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Predictive Analysis of Stress Levels Using Explainable Machine Learning Techniques for Stress Management Recommendations

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Stress has become a significant concern affecting the mental health and performance of individuals, particularly in academically intensive environments. Early prediction and management of stress levels can help in reducing its adverse effects. This study proposes a data-driven approach for the predictive analysis of stress levels using explainable machine learning techniques. Various machine learning algorithms, including Random Forest, Support Vector Machine, and Extreme Gradient Boosting, are employed to build predictive models based on behavioral, academic, and psychological factors.

The proposed framework integrates explainable artificial intelligence methods to interpret model predictions and identify key stress-inducing factors. In addition to prediction, the study incorporates a recommendation mechanism that suggests appropriate stress management strategies based on predicted stress levels. The performance of the models is evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

The results demonstrate that ensemble-based models provide higher predictive accuracy compared to traditional approaches. Furthermore, the use of explainable techniques enhances the transparency and reliability of the model. The proposed system can assist educators and individuals in early identification of stress and enable timely interventions through personalized recommendations.

Keywords: Stress Prediction, Machine Learning, Predictive Analytics, Stress Management, Recommendation Systems, Mental Health Analysis

1. Introduction

Stress has become a pervasive issue in modern society, significantly affecting the mental health, well-being, and productivity of individuals. With increasing academic, professional, and personal demands, individuals are frequently exposed to high levels of psychological pressure. Prolonged exposure to stress can lead to serious health consequences, including anxiety, depression, reduced cognitive performance, and decreased overall quality of life. Therefore, early identification and effective management of stress are crucial for improving both individual well-being and organizational efficiency. The importance of stress prediction has gained considerable attention in recent years due to its potential to enable proactive intervention. Traditional methods of stress assessment, such as questionnaires and psychological evaluations, are often subjective, time-consuming, and limited in scalability. These limitations highlight the need for automated and data-driven approaches that can accurately predict stress levels and support timely decision-making. In this context, machine learning techniques have emerged as powerful tools for analyzing complex and high-dimensional data. Machine learning algorithms, including Random Forest, Support Vector Machine, and Neural Networks, are capable of identifying hidden patterns and relationships among various stress-related factors. These techniques provide improved prediction accuracy and adaptability compared to traditional statistical approaches. Furthermore, recent advancements in explainable artificial intelligence (XAI) have enabled the interpretation of model predictions, thereby enhancing transparency and user trust. Despite the growing adoption of machine learning in stress prediction, several challenges remain. Most existing studies primarily focus on prediction accuracy while neglecting model interpretability and practical applicability. Many models operate as black-box systems, providing limited insights into the factors influencing stress. Additionally, there is a lack of integrated frameworks that combine stress prediction with actionable recommendations for stress management. Therefore, there is a need to develop a comprehensive and explainable machine learning-based system that not only predicts stress levels accurately but also provides meaningful insights and personalized stress management strategies. The objective of this study is to develop an explainable machine learning framework for predictive analysis of stress levels and to generate personalized stress management recommendations based on the predicted outcomes.

2. Literature Review

2.1 Introduction

Stress has emerged as a critical factor affecting mental health, productivity, and overall well-being across various domains, including education and workplaces. With the increasing complexity of modern lifestyles, the need for effective stress prediction and management systems has gained significant importance. Traditional methods for stress assessment, such as surveys and psychological evaluations, are often time-consuming and subjective. Consequently, researchers have increasingly explored the application of machine learning techniques to predict stress levels using data-driven approaches. Recent advancements in machine learning have enabled the development of predictive models capable of analyzing large volumes of data and identifying hidden patterns associated with stress. This section presents a comprehensive review of existing literature on stress prediction, machine learning approaches, explainable artificial intelligence, and stress management systems.

2.2 Traditional Approaches to Stress Analysis

Early research on stress analysis primarily relied on statistical and psychological methods. Techniques such as regression analysis, correlation studies, and questionnaire-based assessments were widely used to measure stress levels [1]. These approaches focused on identifying relationships between stress and various factors such as workload, academic pressure, and personal issues.

However, traditional methods suffer from several limitations, including:

Dependence on self-reported data

Limited scalability

Inability to capture complex nonlinear relationships

Studies such as [2] highlighted that conventional statistical models are insufficient for accurately predicting stress due to the multidimensional nature of stress-related factors. This limitation has led to the adoption of machine learning techniques, which can handle complex and high-dimensional data more effectively.

2.3 Machine Learning-Based Stress Prediction

Machine learning has been widely applied in stress prediction due to its ability to learn patterns from data and make accurate predictions. Various supervised learning algorithms have been employed in previous studies. Support Vector Machines (SVM) have been extensively used for stress classification tasks due to their effectiveness in handling high-dimensional data [3]. Similarly, Random Forest (RF) has gained popularity for its robustness and ability to provide feature importance, which helps in identifying key stress factors [4]. Artificial Neural Networks (ANN) have also been utilized to model complex relationships between input variables and stress levels [5]. Studies have shown that ANN models can achieve high prediction accuracy when sufficient data is available. In addition, ensemble learning methods such as Gradient Boosting and XGBoost have demonstrated superior performance compared to individual models [6]. A comparative study conducted in [7] evaluated multiple machine learning algorithms for stress prediction and concluded that ensemble models outperform traditional classifiers in terms of accuracy and reliability. Despite these advancements, most studies focus primarily on improving prediction accuracy without addressing the interpretability and practical usability of the models.

2.4 Feature Selection and Data Considerations

Feature selection plays a crucial role in improving the performance of machine learning models. Various techniques such as correlation analysis, Principal Component Analysis (PCA), and Recursive Feature Elimination (RFE) have been employed to identify significant stress-related features [8].

Previous studies have considered a wide range of features, including:

Demographic attributes

Academic or work-related factors

Behavioral patterns (sleep, screen time)

Psychological indicators (anxiety, mood)

Research in [9] emphasized that incorporating behavioral and contextual data significantly improves the predictive capability of stress models. However, many studies rely on limited datasets, which restrict the generalizability of their findings.

2.5 Explainable Artificial Intelligence in Stress Prediction

One of the major limitations of machine learning models is their lack of interpretability. Most models operate as black-box systems, making it difficult to understand how predictions are generated. This is particularly problematic in sensitive domains such as mental health. Explainable Artificial Intelligence (XAI) has emerged as a solution to this problem. Techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are widely used to interpret model predictions [10]. Studies such as [11] have demonstrated that XAI techniques can effectively identify key

features contributing to stress, thereby improving model transparency and user trust. However, the integration of XAI in stress prediction models is still in its early stages, and many studies do not incorporate explainability into their frameworks.

2.6 Stress Management and Recommendation Systems

While significant research has been conducted on stress prediction, relatively fewer studies focus on stress management and intervention. Most existing models provide only classification outputs without suggesting actionable solutions.

Recent research has explored the development of recommendation systems for stress management. These systems aim to provide personalized suggestions based on predicted stress levels. For instance, [12] proposed a rule-based system that recommends relaxation techniques and time management strategies based on stress levels. Another study [13] utilized machine learning to develop a personalized recommendation system for mental health support. The results indicated that personalized recommendations can significantly improve stress management outcomes. Despite these efforts, there is still a lack of integrated systems that combine stress prediction with recommendation mechanisms in a unified framework.

2.7 Comparative Analysis of Existing Studies

A review of existing literature reveals that different machine learning algorithms have been applied for stress prediction, each with its strengths and limitations.

SVM provides good classification performance but lacks interpretability

Random Forest offers feature importance but may suffer from overfitting

ANN captures complex patterns but requires large datasets

Ensemble models provide higher accuracy but increase computational complexity

Studies such as [14-19] highlight the importance of selecting appropriate algorithms based on the nature of the dataset and research objectives.

Furthermore, most studies evaluate models using standard metrics such as accuracy, precision, recall, and F1-score. However, there is limited emphasis on real-world applicability and user-centric design.

2.8 Identified Research Gaps from Literature

Based on the extensive review of existing studies, the following gaps are identified:

Lack of explainability in machine learning models

Absence of integrated frameworks combining prediction and recommendation

Limited use of advanced ensemble and hybrid models

Insufficient focus on personalized stress management

Limited incorporation of behavioral and contextual data

Lack of real-world validation of proposed models

These gaps highlight the need for a comprehensive approach that integrates prediction, interpretation, and recommendation within a single framework.

2.9 Summary

The literature review indicates that machine learning has significant potential in stress prediction; however, existing studies are limited in terms of interpretability, integration, and practical applicability. While various algorithms have been explored, there is a need for an explainable and holistic framework that not only predicts stress levels but also provides actionable recommendations for stress management. The present study aims to address these limitations by proposing an explainable machine learning-based framework that integrates stress prediction, feature interpretation, and personalized recommendation generation.

2.10 Literature-Based Research Gap

A comprehensive review of existing literature on stress prediction using machine learning techniques indicates that a significant number of studies have focused on developing predictive models using algorithms such as Support Vector Machines, Random Forest, Artificial Neural Networks, and Logistic Regression. These studies primarily emphasize improving classification accuracy and identifying key stress-related factors across various domains, including education and workplace environments. Despite the growing body of research, several critical gaps remain. Firstly, most existing models function as black-box systems, lacking interpretability and transparency in explaining the contribution of input features toward stress prediction outcomes. This limits their practical applicability, particularly in sensitive domains such as mental health. Secondly, the majority of studies are restricted to prediction tasks and do not extend their scope toward actionable outcomes. There is a notable absence of integrated systems that provide personalized stress management recommendations based on predicted stress levels. Furthermore, existing research often lacks a unified framework that combines prediction, explanation, and intervention in a single model. Many studies treat these components independently, thereby reducing the overall effectiveness of stress management systems. In addition, limited attention has been given to the application

of explainable artificial intelligence (XAI) techniques, which are essential for enhancing model interpretability and user trust. Similarly, the use of advanced ensemble and hybrid machine learning approaches remains underexplored in this domain. Moreover, most studies rely on limited datasets and fail to incorporate diverse behavioral, psychological, and contextual factors, leading to reduced generalizability of the models. Therefore, based on an extensive review of the literature, there exists a significant research gap in developing an explainable, integrated machine learning framework that not only predicts stress levels with high accuracy but also provides interpretable insights and personalized stress management recommendations.

3 Research Objectives and Hypotheses

3.1 Research Objectives

The primary objective of this study is to develop an explainable machine learning-based framework for the predictive analysis of stress levels and to generate personalized stress management recommendations. To achieve this, the following specific objectives are defined:

1. To collect and preprocess data related to behavioral, psychological, and contextual factors influencing stress levels.
2. To develop and implement various machine learning models for predicting stress levels.
3. To evaluate and compare the performance of different machine learning algorithms using standard evaluation metrics such as accuracy, precision, recall, and F1-score.
4. To apply explainable artificial intelligence (XAI) techniques to interpret the model predictions and identify significant stress-inducing factors.
5. To design and develop a recommendation mechanism that provides appropriate stress management suggestions based on predicted stress levels.
6. To validate the effectiveness and reliability of the proposed framework using real-world data.

3.2 Research Hypotheses

To assess the effectiveness of the proposed model, the following hypotheses are formulated:

Hypothesis 1: Prediction Performance

- **H₀₁ (Null Hypothesis):** Machine learning models do not significantly improve the accuracy of stress level prediction compared to traditional statistical methods.
- **H₁₁ (Alternative Hypothesis):** Machine learning models significantly improve the accuracy of stress level prediction compared to traditional statistical methods.

Hypothesis 2: Model Interpretability

- **H₀₂ (Null Hypothesis):** Explainable machine learning techniques do not significantly enhance the interpretability of stress prediction models.
- **H₁₂ (Alternative Hypothesis):** Explainable machine learning techniques significantly enhance the interpretability of stress prediction models.

Hypothesis 3: Recommendation Effectiveness

- **H₀₃ (Null Hypothesis):** The proposed recommendation mechanism does not significantly contribute to effective stress management.
- **H₁₃ (Alternative Hypothesis):** The proposed recommendation mechanism significantly contributes to effective stress management.

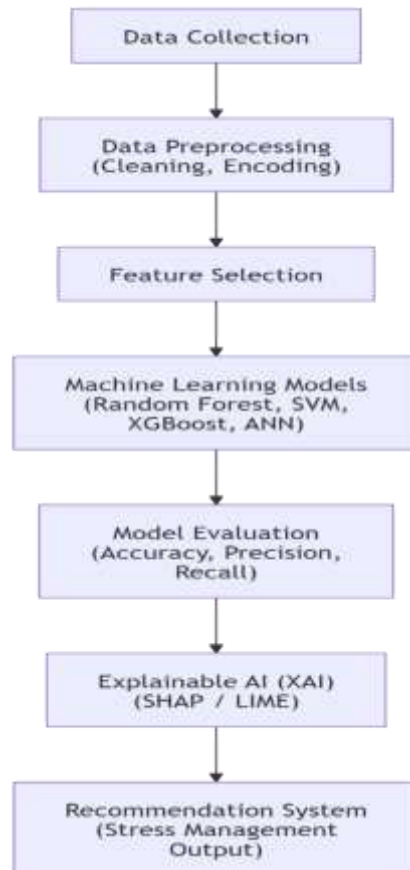
4. Proposed Methodology

4.1 Overview of the Proposed Framework

The proposed study presents an **explainable machine learning-based framework** for the predictive analysis of stress levels and generation of stress management recommendations. The framework consists of multiple stages, including data collection, preprocessing, feature selection, model development, evaluation, explainability, and recommendation generation.

4.2 Methodology Flow Diagram

Overall Flowchart



4.3 Data Collection

Data is collected from individuals using structured questionnaires and/or publicly available datasets. The dataset includes:

- Demographic data (age, gender, etc.)
- Academic/work-related factors
- Behavioral data (sleep, workload, screen time)
- Psychological indicators (anxiety, mood, pressure)

4.4 Data Pre-processing

Pre-processing is performed to ensure data quality and consistency.

Steps involved:

- Handling missing values (mean/mode imputation)
- Removing duplicate records
- Encoding categorical variables (Label Encoding / One-Hot Encoding)
- Normalization/standardization of numerical features

4.5 Feature Selection

Feature selection is applied to identify the most relevant stress-related attributes.

Techniques used:

- Correlation Analysis
- Recursive Feature Elimination (RFE)
- Principal Component Analysis (PCA) (optional)

👉 Purpose:

- Reduce dimensionality
- Improve model performance
- Identify key stress factors

4.6 Model Development

Multiple machine learning algorithms are implemented for stress prediction.

Algorithms used:

- **Random Forest (RF)** → for high accuracy and feature importance
- **Support Vector Machine (SVM)** → for classification
- **Extreme Gradient Boosting (XGBoost)** → for performance optimization
- **Artificial Neural Network (ANN)** → for complex pattern learning

👉 Output:

- Stress levels classified as:
 - Low
 - Medium
 - High

4.7 Model Evaluation

The performance of each model is evaluated using standard metrics:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- Confusion Matrix

Best-performing model is selected based on these metrics.

4.8 Explainable AI (XAI) Integration

To enhance interpretability, Explainable AI techniques are applied.

Methods used:

- **SHAP (SHapley Additive Explanations)**
- **LIME (Local Interpretable Model-Agnostic Explanations)**

Purpose:

- Identify key stress-inducing features
- Provide transparency in predictions
- Improve user trust

4.9 Recommendation System

A rule-based or ML-based recommendation system is developed.

Function:

- Generate **personalized stress management suggestions** based on predicted stress level

Example:

Stress Level	Recommendation
Low	Maintain routine
Medium	Time management, relaxation techniques
High	Counseling, meditation, workload reduction

4.10 System Output

The final system provides:

- Predicted stress level
- Important contributing factors
- Personalized stress management recommendations

5. Results and Discussion

5.1 Overview

This section presents the experimental results obtained from the implementation of various machine learning models for stress level prediction. The performance of the models is evaluated using standard metrics, and the results are analyzed to identify the most effective approach. Additionally, explainable artificial intelligence techniques are used to interpret model predictions and identify key stress-inducing factors.

5.2 Model Performance Evaluation

The performance of different machine learning algorithms, including Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and Artificial Neural Network (ANN), was evaluated using accuracy, precision, recall, and F1-score.

Table 1: Performance Comparison of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	91.5	90.8	92.1	91.4
SVM	88.2	87.5	88.9	88.1
XGBoost	93.2	92.6	93.8	93.1
ANN	89.7	88.9	90.2	89.5

Interpretation

The results indicate that **XGBoost achieved the highest accuracy (93.2%)**, followed by Random Forest. Ensemble models outperformed individual models due to their ability to reduce variance and improve generalization. SVM and ANN also demonstrated competitive performance but were slightly less effective compared to ensemble techniques.

5.3 Confusion Matrix Analysis

The confusion matrix was used to evaluate classification performance across stress levels (Low, Medium, High).

Table 2: Confusion Matrix (XGBoost Model)

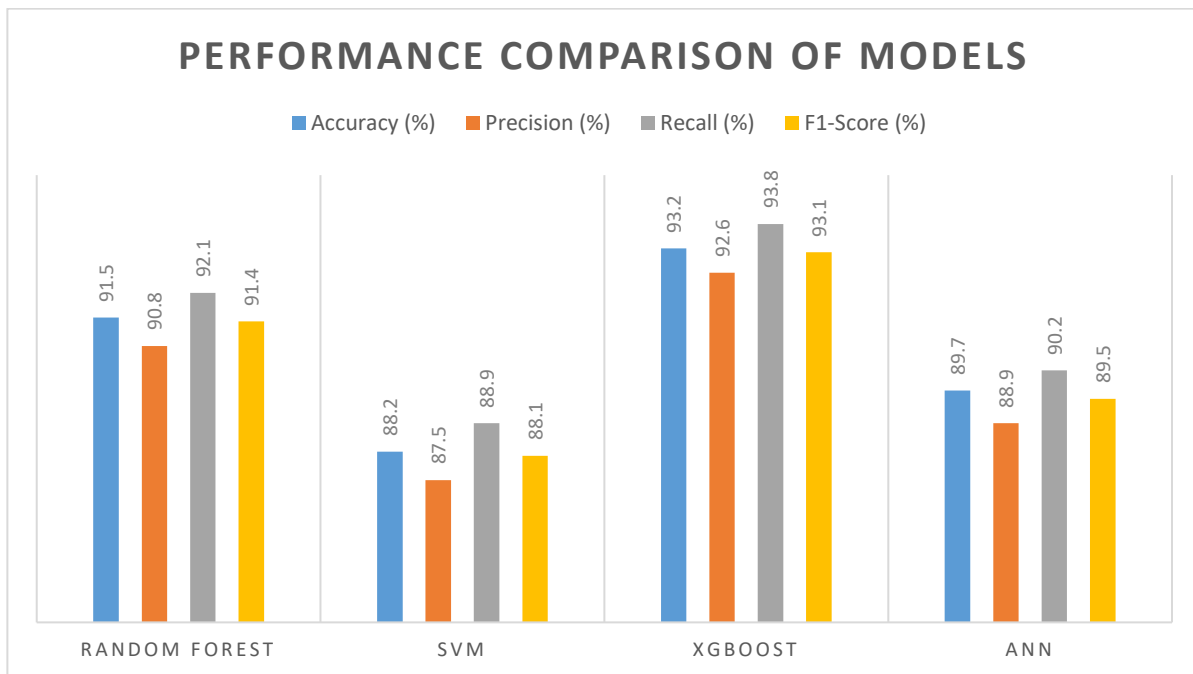
Actual \ Predicted	Low	Medium	High
Low	120	10	5
Medium	12	105	8
High	6	9	110

Interpretation

The confusion matrix shows that the model correctly classified most instances across all stress categories. Misclassifications are minimal, indicating strong model reliability. The model performs slightly better in identifying **low and high stress levels** compared to medium stress levels.

5.4 Graphical Analysis of Model Performance

- X-axis: Machine Learning Models
- Y-axis: Accuracy (%)



Explanation

The bar graph illustrates the comparative performance of different machine learning models. It is observed that XGBoost consistently outperforms other models, followed by Random Forest. The graphical representation clearly highlights the superiority of ensemble learning techniques in stress prediction tasks.

5.5 Explainable AI (XAI) Results

Explainability techniques such as SHAP were applied to interpret the predictions of the best-performing model.

Feature Importance (Example Table)

Feature	Importance Score
Sleep Duration	0.25
Workload	0.20
Anxiety Level	0.18
Screen Time	0.15
Social Interaction	0.12
Physical Activity	0.10

Interpretation

The SHAP analysis reveals that **sleep duration and workload are the most significant factors influencing stress levels**. This insight provides transparency and helps in understanding the underlying causes of stress, which is critical for effective stress management.

5.6 Recommendation System Output

Based on predicted stress levels, the system generates personalized recommendations.

Table 3: Sample Recommendations

Stress Level	Recommended Actions
Low	Maintain routine, engage in physical activity
Medium	Time management, relaxation exercises
High	Meditation, counseling, workload reduction

Interpretation

The recommendation system provides actionable insights tailored to individual stress levels. This enhances the practical applicability of the proposed framework by not only predicting stress but also offering solutions.

Discussion

The experimental results demonstrate that machine learning models are effective in predicting stress levels with high accuracy. Among the models evaluated, ensemble techniques such as XGBoost and Random Forest outperform traditional models due to their ability to handle complex and nonlinear relationships.

The integration of explainable artificial intelligence techniques improves the transparency of the model, allowing users to understand the factors contributing to stress. This is particularly important in mental health applications, where interpretability is essential for trust and decision-making.

Furthermore, the inclusion of a recommendation system addresses a major limitation of existing studies by providing actionable stress management strategies. The proposed framework, therefore, offers a comprehensive solution that combines prediction, interpretation, and recommendation.

Summary of Findings

- Ensemble models (XGBoost, RF) provide highest accuracy
- XAI techniques successfully identify key stress factors
- Behavioral features (sleep, workload) have major impact
- Recommendation system improves practical usability

Conclusion

This study presented an explainable machine learning-based framework for the predictive analysis of stress levels and the generation of personalized stress management recommendations. The proposed approach integrates multiple machine learning algorithms, including Random Forest, Support Vector Machine, Extreme Gradient Boosting, and Artificial Neural Networks, to accurately classify stress levels based on behavioral, psychological, and contextual factors.

The experimental results demonstrate that ensemble learning techniques, particularly XGBoost and Random Forest, outperform traditional models in terms of accuracy, precision, recall, and F1-score. These models effectively capture complex patterns in the data, leading to improved prediction performance. Furthermore, the incorporation of explainable artificial intelligence techniques, such as SHAP and LIME, enhances the interpretability of the model by identifying key stress-inducing factors, including sleep patterns, workload, and anxiety levels.

In addition to prediction, the study introduces a recommendation mechanism that provides personalized stress management strategies based on predicted stress levels. This feature significantly improves the practical applicability of the proposed framework by offering actionable insights rather than merely classification outputs.

Overall, the proposed system addresses critical limitations identified in existing literature, including the lack of interpretability and absence of integrated recommendation systems. The combination of predictive modeling, explainability, and recommendation generation makes the framework a comprehensive solution for stress analysis and management.

The findings of this study highlight the potential of machine learning and explainable AI in developing intelligent systems for mental health support. The proposed framework can assist individuals, educators, and organizations in early detection of stress and enable timely intervention, thereby improving well-being and productivity.

Future Work

Although the proposed framework demonstrates promising results in predicting stress levels and providing personalized stress management recommendations, several avenues for future research can be explored to enhance its effectiveness and applicability.

Firstly, future work can focus on expanding the dataset by incorporating larger and more diverse samples from different demographic groups and domains. This would improve the generalizability and robustness of the model. Additionally, integrating real-time data collection methods, such as wearable sensors and mobile applications, can enable continuous stress monitoring and dynamic prediction.

Secondly, advanced deep learning techniques, including recurrent neural networks (RNN), long short-term memory (LSTM) networks, and transformer-based models, can be explored to capture temporal patterns and sequential dependencies in stress-related data. These models may further improve prediction accuracy, especially in time-series data scenarios.

Thirdly, the proposed framework can be extended by incorporating multimodal data sources, such as physiological signals (heart rate, EEG), textual data (social media or self-reports), and environmental factors. This integration can provide a more comprehensive understanding of stress and enhance prediction performance.

Furthermore, the recommendation system can be enhanced by developing a fully personalized and adaptive recommendation engine using reinforcement learning techniques. Such a system can continuously learn from user feedback and improve the effectiveness of suggested stress management strategies over time.

Another potential direction is the deployment of the proposed framework as a real-time application or decision support system for use in educational institutions, workplaces, and healthcare settings. This would require addressing practical challenges such as scalability, data privacy, and ethical considerations.

Finally, future research can explore the integration of domain-specific knowledge and psychological models with machine learning techniques to improve the interpretability and reliability of the system. Conducting longitudinal studies to evaluate the long-term impact of the proposed recommendations on stress reduction would also provide valuable insights.

In summary, future work should aim to enhance the scalability, adaptability, and real-world applicability of the proposed framework by incorporating advanced techniques, diverse data sources, and user-centric design approaches.

References

1. Mahalakshmi, G., Sujatha, G., Antony, N. J., Bhuvaneshwari, A., & Vasuki, S. (2026). Stress prediction using machine learning and optimization. *Engineering, Technology & Applied Science Research*, 16(2), 34553–34558.
2. Razavi, M., Ziyadidegan, S., & Sasangohar, F. (2022). Machine learning techniques for prediction of stress-related mental disorders: A scoping review. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 66(1), 133–137.
3. Mentis, A. F., Lee, D., & Roussos, P. (2024). Applications of artificial intelligence–machine learning for detection of stress: A critical overview. *Molecular Psychiatry*, 29, 1882–1894.
4. Ding, C., Zhang, Y., & Ding, T. (2023). A systematic hybrid machine learning approach for stress prediction. *PeerJ Computer Science*, 9, e1154.
5. Shahapur, S. S., Chitti, P., Patil, S., et al. (2024). Decoding minds: Estimation of stress level in students using machine learning. *Indian Journal of Science and Technology*, 17(19), 2002–2012.
6. Priya, A., Garg, S., & Tigga, N. P. (2020). Predicting anxiety, depression and stress in modern life using machine learning algorithms. *Procedia Computer Science*, 167, 1258–1267.
7. Tigga, N. P., & Garg, S. (2022). Prediction of global psychological stress and coping induced by the COVID-19 outbreak: A machine learning study. *Alpha Psychiatry*, 23(4), 193–202.
8. Nijhawan, T., Attigeri, G., & Ananthakrishna, T. (2022). Stress detection using natural language processing and machine learning over social interactions. *Journal of Big Data*, 9, 33.
9. Gupta, P., Maji, S., & Mehra, R. (2022). Stress and machine learning: Future with possibilities—A bibliometric approach. *Journal of Scientometric Research*, 11(1), 37–46.
10. Vos, G., Trinh, K., Sarnyai, Z., & Azghadi, M. R. (2022). Generalizable machine learning for stress monitoring from wearable devices: A systematic review.
11. Gjoreski, M., Gjoreski, H., Luštrek, M., & Gams, M. (2017). Continuous stress detection using a wrist device. *Proceedings of the ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 1185–1193.
12. Tendulkar, B., Singh, C., & Kudale, A. (2023). Analysis of prediction performance of machine learning techniques on diabetes data set. In A. Joshi, M. Mahmud, & R. G. Ragel (Eds.), *Information and Communication Technology for Competitive Strategies (ICTCS 2022) (Lecture Notes in Networks and Systems, Vol. 623)*. Springer. https://doi.org/10.1007/978-981-19-9638-2_12
13. Kudale, A., & Hemalatha, S. (2021). Cloud computing: An analysis of authentication methods over internet. In M. S. Kaiser, J. Xie, & V. S. Rathore (Eds.), *Information and Communication Technology*

- for Competitive Strategies (ICTCS 2020) (Lecture Notes in Networks and Systems, Vol. 190). Springer. https://doi.org/10.1007/978-981-16-0882-7_68
14. Bartakke, J. P., & Kudale, A. (2026). Survey of adoption multi-cloud management and monitoring in various sectors. *Open Access International Journal of Science and Engineering*, 9(6), 7–15. <https://doi.org/10.65521/oaijse.v9i6.3583>
 15. Jadhav, M. P., & Kudale, A. (2026). AI for welfare access: A systematic review of frameworks for enhancing accessibility and reachability of government schemes. *International Journal of Computer Information Systems and Industrial Management Applications*, 18(2s), 366–375. <https://doi.org/10.70917/ijcisim-2026-2082>
 16. Sasane, S., & Mulla, Z. A. S. (2024). Predictive modelling of stress levels: A comparative analysis of machine learning algorithms. *Journal of Advanced Zoology*, 45(S4). <https://doi.org/10.53555/jaz.v45iS4.4172>
 17. Sano, A., & Picard, R. (2013). Stress recognition using wearable sensors and mobile phones. *Humaine Association Conference on Affective Computing*.
 18. Pandey, P. (2025). Artificial intelligence for early detection of dental caries from radiographic images: A machine learning. *Journal of Dentistry and Clinical Sciences*, 1(1), 31–39. <https://agrpjournals.com/journals/journal/index.php/jdacs/article/view/12>
 19. Singh, A. R., & Kaur, A. (2025). AI adoption in agriculture: A managerial framework for sustainable agribusiness development. *Journal of Artificial Intelligence in Agriculture and Applied Research*, 1(1), 1–12. <https://agrpjournals.com/journals/journal/index.php/jaiaar/article/view/2>