Decision Tree**	Maximum depth of the decision tree	None	5
3	**Bernoulli Naive Bayes**	Smoothing parameter 'alpha'	1.0	1.0
4	**Random Forest Boosting**	Numbers of decision trees used in the model (n_estimators)	100	250
5	**SVM**	Regularization strength 'c' (linear kernel)	1.0	0.1
6	**AdaBoost**	Maximum number of estimators (n_estimators)	50	300
7	**Bagging**	The number of base estimators in the ensemble(n_estimators)	10	100

4. Results

The objective of this study is to assess the efficacy of machine learning algorithms in predicting levels of anxiety among technical professionals within the technology business. The implementation of the learned models for testing anxiety prediction among technical staff was carried out in Python, utilizing the Scikit-learn library [24]. The evaluation of the trained models' performance encompassed many performance indicators, including as accuracy, precision, recall, F1-score, and confusion matrix. The findings illustrated in Table 2 indicate that the Adaboost algorithm exhibited the highest level of accuracy, reaching 96.23%. This was closely followed by RF boosting, which achieved an accuracy of 96.09%, and Bagging, which achieved an accuracy of 95.74%. Logistic Regression (LR) and Support Vector Machines (SVM) demonstrated high accuracies of 94.98% and 94.91% respectively. On the other hand, Decision Trees (DT) and Bernoulli Naive Bayes (BNB) achieved comparatively lower accuracies of 92.60% and 88.69% respectively. The AdaBoost model demonstrated the highest precision rate of 92.47%, surpassing RF Boosting which achieved a precision rate of 91.80%. This outcome suggests that the AdaBoost model has a notable capability in properly predicting positive instances of anxiety within the population of technical staff.

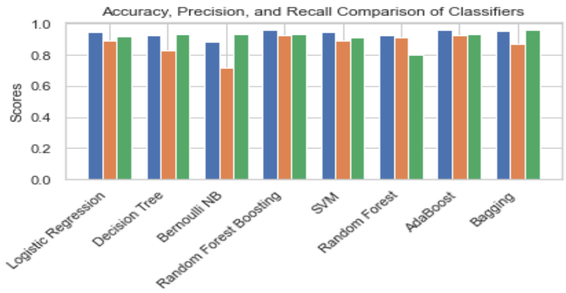

Figure 4. Model performance comparison.

The analysis of the confusion matrices depicted in Figures 5 – 11 discloses that the AdaBoost algorithm (True Positive: 206.2%, False Negative: 69.6%) in Figure 10 and the RF boosting algorithm (True Positive: 206.2%, False Negative: 69.6%) in Figure 9 exhibited the most elevated rates of correctly identified positive cases. This suggests that these algorithms have the potential to accurately detect instances of anxiety among technical employees. These algorithms have the potential to be valuable in the context of early identification and intervention.

The logistic regression (LR) approach demonstrated a notable true positive rate (TP: 203.8%), albeit with a slightly elevated false negative rate (FN: 68.4%), as compared to the support vector machine (SVM) algorithm (TP: 203.8%, FN: 68.2%), as illustrated in Figures 5 and 6. While the performance of the detection system in identifying positive cases is commendable, it is possible that certain instances of anxiety may go undetected. Figure 11 illustrates the performance of the Bagging method, with a true positive rate of 201.8% and the lowest false negative rate of 72% compared to the other two algorithms. Figure 8 illustrates the performance of the Decision Tree (DT) method, with a true positive rate of 196% and a false negative rate of 69.4%. While demonstrating a notable true positive rate, the examined algorithm had a comparatively larger false negative rate in comparison to the SVM and LR algorithms. This suggests that its efficacy in identifying positive instances of anxiety may be less pronounced. The BNB model, as depicted in Figure 7, had a true positive rate of 184.8% and a false negative rate of 69.4%. The findings indicate that the model may not be the optimal method for properly identifying positive instances of anxiety, and its efficacy may not meet the requirements for timely detection and intervention. In the study, it was observed that the

AdaBoost and RF boosting algorithms exhibited superior performance in reliably identifying positive instances of anxiety within the population of technical staff. Conversely, the LR and SVM algorithms also indicated satisfactory performance, albeit with a potential for overlooking certain situations. The performance of the DT algorithm and the BNB model exhibited certain limits, suggesting that both algorithms may not be optimal for early detection and intervention purposes. The findings of the study align with prior research that has employed machine learning algorithms to forecast mental health issues. Previous research [19-25] has documented the efficacy of ensemble approaches, such as boosting and bagging, in addition to decision trees (DTs) and support vector machines (SVM), for achieving desired outcomes. The study demonstrated that RF boosting obtained a greater accuracy of 96.23% compared to earlier studies [19-25], highlighting the potential of machine learning in facilitating early detection of anxiety. While the BNB model demonstrated the lowest accuracy in the present investigation, the remaining models exhibited comparatively good accuracies, hence suggesting the possibility of early detection and intervention. This study expands upon prior scholarly investigations by explicitly examining the prediction of anxiety levels among individuals in technical occupations.

Table 2. Performance of different trained models.

	Algorithms	Accuracy	Precision	Recall	F1 Score
1	Logistic Regression	94.98%	89.18%	91.78%	90.41%
2	Decision Tree	92.60%	82.91%	93.25%	86.36%
3	Bernoulli NB	88.69%	71.84%	93.13%	81.08%
4	Random Forest Boosting	96.23%	92.32%	93.37%	92.83%
5	SVM	94.91%	89.18%	91.49%	90.26%
6	AdaBoost	96.09%	91.93%	93.04%	92.45%
7	Bagging	94.84%	86.23%	95.57%	90.57%

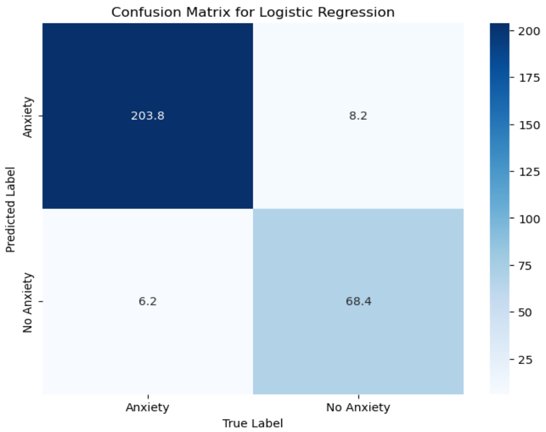

Figure 5. Confusion Matrix for Logistic Regression.

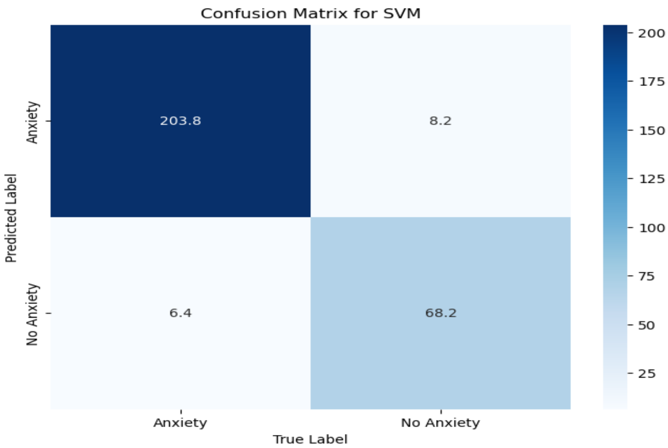

Figure 6. Confusion Matrix for SVM.

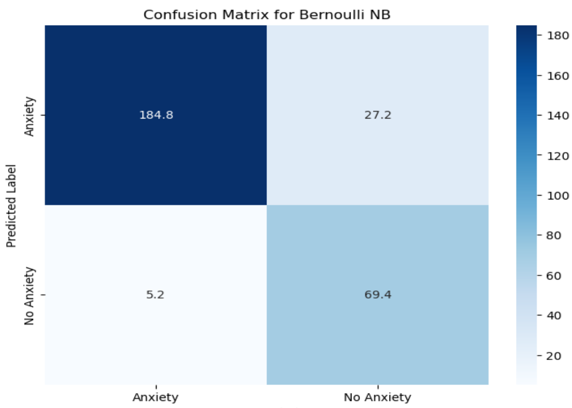

Figure 7. Confusion Matrix for Bernoulli NB.

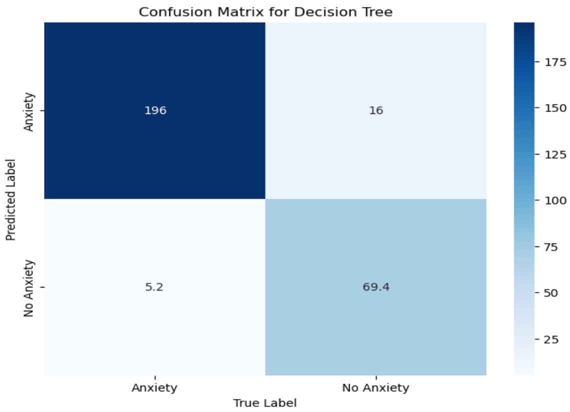

Figure 8. Confusion Matrix for Decision Tree.

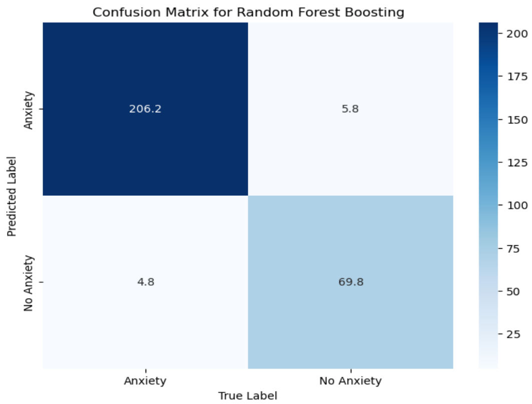

Figure 9. Confusion Matrix for Random Forest Boosting.

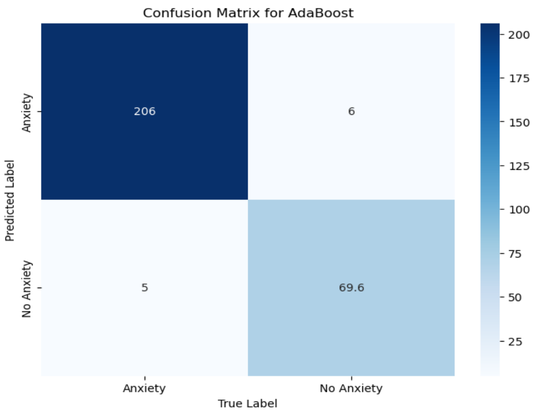

Figure 10. Confusion Matrix for AdaBoost.

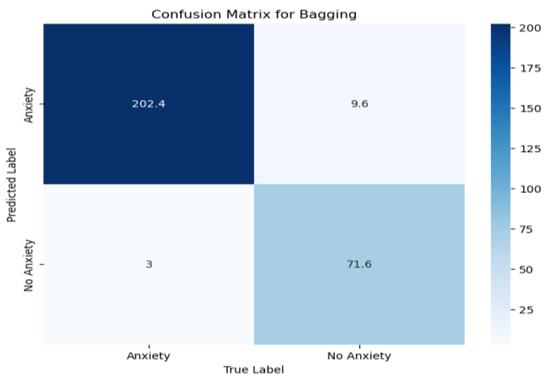

Figure 11. Confusion Matrix for Bagging.

The accuracy of a particular test set for a classifier refers to the proportion of test set instances that are properly classified by the classifier, expressed as a percentage. The efficacy of a classifier is contingent upon its ability to accurately categorize the given dataset during the testing phase. The area under the Receiver Operating Curve was determined through measurement. In the context of the Receiver Operating Characteristic (ROC) area, an ideal test is characterized by an area value of 1, while a test lacking discriminatory power is associated with an area value of 0.5. Figure 12 depicts the graphical representation of seven classifiers, whereby their performance is evaluated based on the values of the Receiver Operating Characteristic (ROC) Area. It was noted that the classifiers exhibited higher accuracy in predicting the presence of Anxiety, as evidenced by the Receiver Operating Characteristic (ROC) area values falling within the range of 0.9 to 1 for all utilized classifiers. The findings indicate that ensemble approaches, including AdaBoost and RF boosting, have superior accuracy in forecasting anxiety levels within the population of technical staff. Hence, the significance of anxiety levels in the identification of those who are susceptible to developing mental health issues is evident. Additionally, it is pertinent in the context of mitigating potential future decline in mental well-being. In general, the findings of the study illustrate the capacity of machine learning algorithms to assist in the timely identification of mental health illnesses among technical staff. The results of this investigation further contribute to the scholarly comprehension of the subject matter, with a specific emphasis on individuals employed in technical roles.

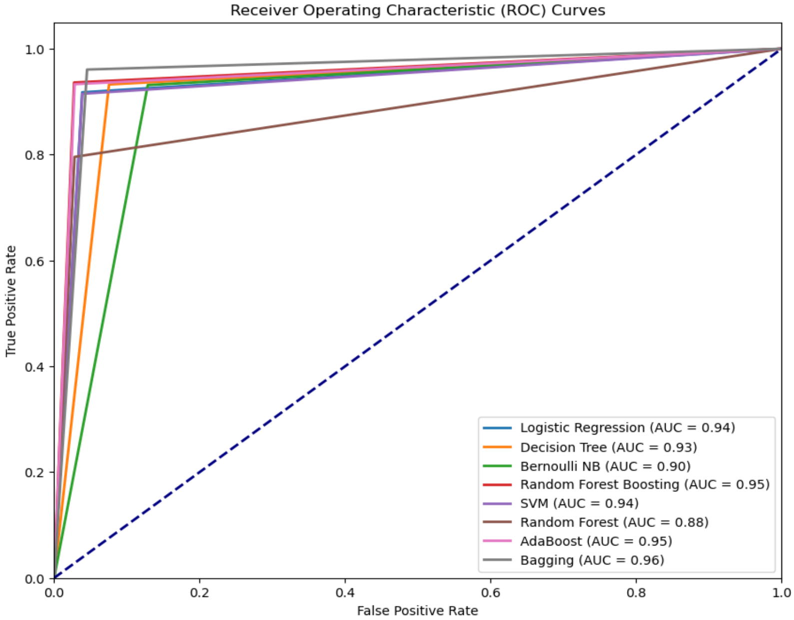

Figure 12. ROC Curve.

5. Discussion

The study aimed to predict anxiety among technical employees using several machine learning algorithms and reported a range of performance metrics, including accuracy, precision, recall, and F1 score. AdaBoost delivered strong results with an accuracy of 96.09%, precision of 91.93%, recall of 93.04%, and an F1 score of 92.45%. AdaBoost's ensemble approach often improves the performance of base models. Random forests demonstrated excellent accuracy at 96.23% and a balanced precision (92.32%) and recall (93.37%), leading to an impressive F1 score of 92.83%. Random forests are known for their robustness and can handle a variety of data types effectively. SVM achieved a high accuracy of 94.91% and balanced precision (89.18%) and recall (91.49%), resulting in an F1 score of 90.26%. SVM is a powerful algorithm for classification tasks, and these results reflect its effectiveness. This study revealed that Support Vector Machine (SVM) achieved a robust balance between precision and recall. This observation is consistent with findings in the healthcare sector, where SVM and RF has shown effectiveness in handling complex and multidimensional datasets [27, 28] and other job sectors [29, 30]. The adaptability of SVM across different domains makes it a versatile choice. These findings are crucial for understanding the effectiveness of different algorithms in addressing this important issue. Findings revealed that ensemble methods, particularly Random Forest Boosting and AdaBoost, demonstrated strong predictive performance. These results are consistent with recent studies in healthcare and psychology, where ensemble methods have been increasingly utilized for predicting mental health conditions [31, 32]. The robustness and adaptability of ensemble methods make them promising candidates for identifying anxiety across various industries.

LR classic algorithm achieved a high accuracy of 94.98%. It also demonstrated good precision (89.18%) and recall (91.78%), resulting in an F1 score of 90.41%. These results suggest that logistic regression is a strong contender for predicting anxiety in this context. Logistic Regression, a traditional yet reliable algorithm, performed admirably in our study. This finding aligns with recent research in the domain of employee mental health [33, 34]. Logistic Regression's simplicity and interpretability make it a valuable baseline model for early-stage investigations and practical applications.

With an accuracy of 88.69%, Bernoulli Naive Bayes showed good recall (93.13%) but comparatively lower precision (71.84%). The F1 score was 81.08%. This algorithm may need additional feature engineering to enhance precision. The performance of Bernoulli Naive Bayes in our study, with a high recall but lower precision, underscores its potential for capturing patterns related to anxiety. Recent research [35, 36] also emphasized the importance of feature engineering when employing Naive Bayes algorithms for mental health prediction.

While decision trees achieved an accuracy of 92.6%, they showed slightly lower precision (82.91%). However, their recall was notably high at 93.25%, resulting in an F1 score of 86.36%. Decision trees offer interpretability but may require pruning to improve precision. Our study highlighted that Decision Trees excel in achieving high recall, suggesting their potential for identifying individuals at risk of anxiety. This aligns with research by Battista et al. [37], where Decision Trees were employed for early intervention in mental health issues among college students. However, the precision of Decision Trees may require improvement through techniques such as pruning.

The implications of our research findings on predicting anxiety among technical employees using machine learning are substantial. These findings offer an opportunity for organizations to proactively address the mental health and well-being of their workforce. By harnessing machine learning algorithms, employers can develop early intervention strategies that identify employees at risk of anxiety, allowing for timely support and resources. Additionally, these results underscore the importance of data quality, feature engineering, and model interpretability in mental health prediction. As such, organizations should invest in comprehensive data collection, ongoing feature exploration, and the deployment of interpretable models to ensure the reliability and effectiveness of predictive systems. Overall, our findings empower organizations to take concrete steps towards creating healthier and more supportive work environments, ultimately benefitting both employees and the organization as a whole.

6. Conclusions

This research has provided valuable insights into the predictive capabilities of various machine learning algorithms for identifying anxiety among technical employees. The findings have significant implications for addressing mental health challenges in the workplace and improving overall employee well-being. Notably, ensemble methods such as Random Forest Boosting and AdaBoost demonstrated exceptional predictive performance, while traditional models like Logistic Regression also proved to be strong contenders. Decision Trees showcased potential for early intervention, especially in high-recall scenarios, and Bernoulli Naive Bayes highlighted the importance of feature engineering. Support Vector Machine exhibited robustness in balancing precision and recall. The utilization of this technology enables the substitution of manual anxiety screening techniques, conducted through the use of diverse rating scales, with an automated computer-based technique that exhibits a reasonable level of accuracy.

These results have important implications for organizations aiming to prioritize mental health in the workplace. Employers and human resource professionals can leverage these findings to implement data-driven early intervention strategies and support systems for employees facing anxiety-related challenges. Furthermore, this research underscores the significance of data quality, continuous feature exploration, and model interpretability in the development of predictive systems for mental health. Nevertheless, the research conducted in this study was constrained by a low sample size and the presence of missing data, albeit only affecting a tiny fraction of the entire dataset. However, it is important to note that the missing data were uniformly distributed across the various groups. Hence, it is improbable that the absence of this data significantly impacted the outcomes.

Future research should aim to analyze larger and more balanced datasets in order to enhance the validity and generalizability of the findings. Additionally, it is crucial to incorporate additional elements, such as work characteristics, working hours, and lifestyle variables, to gain a comprehensive understanding of the phenomenon under study. Furthermore, future research should focus on addressing class imbalance, refining feature engineering techniques, and enhancing model interpretability. Additionally, longitudinal studies can provide a more dynamic understanding of employee well-being, allowing organizations to adapt and respond to changing mental health dynamics. Ultimately, by utilizing machine learning to predict and support employees dealing with anxiety, organizations can create healthier and more resilient work environments that benefit both individuals and the organization as a whole, fostering a culture of well-being and productivity.

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