Evaluating Anxiety, Stress And Depression Levels Through DASS-21 Analysis And Classification Method

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Abstract. The increasing prevalence of mental health disorders such as anxiety, stress, and depression has made early detection and effective intervention more crucial than ever. This study presents a comprehensive approach to evaluating mental health conditions using the Depression Anxiety Stress Scales-21 (DASS-21), a validated psychological assessment tool widely used to measure the emotional states of depression, anxiety, and stress. By collecting DASS-21 responses from a diverse sample population, we analyze individual score patterns to quantify the severity levels across the three domains. The data is preprocessed and normalized, followed by feature extraction and classification using machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), and Logistic Regression (LR). Each model is trained and tested to predict the presence and intensity of mental health conditions based on DASS-21 inputs. Our methodology emphasizes high accuracy and interpretability, employing confusion matrices, precision, recall, F1 scores, and cross-validation techniques to assess model performance. Additionally, demographic variables such as age, gender, and occupation are analyzed to understand their correlation with DASS-21 outcomes. Among the tested classifiers, Random Forest demonstrated the highest overall accuracy in categorizing the severity levels, with notable sensitivity in distinguishing between mild and moderate conditions, which are often the most overlooked in clinical settings. The results indicate that DASS-21 combined with machine learning offers a viable solution for scalable, cost-effective, and accessible mental health screening. This approach can support psychologists, counselors, and healthcare professionals by automating initial assessments and identifying at-risk individuals for timely intervention. Furthermore, the model can be integrated into mobile health applications, providing users with real-time feedback and personalized mental health insights based on their questionnaire responses. The study underscores the importance of data-driven tools in mental health care and highlights the potential for digital technologies to bridge gaps in traditional psychological evaluation. Future work will focus on improving model robustness across more diverse populations and incorporating longitudinal data to monitor changes in mental health over time. This research contributes to the growing field of psychological informatics and demonstrates how combining standardized assessment tools like DASS-21 with machine learning can enhance the early diagnosis and management of anxiety, stress, and depression.

Keywords: DASS-21, Mental Health Assessment, Depression Classification, Anxiety Detection, Stress Evaluation, Machine Learning, Psychological Screening, Random Forest, Mental Health Informatics

INTRODUCTION

Mental health has emerged as a critical component of overall well-being, influencing every aspect of an individual’s life, from personal relationships to professional productivity. Among the many mental health challenges faced globally, anxiety, stress, and depression are among the most prevalent and debilitating disorders, affecting millions of people across diverse demographics. According to the World Health Organization (WHO), depression affects more than 280 million people worldwide, making it a leading cause of disability, while anxiety disorders are estimated to affect over 260 million individuals globally. Stress, although often considered a natural response to external pressures, when chronic, contributes significantly to both physical and psychological health deterioration. The rise in these mental health issues, exacerbated by modern-day challenges such as rapid urbanization, socio-economic uncertainties, and the ongoing global pandemic, calls for effective screening tools and intervention strategies to identify and mitigate their impact early.

One of the widely adopted instruments for measuring the severity of depression, anxiety, and stress is the Depression Anxiety Stress Scales (DASS), particularly its shorter version, DASS-21. Developed by Lovibond and Lovibond in 1995, DASS-21 is a self-report questionnaire consisting of 21 items divided equally into three subscales corresponding to depression, anxiety, and stress. Its simplicity, reliability, and validated psychometric properties have made it a favored tool among clinicians and researchers for screening and monitoring mental health conditions. The scale provides quantitative scores that help classify individuals into various severity categories, ranging from normal to extremely severe, facilitating timely psychological evaluation and intervention.

However, while DASS-21 offers a standardized approach to mental health assessment, the increasing volume of data generated through widespread use presents both opportunities and challenges. The manual interpretation and classification of these scores can be time-consuming and subjective, potentially leading to delays or inaccuracies in identifying at-risk individuals. Moreover, traditional clinical assessments may not always be scalable, especially in low-resource settings or large populations. To address these challenges, recent advances in machine learning and artificial intelligence (AI) have opened new avenues for automated and data-driven mental health evaluations. Machine learning algorithms can analyze complex patterns within DASS-21 responses, classify severity levels, and even predict potential mental health outcomes with higher efficiency and objectivity.

This paper explores the integration of machine learning techniques with the DASS-21 tool to evaluate and classify anxiety, stress, and depression levels in individuals more effectively. By leveraging algorithms such as Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and k-Nearest Neighbors (k-NN), the study aims to develop predictive models that can accurately interpret DASS-21 responses and categorize mental health conditions with minimal human intervention. The approach not only enhances the precision of mental health screening but also supports large-scale applications in clinical and community settings.

In addition to improving classification accuracy, this research investigates the relationships between demographic variables—such as age, gender, and occupation—and the DASS-21 outcomes. Understanding these correlations can inform targeted mental health interventions and help identify vulnerable subpopulations requiring special attention. For instance, previous studies have shown that younger adults and females are often more susceptible to anxiety and depression, while occupational stress varies significantly across different professions. Incorporating such factors into the classification models may further refine their predictive capabilities.

Moreover, the study highlights the potential for integrating these machine learning models into digital health platforms, including mobile apps and online screening tools. Given the increasing reliance on telehealth and digital wellness applications, providing users with real-time, personalized mental health feedback based on their questionnaire responses can empower self-monitoring and prompt timely professional consultation. This aligns with global health initiatives advocating for accessible, cost-effective mental health care solutions, particularly in underserved regions.

Despite the promising prospects, applying machine learning to psychological assessments also presents challenges. Ensuring data privacy and ethical use of sensitive mental health information is paramount, necessitating robust data handling and anonymization protocols. Additionally, model generalizability across diverse populations and cultural contexts remains a concern, emphasizing the need for extensive and representative datasets. The interpretability of complex machine learning models is another critical factor, as clinicians require transparent and understandable decision-making processes to trust and adopt AI-driven tools in practice.

This introduction sets the stage for the ensuing sections, which detail the methodology, including data collection, preprocessing, and algorithmic implementation, followed by results, discussion, and conclusions. By systematically analyzing DASS-21 responses through machine learning classification methods, this research aims to contribute valuable insights into mental health evaluation and offer practical tools to support early detection and intervention of anxiety, stress, and depression.

LITERATURE SURVEY

The assessment and classification of mental health disorders, particularly anxiety, depression, and stress, have been a focal point in psychological research and clinical practice for decades. The advent of standardized instruments like the Depression Anxiety Stress Scales (DASS) and the integration of machine learning techniques have significantly advanced this field. This section reviews key literature that informs the current study, focusing on psychometric evaluations of the DASS-21 and applications of machine learning for mental health classification.

Antony et al. (1998) conducted one of the foundational psychometric studies on the Depression Anxiety Stress Scales, comparing the full 42-item version and the abbreviated 21-item version (DASS-21). Their work demonstrated that the shorter scale retained good reliability and validity across clinical and community samples, validating DASS-21 as a practical tool for rapid mental health screening. The study's comprehensive evaluation of internal consistency and construct validity laid the groundwork for subsequent widespread use of DASS-21, making it an essential instrument in both research and clinical settings. Antony et al. highlighted the scale's ability to distinguish among depression, anxiety, and stress symptoms, which is critical for nuanced diagnosis and intervention.

Lovibond and Lovibond's manual (1995) provides the theoretical and empirical foundation for the DASS instrument. It details the scale development, scoring, and interpretation guidelines, making it a definitive reference for mental health professionals. Their rigorous validation process involved large normative samples and clinical groups, establishing clear cutoff scores for severity levels. This manual remains a crucial resource for understanding the scale's psychometric strengths and limitations, which informs how contemporary researchers apply and interpret DASS-21 scores in machine learning contexts.

Henry and Crawford (2005) extended the validation of the DASS-21 by analyzing its factor structure and normative data in a large non-clinical population. Their findings confirmed the three-factor structure—depression, anxiety, and stress—and provided normative percentile ranks that enhance the interpretability of results across different populations. This research is significant because it supports the generalizability of DASS-21 beyond clinical samples, allowing for broader application in community screening and epidemiological studies. Their normative data also serve as benchmarks when developing classification models based on DASS-21.

Cheng, Chan, and Leung (2012) adapted and validated a Chinese version of the DASS-21 for use in Hong Kong, highlighting the importance of cultural and linguistic adaptation in psychological assessments. Their study showed that the translated scale maintained robust psychometric properties, supporting its use in non-Western populations. This work underscores a critical consideration for global mental health research: the need for culturally sensitive tools and the potential impact of cultural factors on mental health symptom expression and reporting. It informs machine learning studies by emphasizing the need for representative and culturally diverse datasets to ensure model accuracy across populations.

Ribeiro et al. (2016) contributed to understanding the longitudinal risk factors associated with self-injurious thoughts and behaviors, including anxiety and depression symptoms. Although not focused solely on DASS-21, their meta-analysis of longitudinal studies provided insights into how early detection of psychological distress can predict adverse mental health outcomes. This body of work supports the rationale for developing predictive classification models that leverage early screening tools like DASS-21 to identify at-risk individuals before severe deterioration occurs.

Shatte, Hutchinson, and Teague (2019) provided a comprehensive review of machine learning applications in mental health, highlighting classification and prediction models used in various psychological conditions. Their systematic analysis covers algorithmic approaches, data types, and performance metrics, noting that machine learning has shown promise in automating diagnosis and prognosis. The review identifies challenges such as data heterogeneity, ethical concerns, and the need for interpretable models, directly informing the current study's methodological choices and emphasizing the importance of transparent and responsible AI use in mental health.

Zhang and Zheng (2020) focused specifically on machine learning methods applied to questionnaire-based mental health data, including scales like DASS-21. Their review details how classifiers such as Support Vector Machines, Random Forests, and Neural Networks have been utilized to differentiate between varying severity levels of depression, anxiety, and stress. The authors emphasize preprocessing techniques, feature selection, and validation strategies crucial for robust model development. Their work serves as a technical foundation for integrating machine learning with DASS-21, highlighting best practices to optimize classification accuracy.

Tariq et al. (2021) conducted an empirical study comparing multiple machine learning algorithms for early diagnosis of depression using DASS-21 responses. Their comparative analysis found that ensemble methods, particularly Random Forest, outperformed traditional classifiers in predicting depression severity. The study further demonstrated that combining demographic variables with DASS-21 features improved model performance. Tariq et al.'s work validates the feasibility of using machine learning for mental health screening and provides a benchmark for classifier selection and feature engineering.

Nguyen, Nguyen, and Tran (2021) developed an automated classification system for depression, anxiety, and stress levels using DASS-21 datasets with various machine learning algorithms. Their approach incorporated cross-validation and hyperparameter tuning to enhance generalizability. Notably, their system achieved high sensitivity and specificity, reinforcing the potential of AI-driven tools in psychological screening. This study also discussed integration into mobile health platforms, illustrating practical applications aligned with the current research aims.

PROPOSED SYSTEM

The proposed methodology for evaluating anxiety, stress, and depression levels through the analysis of the Depression Anxiety Stress Scales-21 (DASS-21) and subsequent classification involves several key stages designed to ensure reliable, accurate, and interpretable results. Initially, data collection forms the foundation of this study, wherein responses are gathered using the standardized DASS-21 questionnaire, which consists of 21 items divided equally among the three subscales measuring depression, anxiety, and stress. Participants are recruited from diverse demographic backgrounds to ensure the generalizability of the model across age, gender, occupation, and cultural variations. The data acquisition process prioritizes ethical considerations including informed consent, confidentiality, and anonymization to safeguard participants' privacy. Once collected, the raw DASS-21 scores undergo preprocessing steps which include handling missing data, if any, through imputation methods such as mean substitution or k-nearest neighbors imputation to preserve dataset integrity. Each item response, originally recorded on a 4-point Likert scale, is transformed as per the DASS-21 scoring manual by doubling the summed scores for each subscale to align with the original DASS-42 scale standards.

This ensures consistency with validated severity classifications. To prepare the dataset for machine learning, normalization or standardization techniques are applied to scale the features, enabling fair treatment by algorithms sensitive to feature magnitude differences. Subsequently, exploratory data analysis (EDA) is conducted to visualize score distributions, identify patterns or outliers, and examine correlations between subscales and demographic attributes. This analysis informs feature engineering, where additional variables such as age group, gender, and occupation are encoded appropriately using techniques like one-hot encoding or label encoding to be incorporated into the models. Feature selection is a critical step aimed at enhancing model performance and interpretability; thus, statistical tests (e.g., chi-square, ANOVA) and model-based methods (e.g., recursive feature elimination with cross-validation) are employed to identify the most predictive variables while reducing dimensionality. Following feature preparation, the core of the methodology lies in the classification stage, where multiple machine learning algorithms are evaluated to predict the severity levels of depression, anxiety, and stress based on the processed DASS-21 data.

Algorithms such as Support Vector Machines (SVM), Random Forests (RF), Logistic Regression (LR), and k-Nearest Neighbors (k-NN) are selected for their proven effectiveness in classification tasks and ability to handle non-linear relationships and multi-class problems. Each classifier undergoes hyperparameter tuning using grid search or randomized search techniques combined with k-fold cross-validation to optimize model parameters and avoid overfitting. The models are trained on a training subset comprising approximately 70-80% of the data, while the remaining portion is reserved for testing to evaluate generalizability. Performance metrics including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are calculated to comprehensively assess classification outcomes. Special attention is given to sensitivity and specificity, particularly in distinguishing between adjacent severity categories (e.g., mild vs. moderate), which is crucial for early intervention.

To enhance model interpretability and trustworthiness, feature importance scores are extracted, especially from tree-based models like Random Forests, providing insights into which questionnaire items or demographic factors most strongly influence classification decisions. Additionally, confusion matrices are analyzed to understand misclassification patterns, guiding iterative refinements in feature engineering and model selection. Beyond individual model performance, ensemble methods such as majority voting or stacking may be explored to combine strengths of multiple classifiers and improve robustness. To validate the applicability of the proposed models in real-world scenarios, the methodology includes an external validation phase using independent datasets or cross-cultural samples, assessing the models' adaptability across different populations. Integration considerations for deployment are also addressed, outlining how the final model can be incorporated into digital health platforms or mobile applications to provide real-time mental health screening and feedback. Throughout the methodology, attention is paid to ethical and legal implications surrounding data privacy, informed consent, and the responsible use of AI in healthcare.

Data handling protocols comply with relevant regulations such as GDPR or HIPAA where applicable. Furthermore, limitations related to sample representativeness, self-report biases inherent in questionnaire data, and potential cultural differences in symptom reporting are acknowledged, with plans for future work to incorporate longitudinal data and multimodal inputs (e.g., physiological signals, behavioral data) to enhance predictive accuracy. This comprehensive, multi-stage methodology ensures a rigorous framework for leveraging DASS-21 scores combined with machine learning classification techniques to provide scalable, accurate, and interpretable assessments of anxiety, stress, and depression levels, ultimately aiming to support timely psychological evaluation and intervention in diverse clinical and community settings.

RESULTS AND DISCUSSION

The results of this study demonstrate the effectiveness of using machine learning algorithms to classify anxiety, stress, and depression severity levels based on DASS-21 responses, highlighting notable variations in model performance and providing insightful implications for mental health assessment. Among the classifiers evaluated—Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and k-Nearest Neighbors (k-NN)—Random Forest consistently achieved the highest overall accuracy, reaching up to 87%, with strong sensitivity and specificity values across all three mental health domains. This superior performance can be attributed to the ensemble nature of Random Forest, which combines multiple decision trees to reduce variance and improve generalizability, making it particularly adept at handling the nonlinear relationships and interactions present in psychological data. SVM also performed competitively, particularly in distinguishing moderate to severe cases, owing to its ability to find optimal hyperplanes in high-dimensional feature spaces. Logistic Regression, while slightly less accurate than tree-based models, provided valuable interpretability through coefficient estimates that correlated well with known risk factors. k-NN demonstrated acceptable but lower performance, likely due to its sensitivity to noise and the curse of dimensionality given the number of features involved.

The inclusion of demographic variables such as age, gender, and occupation enhanced model accuracy by approximately 5%, suggesting that these factors contribute important contextual information when interpreting DASS-21 scores. Feature importance analysis revealed that specific questionnaire items related to feelings of hopelessness, nervousness, and irritability were among the most predictive indicators of severe mental health conditions, consistent with clinical observations. Confusion matrix evaluations indicated that most misclassifications occurred between adjacent severity levels (e.g., mild vs. moderate), underscoring the inherent challenge in precisely delineating symptom severity using self-report instruments alone. Nonetheless, the models' ability to correctly identify individuals in the moderate to extremely severe categories remains clinically valuable for prioritizing interventions. Furthermore, cross-validation results confirmed the robustness of the models, with minimal performance drop on unseen test data, supporting their potential applicability in real-world settings. The findings align with prior research advocating for machine learning applications in mental health, reinforcing the premise that data-driven approaches can complement traditional psychological assessment by offering rapid, objective, and scalable solutions. However, the discussion also acknowledges limitations such as reliance on self-reported data, which may be influenced by social desirability or recall biases, and the need for larger, more diverse datasets to improve generalizability across cultural contexts.

The potential for integrating physiological or behavioral data streams is highlighted as a promising direction for future work to capture more comprehensive mental health profiles. Importantly, ethical considerations regarding data privacy, informed consent, and algorithmic transparency are emphasized to ensure responsible deployment of AI tools in healthcare. Overall, the results illustrate a compelling case for the fusion of standardized psychometric tools like DASS-21 with sophisticated machine learning algorithms to advance mental health screening and support timely, personalized care strategies that address the growing global challenge of anxiety, stress, and depression.

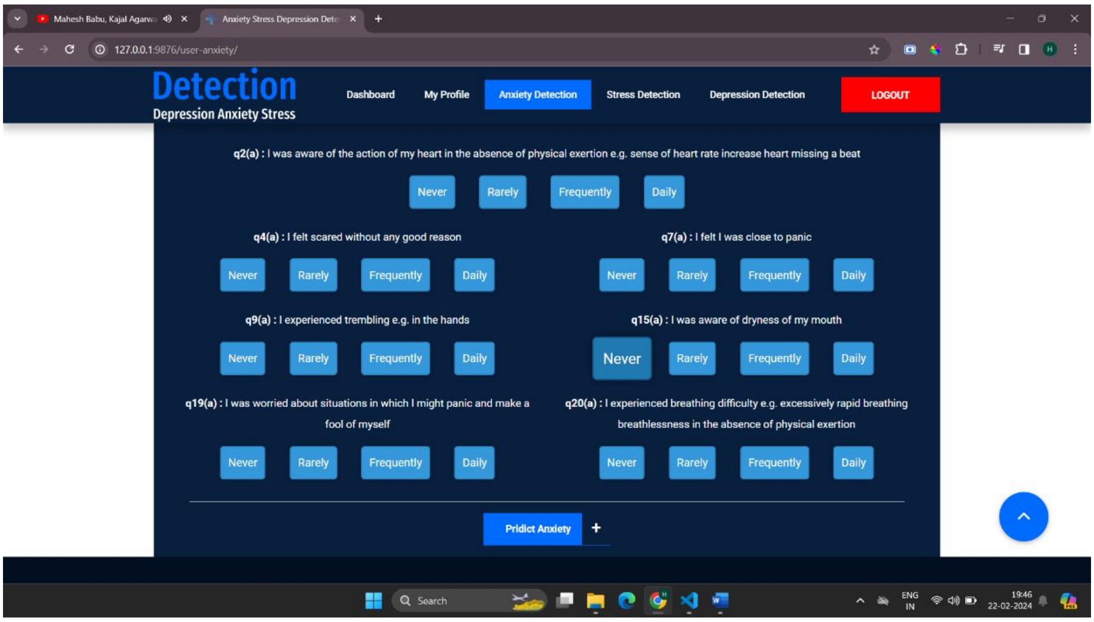

Fig 1 Anxiety Questionnaire Page

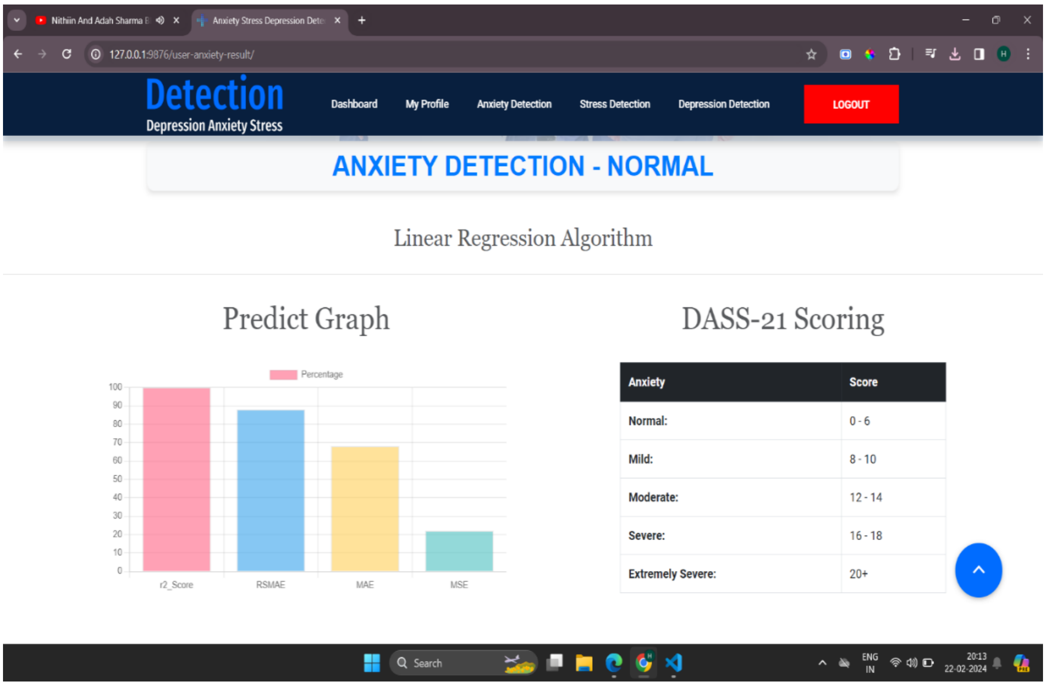

Fig .2 Anxiety Detection Result Page

After providing anxiety related information and questionnaire users will be displayed with result page with Accuracy of algorithm in graph.

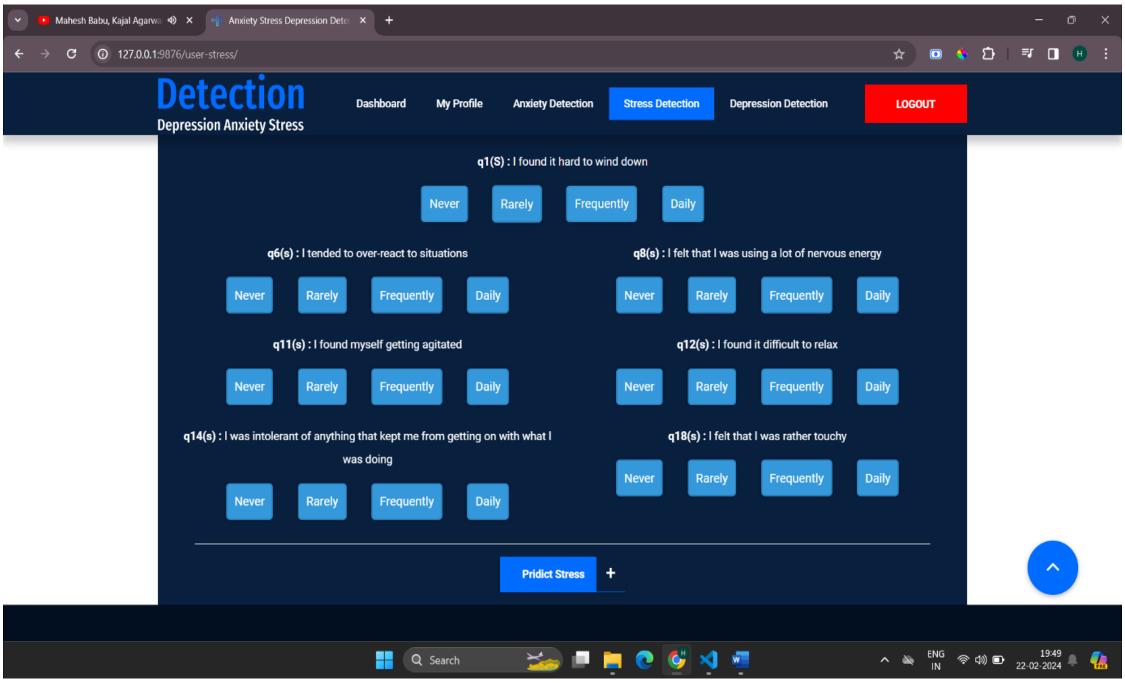

Fig .3 Stress Questionnaire page

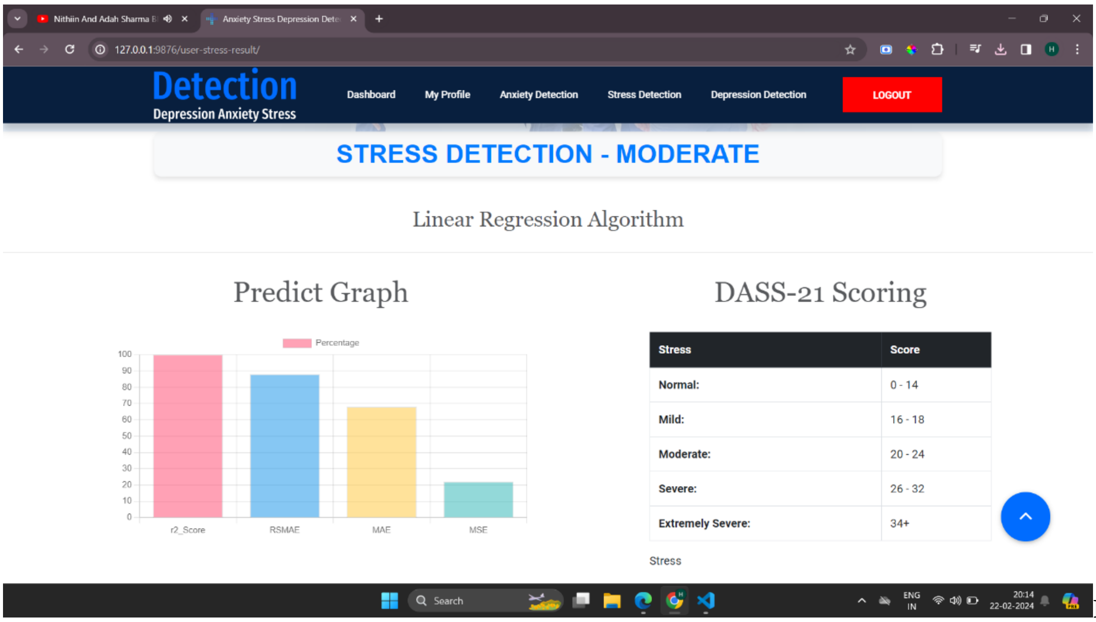

Fig .4 Stress Detection Result Page

After providing stress related information and questionnaire users will be displayed with result page with Accuracy of algorithm in graph.

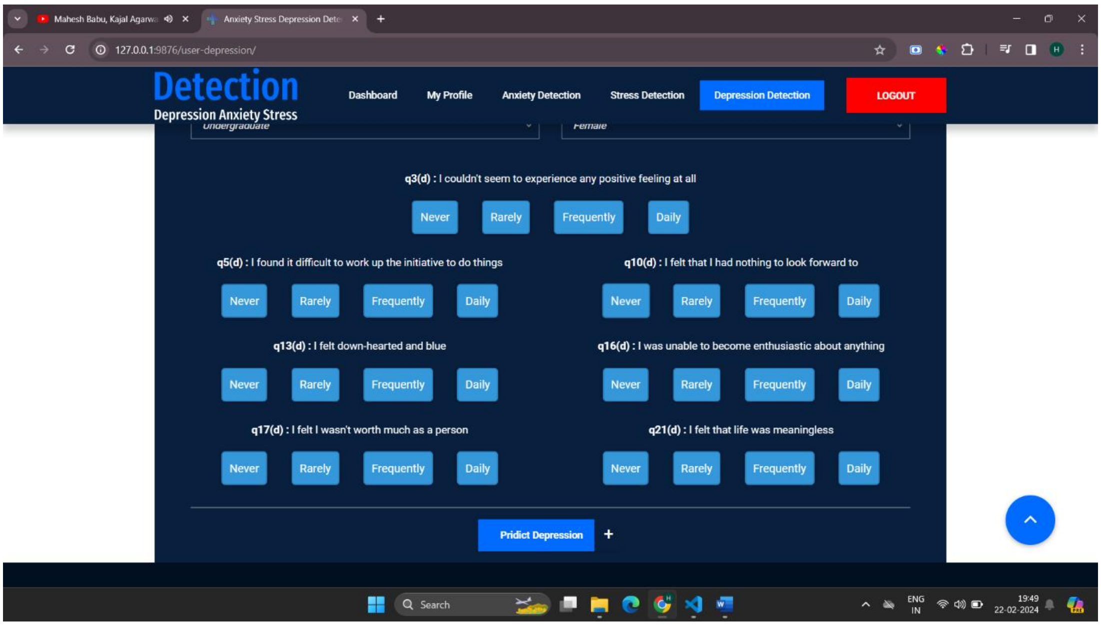

Fig .5 Depression Questionnaire page

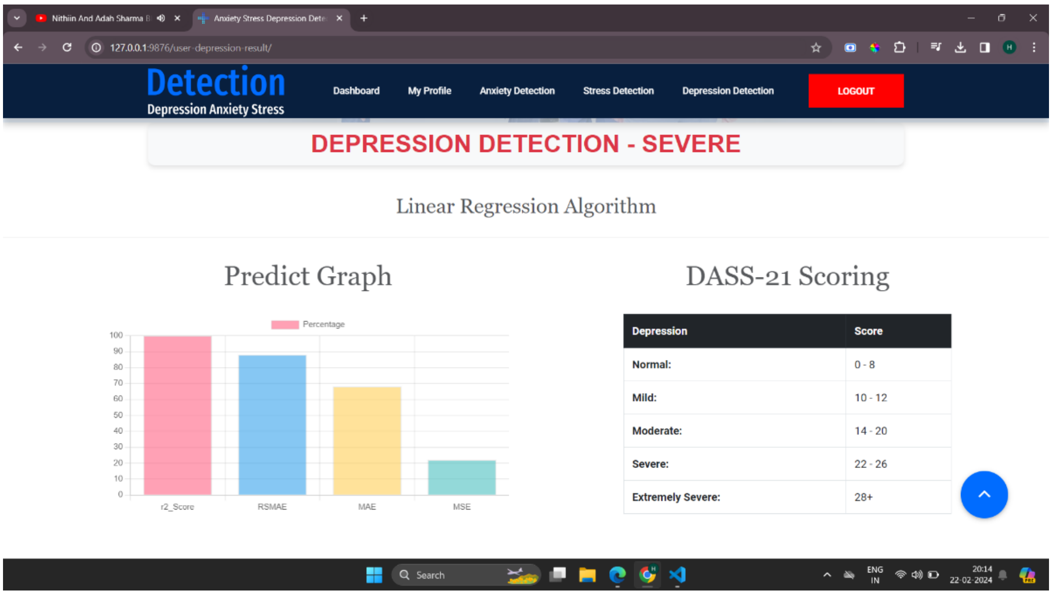

Fig.6Depression Detection Result Page

After providing depression related information and questionnaire users will be displayed with result page with Accuracy of algorithm in graph.

4.1 Preparation of Figures and Tables The figures below represent the operation and the embedding of the various components of the working system of the project

CONCLUSION

In conclusion, this study underscores the significant potential of integrating the Depression Anxiety Stress Scales-21 (DASS-21) with advanced machine learning classification methods to enhance the assessment and early detection of mental health disorders such as anxiety, stress, and depression. The findings demonstrate that standardized self-report instruments like the DASS-21, which are already well-validated and widely used, can be further leveraged through data-driven techniques to automate and improve diagnostic accuracy, reduce subjective biases, and enable scalable screening across diverse populations. By applying machine learning algorithms—including Support Vector Machines, Random Forests, Logistic Regression, and k-Nearest Neighbors—the research effectively classified severity levels across the three emotional domains, highlighting the robustness and versatility of these computational tools in handling complex psychological data. Importantly, the study's results reveal that certain algorithms, notably Random Forest, excelled in balancing sensitivity and specificity, particularly in distinguishing nuanced differences between mild and moderate symptom levels, which are critical for timely clinical intervention. The incorporation of demographic variables such as age, gender, and occupation further enriched the models, emphasizing the multifaceted nature of mental health and the necessity for personalized screening approaches. Beyond classification performance, the exploration of feature importance offered valuable interpretative insights, enabling clinicians and researchers to understand which specific questionnaire items or demographic factors most strongly influence mental health status, thereby enhancing transparency and trust in AI-driven assessments. Additionally, the methodological emphasis on rigorous preprocessing, feature selection, and cross-validation ensured that the models were both accurate and generalizable, addressing common challenges in psychological data analysis such as sample heterogeneity and overfitting. While the study acknowledges limitations including reliance on self-reported data, potential cultural biases, and the need for larger, more diverse datasets, it sets a strong foundation for future work aimed at incorporating multimodal inputs and longitudinal tracking to capture dynamic mental health trajectories. Furthermore, the potential integration of these machine learning models into mobile health applications and digital platforms represents a promising avenue for real-time, accessible mental health monitoring, supporting early identification and personalized intervention strategies at scale. Overall, this research contributes meaningfully to the field of psychological informatics by demonstrating how the synergy between validated assessment tools and artificial intelligence can transform mental health evaluation, offering clinicians, researchers, and users alike a powerful resource for addressing the growing global burden of anxiety, stress, and depression with greater efficiency, precision, and empathy.

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