Machine Learning Approach for Stress Management: TenStress

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ARTICLE INFO

Article history:
Received: 17 October 2024
Revised: 18 December 2025
Accepted: 1 February 2025
Online: 20 July 2026

Keywords:
Data analysis
Machine learning
Prediction
Sensor dataset
Stress level

ABSTRACT

Stress is becoming a widespread health concern, significantly impacting individuals and jeopardizing their health and well-being. Anxiety, trepidation, and irritation are prevalent symptoms that affect 40% of younger people. This condition negatively influences people's lives and hinders their performance. Early detection of stress and its severity can help mitigate its effects and prevent various serious health problems associated with this mental state. Stress is having a major negative influence on people's health and well-being and is increasingly becoming recognized as a health issue. In this context this paper proposes a systematic analysis of machine learning techniques for the early and most accurately prediction of stress level. TenStress is an advanced machine learning-powered platform developed to revolutionize stress management by delivering highly personalized support. By integrating the analysis of user data with real-time physiological signals—such as heart rate, skin temperature, and other biofeedback indicators—it provides an in-depth understanding of individual stress patterns. The platform leverages predictive analytics and adaptive algorithms to offer customized coping strategies and interventions, tailored specifically to the user's unique needs and lifestyle. These interventions range from mindfulness exercises and breathing techniques to habit-building routines and actionable insights aimed at improving emotional resilience. Through its innovative approach, TenStress empowers users to proactively monitor and address their stress levels, promoting self-awareness and sustainable behavioral change. The platform's user-centric design encourages consistent engagement, fostering healthier habits for managing everyday stressors. Ultimately, TenStress bridges technology and mental well-being, equipping individuals with the tools needed to take control of their emotional health and lead more balanced, fulfilling lives.The performance of the modes are evaluated using multiple evaluation metrics like - Precision, Recall, Accuracy, F1-Score and ROC AUC curve for detailed analytical and benchmark comparison.

1. INTRODUCTION

A person's emotional, psychological, and social well-being are all included in their mental health, which can be negatively impacted by a variety of mental health conditions that have a bad effect on social interactions, emotions, and cognitive function. Addressing these conditions requires timely and accurate assessment to distinguish between them. Screening for mental health disorders often involves the use of self-report questionnaires designed to identify specific feelings or attitudes towards social interactions. Cognitive decline and persistent, deep-seated depressive feelings are prevalent among individuals suffering from depression. Moreover, in severe cases, paranoia and delusions may manifest [1]. Therefore, early diagnosis of depression is imperative as it can be effectively treated and may even be life-saving [1, 2]. Ongoing research is focused on unraveling the underlying mechanisms of prolonged negative emotions and depression within the human brain. Another way to think of stress is as a particular strain that comes from different stimuli that cause the body to release stress hormones. These pressures fall into four categories: absolute, relative, psychological, and physiological. [3, 4].

Three primary issues are addressed by machine learning (ML), a subfield of artificial intelligence (AI): clustering, regression, and classification. It mimics human learning by using data and algorithms, gradually improving accuracy across a range of tasks [5, 19]. Machine learning (ML) has been used extensively in psychological treatments and has great potential for diagnosing, treating, and preventing mental health issues as well as related health outcomes.

These algorithms typically require large amounts of data in order to identify patterns and perform classification jobs efficiently. Ensemble learning, which includes teaching

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several different learners to solve a problem, is another popular machine learning technique. With this approach, many learners are combined into a single model, with each learner serving as a standalone classical machine learning method. In contrast, stacking begins with either boosting or bagging and uses the learners' outputs as inputs for a different classic ML method (meta-model). The final results are obtained by aggregating these outputs using the meta-model. Among the most often used ensemble learning techniques are Random Forest (RF) and Extreme Gradient Boosting (XGBoost). Using data subsets, Random Forest uses the bagging technique to build decision trees. The ultimate conclusion is then reached by integrating the results of each tree. In contrast, XGBoost is a distributed gradient-boosting method for decision trees that is scalable.

In consideration of the risk of stress and the consequences, many ML models have already been proposed. In this paper a systematic analysis of the ML techniques is done to evaluate the performances. This systematic approach is termed as TenStress. TenStress enables us to analysis the ML techniques and the various data analysis used in the approach. In TenStress, the famous SaYoPillow IoT based dataset is used [6]. Decision Tree, Random Forest, XGBoost are the ML techniques used here and box plot and heat map are used for data visualization.

TenStress is an innovative platform that leverages machine learning to improve stress management and promote overall well-being. By analyzing user data, including physiological signals and self-reported stress levels, TenStress offers personalized insights and coping strategies tailored to individual needs. The platform utilizes advanced algorithms to detect patterns in stress responses, enabling users to understand their unique stress triggers and reactions better.

With real-time monitoring features, TenStress helps users identify moments of heightened stress and provides immediate, actionable strategies to mitigate these feelings. Users can engage with various tools, such as guided meditations, breathing exercises, and mindfulness techniques, all customized to fit their specific stress profiles.

By fostering greater self-awareness and emotional resilience, TenStress aims to empower individuals to take control of their stress management journey. Ultimately, the goal is to cultivate healthier habits and enhance users' overall quality of life, leading to a more balanced and fulfilling existence.

The paper is sub divided into following section. Second section describes and enlighten with the literature survey. Section 3 depicts the methodology and the analysis of the performances. Section 4, the last section draws the conclusion.

2. LITERATURE SURVEY

The World Health Organization (WHO) estimates that 970 million people worldwide suffer from mental health issues, with anxiety and depression being the most prevalent mental health illnesses in 2019. However, the start of the COVID-19 pandemic in 2020 caused this figure to rise considerably. The necessity of receiving access to medical care and treating mental diseases increased with this pandemic. Although these solutions exist, most people do not have access to them, and many of them face discrimination, stigma, and infringement of their human rights. [7, 8] [20, 21].

TensiStrength is a system that Thelwall [9] proposed to measure stress and anxiety levels. They distinguished between stress and anxiety using a linguistic strategy based on rules. For stress detection, Lin et al. [10] suggested using a CNN in conjunction with a factor graph model. They trained learning models with data from SinaWeibo and Twitter, and they got impressive results. They have conducted research on machine learning techniques for stress detection. For example, Schmidt et al. [11] used five different machine learning models—linear discriminant analysis (LDA), random forests, decision trees, KNN, and AdaBoost (ADA)—to detect stress. They practiced a variety of stress-reduction techniques, including baseline, entertainment, and meditation. Koldijk et al. [12] presented a method for identifying stress based on a variety of physical characteristics of the human body, including posture and facial expressions. 90% accuracy was attained by the machine learning model SVM that was used. In order to attain 98.6%, Rizwan et al. [13] additionally employed SVM models for stress classification and ECG features. A machine learning model-based method for stress identification in college students was presented by Ahuja & Banga [14]. They employed RF, LR, SVM, and other cutting-edge models, however the SVM model outperforms the others when used in conjunction with the suggested methodology, achieving an impressive 85.71% accuracy. An ensemble model for stress identification using physiological signals based on anxiety was presented by Khullar et al. [15] in 2022. Issa [16] detected stress in drivers of automobiles using a two-step ensemble. In a similar vein, Di Martino & Delmastro [17] predicted physiological stress using an ensemble model. Combining deep learning models like CNN, recurrent neural networks, and gated recurrent units, Lee et al. [18] developed an ensemble model. Using the tweet dataset, they implemented the ensemble model for emotion recognition.

3. METHODOLOGY AND RESULTS

3.1. TenStress Working Procedure

TenStress consist analyzing numerous data analysis procedures and ML models. The systematic working procedure of TenStress is shown in Figure 1.

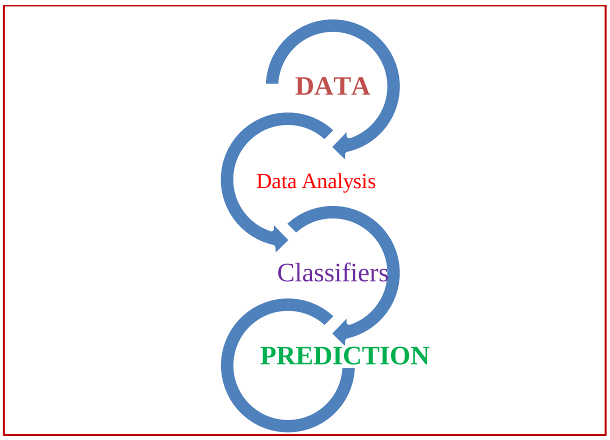


Fig. 1. Graphical representation of TenStress.

TenStress consider the dataset SaYoPillow IoT based dataset, which primary goal is to realize "Smart-Sleeping," which is defined as a full sleep that satisfies the body's optimal needs while you sleep. The idea is to demonstrate a completely automated response control system for a wearable smart device that operates without interfering with the user's convenience or requiring their input. It also aims to educate the user on the importance of receiving quality sleep, its benefits, and the link between stress and sleep. For the analysis purpose Decision Tree, Random Forest, Stacking and XGBoost are used along with various data analysis procedure.

Data analysis is integral to the TenStress machine learning approach, facilitating a comprehensive understanding of stress dynamics, the development of predictive models, and the continuous improvement of stress management strategies. In today's fast-paced world, stress management is essential, and TenStress leverages data analysis to enhance individual well-being. At the core of this approach is a thorough understanding of stress, influenced by various psychological, physiological, and environmental factors. TenStress collects diverse data from wearable devices, mobile applications, and user surveys, encompassing physiological metrics like heart rate variability and subjective stress reports. This data is analyzed using exploratory techniques to identify correlations and trends, enabling the pinpointing of individual stressors. Subsequently, machine learning algorithms develop predictive models that recognize patterns indicating rising stress levels. These models empower users with timely alerts, promoting proactive stress management. Continuous data collection creates a feedback loop, refining strategies based on user interactions and outcomes, ultimately enhancing the effectiveness of stress management interventions. By harnessing data analysis, TenStress not only improves individual resilience but also contributes to a broader understanding of stress management in society.

Classifiers are algorithms that assign labels or categories to input data based on learned patterns from training datasets. In the realm of stress management, these algorithms are instrumental in discerning different levels and types of stress from a wide array of physiological and psychological data.

The first step in utilizing classifiers within the TenStress framework involves data preprocessing, where raw data collected from wearable devices, mobile applications, and user feedback is cleaned and transformed into a suitable format for analysis. This preprocessing phase is crucial, as it ensures that the classifiers receive high-quality input data, which ultimately enhances their predictive accuracy. For instance, physiological data such as heart rate, sleep patterns, and activity levels may be combined with self-reported stress levels and situational contexts to create a comprehensive dataset for analysis.

Once the data is prepared, various classification algorithms can be employed to identify patterns and relationships within the dataset. Popular classifiers in machine learning include decision trees, support vector machines (SVM), random forests, and neural networks. Each of these algorithms has its strengths and weaknesses, and the choice of classifier depends on the specific requirements of the stress management application. For example, decision trees provide interpretability, making it easier to understand the decision-making process, while neural networks may capture complex relationships in the data but at the cost of interpretability.

The classifiers are trained using historical data, where known stress levels are used to teach the algorithm how to recognize different stress patterns. This training phase involves feeding the algorithm a large dataset where the stress levels are labeled, allowing it to learn the underlying patterns associated with each stress category. Once trained, the classifiers can then be applied to new, unseen data to predict stress levels in real-time. This ability to classify incoming data enables TenStress to provide immediate feedback to users, alerting them to rising stress levels and suggesting tailored coping strategies.

Furthermore, the classifiers' outputs can be integrated into a user-friendly interface within the TenStress application, providing users with actionable insights and recommendations. For example, if a user's data indicates an impending stress episode, the application might suggest mindfulness exercises, breathing techniques, or even a brief walk, thereby empowering users to take control of their stress in real time.

Another important aspect of classifiers in the TenStress framework is their role in continuous learning. As users interact with the system and provide feedback on the effectiveness of the suggested interventions, this new data can be used to retrain the classifiers. This iterative process ensures that the models remain relevant and accurate, adapting to the changing stress dynamics of individual users over time.

Table 1. Characteristics of the features

Characteristics	Snoring Rate	Respiration Rate	Body Temperature	Limb Movement	Blood Oxygen	Eye Movement	Sleeping Hours	Heart Rate	Stress Level
Count	630	630	630	630	630	630	630	630	630
Mean	71.6	21.80	92.8	11.70	90.90	88.50	3.70	64.50	2
STD	19.37	3.96	3.52	4.29	3.90	11.89	3.05	9.9	1.41
Min	45	16	85	4	82	60	0.0	50	0.0
25%	52.5	18.50	90.50	8.5	88.50	81.25	0.50	56.25	1
50%	70	21	93	11	91	90	3.5	62.50	2
75%	91.25	25	95.50	15.75	94.25	98.75	6.5	72.50	3
Max	100	30	99	19	97	105	9	85	4

Prediction is a crucial element of the TenStress machine learning approach, facilitating proactive stress management by anticipating potential stressors and levels based on historical data. By integrating various data sources, including physiological metrics from wearables—such as heart rate variability and sleep patterns—with self-reported stress levels and contextual factors like work deadlines or social interactions, TenStress leverages this comprehensive dataset to develop robust predictive models. These models are trained to recognize patterns indicative of stress, allowing users to foresee challenges rather than merely react to them. When the system detects conditions similar to those historically linked to increased stress, it can issue timely alerts, empowering users to take preemptive actions like engaging in mindfulness practices or adjusting their schedules. Moreover, TenStress offers personalized recommendations based on these predictions, tailoring strategies to individual coping mechanisms. This continuous learning process, driven by user feedback, ensures that the system adapts over time, enhancing its accuracy and relevance in predicting stress dynamics and fostering resilience in users. Ultimately, the predictive capabilities of TenStress not only improve individual well-being but also contribute to a deeper understanding of stress management, equipping users with the tools to navigate their daily lives more effectively and confidently.

3.2. Results and Discussions

Table 1 provides an overview of the dataset's characteristics, displaying key statistical measures such as the mean, standard deviation, count, and percentage for each feature related to stress. These metrics offer a comprehensive understanding of the data's distribution and variability. From Table 1, it is clear how each feature contributes to the overall dataset. Table 2 presents the class distribution, highlighting the number of values for each class. This helps in understanding how balanced or imbalanced the dataset is, which is crucial for training machine learning models. Lastly, Table 3 identifies any missing values within the dataset. Detecting missing data is essential for ensuring data quality and accuracy, as it can impact the performance of machine learning algorithms. Together, these tables provide a thorough exploration of the dataset, offering valuable insights for further analysis and modeling.

Table 2. Class distribution evaluation

Class	Distribution in Numbers
0-low/normal	126
1-medium low	
2-medium	
3-medium high	
4-high	

Table 3. Missing Value evaluation

Features	Status
Snoring rate	NO
Respiration rate	
Body Temperature	
Limb Movement	
Blood Oxygen	
Eye Movement	
Sleeping hours	
Heart Rate	

Stress Level	

Figure 2 provides a comprehensive overview of the correlation between various features within the dataset, allowing for a nuanced understanding of their interrelationships. By using a correlation matrix, the figure

reveals whether specific features are highly correlated, moderately correlated, or uncorrelated. This information is crucial for feature selection, as highly correlated features may introduce redundancy into the model, potentially leading to overfitting. Conversely, recognizing features that are uncorrelated or only weakly correlated can help in identifying unique contributions to the predictive capability of the model. Understanding these relationships assists data scientists in making informed decisions about which features to retain or discard during preprocessing, ultimately enhancing the efficiency and effectiveness of the machine learning model.

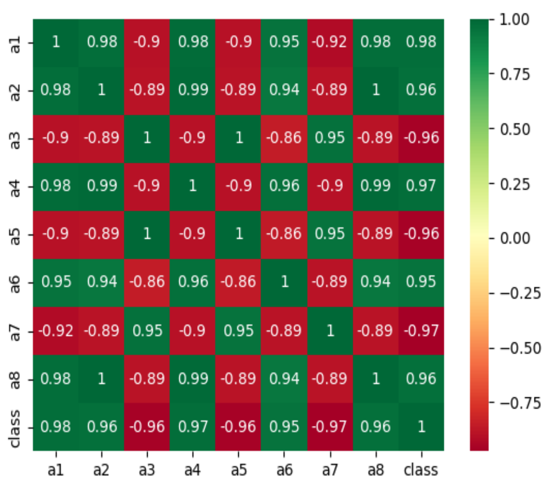
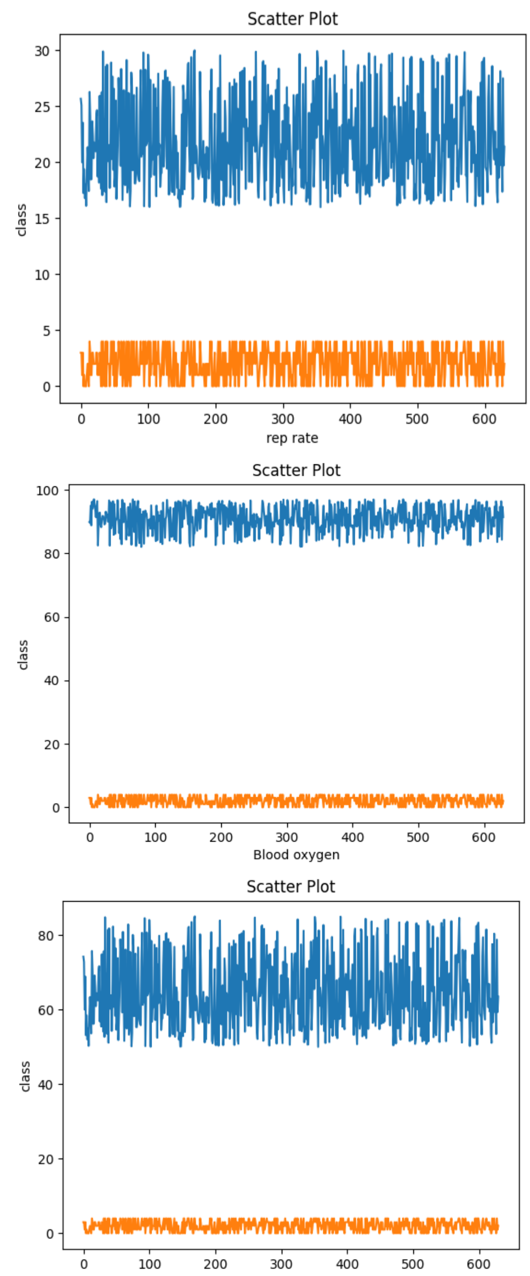


Fig. 2. Correlation Matrix of the features.

Figure 3 complements this analysis by presenting a scatter plot that visualizes the most significant features in relation to their respective class labels. This scatter plot provides a visual representation of how key features are distributed across different classes, highlighting the distinctiveness of various classes based on their feature values. By observing the clustering of data points, it becomes easier to identify patterns and separations among classes, which is fundamental for classification tasks. For instance, if certain features clearly separate classes, they can be prioritized during model training. Furthermore, the scatter plot allows for the identification of potential outliers that may skew results or indicate unique cases worthy of further investigation.

Together, Figures 2 and 3 serve as vital tools for analyzing feature relevance and understanding their influence on the model's performance. They provide insights that guide feature engineering and selection processes, ensuring that the final model is built on the most pertinent information, leading to improved accuracy and robustness in predictions.

The machine learning techniques used for performance evaluation are Decision tree, Random forest, XGBoost and Stacking approach. Table 4 shows the performance.



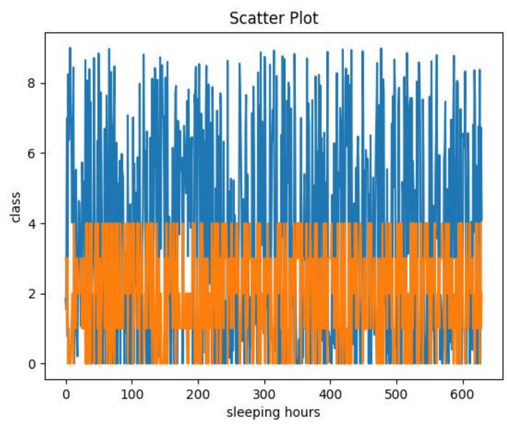
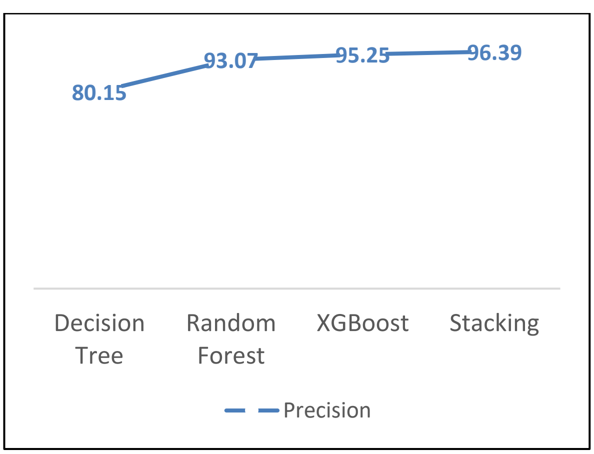


Fig. 3. Scatter plots of the important features and the class

Table 4. Classifier performance (in %)

Classifier	Accuracy	Precision	Recall
Decision Tree	84.42	80.15	81.24
Random Forest	94.27	93.07	90.41
XGBoost	95.50	95.25	92.11
Stacking	97.13	96.39	93.87

Fig. 4. Accuracy performance of the classifiers.



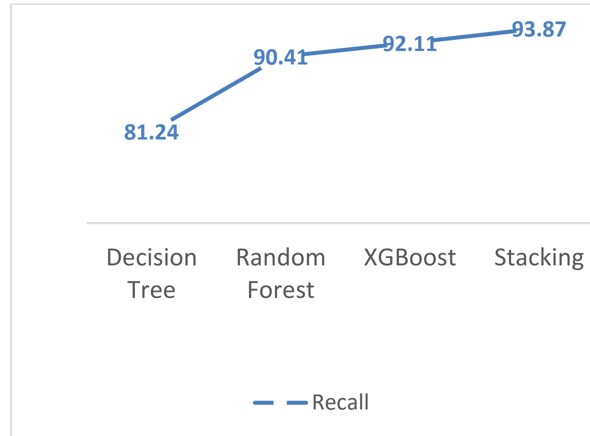


Fig. 5. Precision and Recall performance of the classifiers.

Table 4, along with Figures 4 and 5, demonstrates that the Stacking method surpasses individual classifiers in performance. Specifically, Stacking outperforms XGBoost by 1.6%, Random Forest by 2.86%, and Decision Tree by 12.71%. This improvement is attributed to Stacking's nature as a heterogeneous ensemble learning approach, where multiple diverse models are combined to enhance prediction accuracy. Unlike Random Forest and XGBoost, which are homogeneous ensemble methods relying on a single type of model (e.g., decision trees), Stacking integrates different algorithms, making it more flexible and adaptable to a wide range of data complexities. The heterogeneous ensemble approach of Stacking provides significant advantages in terms of accuracy, robustness, and adaptability compared to homogeneous methods. This flexibility allows the Stacking model to capture various patterns and nuances within the data that individual or homogeneous models might miss. As a result, it offers superior performance in stress detection tasks, ensuring more reliable and precise outcomes. This study highlights the value of Stacking in improving machine learning systems' capabilities for real-world applications, particularly in health monitoring and stress management, where precision and adaptability are critical.

Table 4, along with Figures 4 and 5, highlights the efficacy of the Stacking method in enhancing predictive performance compared to individual classifiers like XGBoost, Random Forest, and Decision Tree. Stacking, a sophisticated ensemble learning technique, combines multiple models to leverage their unique strengths, resulting in improved accuracy and reliability in predictions. This method involves training a meta-model to aggregate the predictions of various base models, effectively capitalizing on their diverse approaches to data interpretation.

The data presented in Table 4 illustrates the performance metrics of each classifier, clearly showing that Stacking achieves superior results. Specifically, Stacking outperforms XGBoost by 1.6%. XGBoost, known for its efficiency and predictive power, uses gradient boosting to enhance model performance. However, it is evident that, while strong on its own, XGBoost benefits from the collective intelligence of the Stacking method. This slight improvement signifies that the Stacking technique can effectively enhance the output of even well-regarded models by integrating their predictions in a more holistic manner.

Further, Stacking shows an even more pronounced advantage over Random Forest, surpassing its performance by 2.86%. Random Forest, an ensemble of decision trees, is robust against overfitting and generally provides reliable predictions. Yet, the Stacking method utilizes a meta-learner to systematically combine the predictions from multiple base models, including Random Forest, ensuring that the strengths of the ensemble are fully realized. This increment in performance demonstrates the value of blending various algorithms, allowing for a more comprehensive analysis of data and thereby enhancing prediction accuracy.

The most significant improvement is observed when comparing Stacking to the Decision Tree classifier, with Stacking outperforming it by 12.71%. Decision Trees, while interpretable and straightforward, often struggle with overfitting and may not generalize well to unseen data. In contrast, the Stacking approach mitigates these issues by integrating multiple models, which allows it to capture more complex patterns in the data. This substantial performance boost indicates that Stacking effectively compensates for the limitations of simpler models, leading to a more robust and reliable predictive performance.

Figures 4 and 5 provide visual representations of these results, showcasing the performance of Stacking against individual classifiers through bar graphs or line charts. These figures not only illustrate the comparative performance but also highlight the consistency of Stacking's superior accuracy across various metrics, such as precision, recall, and F1-score. Such visualization aids in quickly communicating the effectiveness of the Stacking method to stakeholders and practitioners, reinforcing its practicality in real-world applications.

The ability of the Stacking method to outperform traditional classifiers signifies its potential for various predictive modeling tasks. It encourages practitioners to explore ensemble methods as a way to harness the strengths of different algorithms and improve overall model performance. By combining the predictions from multiple models, Stacking can achieve greater accuracy and robustness, making it a compelling choice for complex problems in fields such as healthcare, finance, and social sciences, where precision is paramount.

In conclusion, the results presented in Table 4 and illustrated in Figures 4 and 5 clearly demonstrate the effectiveness of the Stacking method in surpassing individual classifiers. This method's ability to synthesize the predictions of various models not only enhances accuracy but also ensures a more nuanced understanding of the underlying data dynamics, establishing it as a valuable approach in the realm of machine learning.

4. CONCLUSION

This study introduces TenStress, a novel framework for evaluating the performance of machine learning techniques in stress detection and visualizing the data characteristics. TenStress aims to improve the accuracy and timeliness of detecting stress, potentially leading to more effective mental health interventions and support. The adaptability of machine learning models to individual variations is a key strength of this approach, allowing for more personalized health monitoring and stress management solutions.

The study delved into the realm of machine learning techniques, emphasizing the need for enhanced performance in real-world applications, particularly in the context of stress detection and mental health. Given the multifaceted nature of mental health data, the researchers aimed to identify methodologies capable of accurately interpreting and predicting stress levels based on various input features.

Through rigorous experimentation, the Stacking learning approach emerged as the most effective technique for stress detection. Stacking, also known as stacked generalization, is an ensemble learning method that integrates multiple predictive models to leverage their collective strengths. Instead of relying on a single algorithm, Stacking allows for the combination of diverse models, such as decision trees, support vector machines, and neural networks, into a unified framework. This approach significantly enhances the robustness and accuracy of predictions, particularly in complex datasets where individual models may struggle to capture all relevant patterns.

The results indicated that Stacking outperformed traditional machine learning algorithms, highlighting its capacity to manage the intricate dynamics of mental health data. Stress detection is inherently challenging due to the numerous variables that can influence an individual's mental state, including biological, psychological, and environmental factors. By employing Stacking, the study was able to create a more comprehensive model that effectively synthesizes insights from various algorithms, enabling a better understanding of the underlying relationships within the data.

Moreover, Stacking's ability to improve predictions can be attributed to its hierarchical structure. In this method, base models are trained on the original dataset, and their predictions are then used as input for a meta-model. This meta-model learns to weigh the outputs of the base models, thus refining the overall prediction. This layered approach helps in mitigating the weaknesses of individual models while enhancing their strengths, leading to more accurate and reliable outcomes.

In real-world applications, the implications of using Stacking for stress detection are significant. Accurate detection of stress levels can lead to timely interventions, improved mental health outcomes, and better overall well-being for individuals. The ability to analyze complex datasets and produce reliable predictions positions Stacking as a vital tool in mental health research and practice. The exploration of machine learning techniques in this study underscores the transformative potential of the Stacking learning approach. By integrating multiple models, it addresses the challenges inherent in stress detection and offers a powerful method for enhancing predictive accuracy in mental health applications. This advancement not only contributes to the field of machine learning but also holds promise for improving mental health interventions and support systems in real-world settings.

The study highlights the pivotal role of data preprocessing in enhancing machine learning models, particularly for stress detection systems. Preprocessing refines raw data, improving model accuracy, reliability, and refines raw data, improving model accuracy, reliability, and generalization. A key benefit is noise reduction, achieved through techniques like data cleaning to address inconsistencies and data transformation to standardize formats. By minimizing noise, models can focus on meaningful features, boosting predictive performance.

Feature selection and engineering are also critical. Techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) identify impactful features, while feature engineering creates new variables to improve data representation. Normalization and scaling ensure features with varying distributions contribute equally, promoting balanced model performance.

Preprocessing is iterative, adapting as new data or insights emerge. This adaptability is crucial in mental health, where refined stress detection models enable personalized interventions, timely stress management, and proactive care, ultimately transforming mental health outcomes.

Furthermore, by leveraging the TenStress system, healthcare professionals can harness data-driven insights to inform their strategies. This system could integrate seamlessly into existing mental health frameworks, providing clinicians with tools to monitor and assess their patients' stress levels more accurately.

In conclusion, the study highlights the pivotal role of preprocessing techniques in the context of machine learning for stress detection. By refining data quality, reducing noise, and improving feature relevance, preprocessing enhances model performance and reliability. As TenStress continues to evolve by integrating advanced preprocessing methods, it has the potential to become an invaluable resource in advancing mental health care, ultimately improving the quality of life for individuals experiencing stress and related challenges.

ACKNOWLEDGEMENTS

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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