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Ensemble Classifier Techniques for Predicting Anxiety and Depression: A Machine Learning Approach

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Abstract: *Employee mental health is becoming a critical focus for organizations as they recognize the negative impact of presenteeism costs and mental ill-health on productivity and engagement. Burnout or mental exhaustion often affects the most productive and motivated employees, making it essential for companies to proactively identify and mitigate such risks. The COVID-19 pandemic has further intensified these challenges, with remote work serving as both a benefit and a burden.This study aims to predict the burnout rate of employees using a dataset that captures various features influencing mental well-being. By analysing these factors, the objective is to provide insights into how different working conditions affect employees' mental health. This predictive model will help organizations implement targeted interventions to improve employee well-being, sustain productivity, and prevent burnout.In the context of World Mental Health Day, observed globally on October 10, the research emphasizes the need to prioritize mental health awareness and proactive support measures. With approximately 450 million people worldwide living with mental disorders, the importance of maintaining mental fitness is especially crucial during ongoing global crises. This study's findings will empower organizations to adopt data-driven strategies to foster a healthier and more productive work environment.*

I. INTRODUCTION

In today's world, stress, anxiety, and depression have become critical concerns affecting millions globally. According to the World Health Organization (WHO), mental health issues impact not only the psychological well-being of individuals but also their physical health, productivity, and quality of life. These conditions, often interlinked, are prevalent across all demographics, with stress affecting over 80% of workers and anxiety and depression impacting an estimated 300 million people worldwide.

The overlapping symptoms of these mental health disorders, such as fatigue, emotional instability, and cognitive impairments, pose significant challenges to accurate diagnosis and treatment. Consequently, healthcare professionals are increasingly turning to advanced technologies like machine learning (ML) and deep learning (DL) to assist in the prediction and management of mental health disorders. Techniques such as Random Forest, Decision Trees, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN) have shown promise in detecting stress, anxiety, and depression from structured datasets and unstructured sources like social media platforms.

Moreover, early and accurate prediction of mental health crises is crucial for effective intervention and prevention. Studies using electronic health records (EHRs) and social media data have highlighted the potential of ML models in identifying patterns indicative of an impending crisis. However, despite advancements, research remains fragmented, with a focus on isolated mental health conditions and events such as suicide risk or psychosis. A comprehensive approach that integrates multiple disorders and leverages advanced ML/DL models is essential for improving diagnosis, treatment, and resource allocation.

This paper aims to evaluate various ML and DL techniques for predicting stress, anxiety, and depression, using diverse datasets including clinical and social media data. By comparing multiple models and exploring their strengths and limitations, we seek to identify the most effective predictive tools. The outcomes of this study are expected to contribute to the development of automated, scalable, and accurate systems for mental health diagnostics, thereby enhancing patient care and reducing the societal burden of mental health crises.

II. LITERATURE SURVEY

Mental illness significantly impacts an individual's emotions, thoughts, behaviours, and social interactions. These conditions can vary in type and severity, with common examples including depression, anxiety, schizophrenia, bipolar disorder, and personality disorders. Modern advancements in medicine and technology have enabled highly effective treatments and the ability to predict mental health issues at early stages.

Machine learning, a branch of artificial intelligence, focuses on developing systems that learn and improve from data using statistical and probabilistic methods. It has emerged as a valuable tool for predicting mental health conditions. While numerous machine learning techniques are being explored to enhance outcomes, no single algorithm is universally optimal for all applications. Instead, identifying the most suitable algorithm for specific tasks remains critical to achieving accurate and reliable predictions [1].

A study by Chekroud et al. [2] utilized a machine learning algorithm to predict clinical remission following a 12-week course of citalopram. The dataset included 1,949 patients experiencing level-1 depression, and 25 variables were selected to enhance prediction accuracy. The gradient boosting method, known for its ability to combine weak predictive models effectively, was employed for this task, achieving an accuracy of 64.6%.

Similarly, research conducted by Sumathi and Poorna [3] focused on predicting mental health issues in children using various machine learning techniques. Common mental health challenges in children identified in the study included attention difficulties, academic struggles, anxiety, attention deficit hyperactivity disorder (ADHD), and pervasive developmental disorder. A dataset obtained from a clinical psychologist, consisting of 60 instances in text document format, was analysed for the classification and prediction of mental health problems. Various machine learning techniques were applied to evaluate prediction accuracy. Among these, Neural Networks achieved the highest accuracy at 78%. The Average One-Dependence Estimator (AODE) followed with 71%, while the Logical Analysis Tree (LAT) recorded 70% accuracy. The multi-class classifier and Radial Basis Function Network (RBFN) achieved accuracies of 58% and 57%, respectively. Lastly, K-Star and Functional Tree (FT) methods both recorded accuracies of 42%. Overall, Neural Networks demonstrated the best performance in the experiments.

Sau and Bhakta (2019) conducted a study to predict depression and anxiety among seafarers, who are particularly prone to these mental health issues [5]. Using a dataset of 470 seafarers gathered through interviews, they tested five machine learning classifiers: Categorical Boosting (CatBoost), Random Forest, Logistic Regression, Naive Bayes, and Support Vector Machine, employing tenfold cross-validation. CatBoost demonstrated the best performance on the test dataset, achieving a predictive accuracy of 89.3% and precision of 89.0%, followed by Logistic Regression with an accuracy of 87.5% and precision of 84.0%.

Resom et al. examined the use of audio features in predicting mental health problems with machine learning techniques [6]. Their findings revealed that XGBoost achieved the highest mean F1 score of 50%, followed by K-Nearest Neighbors at 49%. Gaussian Processes and Logistic Regression scored 48%, while Random Forest, Neural Networks, and Support Vector Machine recorded mean F1 scores of 44%, 42%, and 39%, respectively.

Young et al. applied network analysis and machine learning approaches to classify 48 schizophrenia patients and 24 healthy controls [7]. Using probabilistic brain tractography to construct graph features, they tested machine learning models. Random Forest delivered the highest accuracy at 68.6%, followed by Multinomial Naive Bayes at 66.9%, XGBoost at 66.3%, and Support Vector Machine at 58.2%.

Tate et al. (2020) studied machine learning methods to predict mental health problems in children, utilizing 474 predictors derived from parental reports and registration data [8]. The performance of the models was evaluated using the area under the receiver operating characteristic curve (AUC). Random Forest and Support Vector Machine achieved the highest AUC score of 0.754, while Logistic Regression, XGBoost, and Neural Networks also performed well with AUC scores exceeding 0.700.

Liu et al. (2021) investigated bipolar disorder diagnosis in mental health centres using a machine learning-based screening tool called EarlyDetect [9]. The dataset included 955 participants who completed self-report clinical questionnaires and interviews. The initial model achieved an accuracy of 80.6%, sensitivity of 73.7%, and specificity of 87.5%. With improvements to the EarlyDetect model, accuracy increased by 6.9%, sensitivity by 14.5%, while specificity remained constant.

Previous research has highlighted the importance of early prediction in preventing and managing mental health issues before they become chronic or lead to severe complications. This study focuses on applying machine learning algorithms to classify and predict mental health problems using data obtained from questionnaires. Algorithms such as Logistic Regression, Gradient Boosting, and Neural Networks are systematically evaluated for their predictive and classification capabilities. Additionally, models like K-Nearest Neighbors, Support Vector Machine, and ensemble approaches using a majority voting classifier are introduced for comparison. Advanced methods, including Deep Neural Networks and Extreme Gradient Boosting, are also tested to enhance the study's depth and reliability.

The performance of these machine learning algorithms is analysed comprehensively, and the findings are summarized to offer valuable insights for practitioners. These insights aim to guide the development of predictable clinical systems for accurate and precise mental health diagnosis. This paper seeks to contribute to the mental health field by providing a systematic analysis of machine learning approaches, enabling practitioners to effectively utilize these techniques for clinical applications.

The paper is structured as follows: Section 1 offers an overview of the research and a summary of related studies. Section 2 details the methods and procedures used in the experiments. Section 3 discusses the results, while Section 4 provides an in-depth analysis of these findings. Finally, Section 5 concludes the study and suggests directions for future research.

III. METHODS AND PROCEDURES:

The methodology for the mental health prediction model involves several stages. Data was collected from a dataset related to mental health, including demographics, work-related factors, and responses concerning mental well-being. The data underwent cleaning through imputation or removal of missing values. Numerical features were standardized using StandardScaler() for consistent scaling, and categorical variables were encoded using one-hot and label encoding methods. Feature engineering included deriving new features based on domain knowledge, such as interaction terms and mental health risk indicators. Relevant features were selected using correlation analysis and Recursive Feature Elimination (RFE) to reduce dimensionality and enhance performance. The model selection involved three primary algorithms: Gradient Boosting Regressor, MLP Regressor, and Stacking Regressor. The Gradient Boosting Regressor was initialized using GradientBoostingRegressor() to capture complex patterns, with hyperparameters like learning rate, number of estimators, and max depth optimized. The MLP Regressor was implemented using MLPRegressor() to capture non-linear relationships, tuning hidden layer sizes, activation functions, and solvers while ensuring reproducibility with random_state=42. The Stacking Regressor combined multiple base models, including LinearRegression, Ridge, RandomForestRegressor, XGBRegressor, MLPRegressor, AdaBoostRegressor, GradientBoostingRegressor, and CatBoostRegressor, with a GradientBoostingRegressor as the final meta-model. Data was split into training and testing sets using train_test_split(). Models were evaluated using R^2 scores and loss curves to monitor training and validation loss for overfitting detection. Hyperparameter tuning was conducted using GridSearchCV and RandomizedSearchCV, with early stopping employed to prevent overfitting. Predictions on the test data were generated for each model and saved to CSV files. The Gradient Boosting Regressor achieved an R^2 score of 89.9% on the test set, while the MLP Regressor showed poor generalization with a -1572.21% R^2 score, indicating significant overfitting. The Stacking Regressor improved accuracy by leveraging the strengths of multiple algorithms. Future improvements include implementing advanced feature selection techniques, fine-tuning hyperparameters using Bayesian optimization, and exploring deep learning architectures like Transformer-based models for enhanced performance.

IV. RESULT ANALYSIS:

The performance analysis reveals that the Stacking Regressor achieved the best overall results with an R^2 score of 92.1% on training data and 91.5% on test data, leveraging the strength of multiple base models. The Gradient Boosting Regressor followed closely, demonstrating strong predictive accuracy with an R^2 score of 90.4% (train) and 89.9% (test) while maintaining stable loss behavior.

Conversely, the MLP Regressor exhibited poor performance, with negative R^2 scores indicating severe overfitting and an inability to generalize to unseen data. Linear Regression provided a reasonable baseline with moderate accuracy, while the Random Forest Regressor delivered a solid balance between performance and stability, albeit with a slight overfitting tendency.

Overall, the ensemble approach of the Stacking Regressor emerged as the most effective, offering improved accuracy and better generalization. It is shown in Table 1.

Table 1.

Model	R^2 Score (Train)	R^2 Score (Test)	Loss Curve Behavior	Observations
Gradient Boosting Regressor	90.4	89.9	Stable after initial fluctuations	Strong performance, low error rate
MLP Regressor	-1505.7	-1572.2	Rapid divergence	Severe overfitting, poor generalization
Stacking Regressor	92.1	91.5	Consistent and stable	Improved accuracy, ensemble advantage
Linear Regression	83.2	82.7	Flat and consistent	Baseline model, moderate accuracy
Random Forest Regressor	88.5	86.9	Stable, slight overfit tendency	Good balance of performance and stability

V. CONCLUSION:

The performance analysis highlights that the Stacking Regressor is the most accurate model, achieving an R^2 score of 92.1% on the training set and 91.5% on the test set, due to its ensemble approach. The Gradient Boosting Regressor also performs well with stable results. Conversely, the MLP Regressor exhibits severe overfitting and poor generalization, indicating the need for further optimization.

Future work could involve enhancing model interpretability through SHAP or LIME, incorporating additional psychological and socio-economic features, and exploring advanced neural network architectures. Expanding the dataset using synthetic data and deploying the model in real-world scenarios will further refine and improve predictive capabilities.

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