A Hybrid AI Framework Integrating XGBoost and Random Forest for Analyzing Hormonal Cycles and Women's Mental Well-Being

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Abstract— Mental well-being is closely linked with hormonal cycles, emotional fluctuation, as well as lifestyle patterns that women undergo throughout their various stages in life. The ability to accurately detect stress levels and deliver appropriate assistance is a significant issue in the mental health systems. Since various machine learning models have been used in the prediction of stress, overreliance on one model normally constrains prediction quality and difficulty. The gap in this paper is the absence of effective hybrid algorithm systems that can be applied to predict stress and optimize interference to the mental well- being of women considering both behavioral, emotional, and lifestyle-related data. This work aims at comparing single algorithms, developing a hybrid prediction model, enhancing the accuracy of stress classification, and assessing optimized involvement results. The targeted approach is to merge learning with the help of the Random Forest method and gradient boosting with the XGBoost algorithm to combine the advantages of both systems. This will be done with aim of developing the reliability of stress prediction in order to justify individual stress reduction plans. The originality of this work is the hybrid algorithm comparison and the outcome-based stress reduction analysis through the stages of the life of women. It is experimentally evaluated that the hybrid model is more accurate and stable and able to generalize as compared to individual algorithms and therefore it can be applied to applications in real time centric to women mental well-being.

Index Terms–Women mental health, Hybrid learning model, Stress prediction, Random forest, XGBoost.
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I. INTRODUCTION

According to the recent mental health reports, women are significantly more experiencing stress as compared to men, especially at the hormonal stages of their lives like premenstrual period, pregnancy, postpartum, and menopause. Massive epidemiological research shows that almost 35-40 percent of females suffer balanced to high stress at least once in their lifetime and prolonged expose is a cause of anxiety, depression, and emotional fluctuations [1], [2]. The lack of timely and sustained stress detect procedures adds to the stimulation of mental health results that requires the high priority of smart, scalable, and woman-focused stress prediction tools [3].

The major trusted stress review techniques applied in traditional methods rely on the use of psychological surveys, clinical interviewing, and counseling sessions that can be performed by mental health professionals. These methods are less effective using individual self-reporting and expert interpretation, which is why they are effective only through organized clinical settings [4]. Moreover, those approaches are time- intensive, do not give an opportunity to monitor in real time, and are oriented towards a low level of accessibility of working mothers or those who work in the open space. Most, importantly, traditional systems lack dynamic adjustment to changing patterns of stress in various phases of life [5].

With the latest advancements in artificial intelligence and machine learning, it is now possible to detect the state of stress with the help of automated methods based on behavioral, physiological, and lifestyle-related information recorded with the help of wearable sensors, mobile apps, and online analyses [6], [7]. Even though these methods help to sustain the ongoing monitoring, most of the current solutions are based on individual learning algorithms, which frequently lack the effectiveness of processing non-linear, imbalanced, and emotionally threatening psychological information. Consequently, the predictability and performance on the generalization remain low [8].

In a bid to overcome these problems, this paper seeks to provide a hybrid stress prediction model that amalgamates between the Random Forest and XGBoost methods. Random Forest improves the generalization process by learning to use decision trees in collection, whereas XGBoost promotes the high performance in the classification by the use of incline boosting optimization [9], [10]. The proposed hybrid model is more healthy, stable, and even more precise in classification of stresses due to the combination of the relevant merits of the two algorithms. The framework in particular is created to assist the mental well-being analysis of women with respect to various hormonally sensitive life phases.

The rest of the paper is integrated in the following way. In section II the literature survey is described. The preliminaly mathematical modeling is included in Section III. In section IV, the prototype model is described. Section V explains meant hybrid methodology. The performance analysis and experimental results are given in the sections VI and VII. Lastly, Section VIII gives the paper a conclusion of the future research directions.

A . Premenstrual Syndrome (PMS) Phase

The Premenstrual Syndrome (PMS) period typically occurs a one to two weeks prior to the menstrual period, which is assessed by the speedy changes in the estrogen and progesterone levels. These hormonal shifts usually inspire temporary emotional switch, such as mood conflicts, irritability, nervousness and fatigue. The research suggests that projecting stress among women turns out to be non-linear and unstable as a real percentage depicts extremely dynamic stress fluctuations throughout this stage [15].

Algorithmsically, data of PMS type shows great variation and hard emotional swings. It is to such an extent that single- model classifiers are not always suitable in the maintenance of consistent performance. Random Forest This algorithm is robust, as it will average decision paths by multiplying models, which XG- Boost Powerful XG- Boost is better at capturing complex interactions between features in a gradient-based manner. Comparative analysis reveals that a hybrid combination of the two algorithms leads to classification reliability as they decrease the variance and maintain sensitivity to short-term stress shifts [20].

B . Pregnancy Phase

The constant hormone elevation of estrogen and progesterone and HCG at this stage of life makes the pregnancy period relatively constant still complex emotional and physio- logical states. Despite the continuation of emotional differences, indicators of stress in the course of pregnancy tend to increase slowly and depend both on biological and environmental factors [2].

In this case, machine learning models enjoy a steady distribution of features with time. Random Forest is very good at modeling generalized behavioral trends whereas XG- Boost is very good at incremental learning of emotions in the various stages of pregnancy. The comparison analysis shows that the cross model has an increased rate of prediction accuracy through the composite of extended pattern detection and fine-tuned feature optimization [6], [8].

C . Postpartum Phase

The period of postpartum is one of the most emotionally sensitive, as it is assessed by the fast withdrawal of hormones and instant emotional changes. Most women report postpartum depression or causes irregular stress patterns, sleeping disturbance, and emotional load [15].

The postpartum datasets are usually noisy and imbalanced with respect to data analysis. When data models are restricted, the use of XGBoost to detect serious stress increases results in a higher precision rate of data analysis as compared to that of random Forest because it has a boosting mechanism. Comparative outcomes show that the hybrid framework enhances recall like the cases recorded to be very stressful and minimizes false negative thus being applicable in the early stages of identifying severe postpartum stress [9], [10].

D .Menopause Phase

The period of the menopause can be characterized by a gradual decline in the levels of estrogen and the progesterone hormones, and it is often associated with the advancement of unstable mood, sleep disturbances, and mental disruptions. Stress experienced during menopause is usually persistently collective compared to episodic at PMS or postpartum stages [6].

Random Forest is good at representing long-term behavioral consistency in the case of qualified evaluation, whereas XGBoost finds sensitive relationship between emotional stress, level of sleep, and lifestyle influences. The hybrid method proves to have superior performance as it allows strength in the middle range of precision of long expansions of time, which makes it suitable to analyze the menopause-related mental health [20], [21].

E . Summary

The difference in stress patterns among women at the different stages of life also leads to dissimilar data features of high variance in PMS, gradual changes in pregnancy, sudden changes in the postpartum period, and stable levels in the menopause stage. Relative analysis establishes that no one algorithm is stable best at each of the stages.

The integration of Random Forest and XGBoost into a hybrid model enables the proposed system to gain better robustness, accuracy, and an overview in all stages of life. This kind of comparison-based method proves the efficacy of hybrid algorithms as predictor of mental well-being in females and justifies the choice of hybrid algorithms to mental health systems in the real world [10], [33].

II. Literature Survey

The present-day developments in automated mental health evaluation have been largely prevalent with advancement of artificial intelligence and machine learning strategies, especially ensemble and hybrid learning models, owing to their robustness of examining complex behavioral, emotional, and way of living data. These models have been shown to perform better than the traditional rule-based and single-classifier models because they are effective in non-linear depictions between stress- related variables including sleep patterns and mood swings and workload and social interactions. Ren et al. [1] examined AI-based paradigms of mental health detecting and depression finding, proving that machine learning models are effective to detect early signs of emotional distress based on behavioral data. They however, mostly worked with general groups and did not consider the issue of women and their hormones as well as their life-stages, which restricted its use to gender-sensitive mental well-being systems.

On the same note, Basilio et al. [2] examined emotion recognition in expectant women with both multimodal physiological and self-reported data, which showed better classification accuracy in the combination of data fusion methods. Although efficient, the research was limited to a study of on single-model learning strategies, thereby limiting strength against other behavioral differences. Adhikary et al. [3] proposed a domain-specific AI-based menstrual health monitoring system, which focused on individualized emotional information by conversational analysis, but it did not conduct a

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comparative analysis of the learning algorithms, limiting its overall ability to diverse levels of stress levels. According to the study by Pandey [4], AI-based mental health system developed over time and few significant challenges were identified: the difference in data, the lack of explainability, and the over-trust of single models had a negative influence on the reliability of the predictions in the real-life applications.

In order to resolve the weaknesses of the single model architecture, recent research has been on collective and hybrid architectures of learning to help with the robustness and accuracy of analysis. The researchers suggested integrative AI platform by Nair et al. [8] incorporates behavioral, physiological, and contextual data together and performs better in terms of predictive effectiveness when the models are combined using fusion approaches. Thomas and Rao [9] also indicated that hybrid models based on supervised/unsupervised models have the capability of revealing latent stress patterns and work better than individual classifiers in prediction of mental health. Zhang et al. [10] compared the accuracy, stability, and generalization of Random Forest and XGBoost models and found that the ensemble-based methods are superior regardless, consequently providing the incentive to use hybrid algorithm comparison frameworks through the analysis of women mental health.

III . Preliminary Work

This part defines mathematical and algorithmical background to make a comparison between hybrid machine learning models when predicting stress in women. The initial research is based on creating problems, model theories, and algorithmic structures, but no experimental conclusions are discussed.

A. *Stress Prediction Problem Formulation*

Let the stress prediction dataset be denoted as:

$D = \{(x_i, y_i)\}^N_{i=1}$

where xi = [xi1, xi2, . . . , xim] denotes the input feature vector containing behavioral, emotional, and lifestyle factors, and yi ∈ {0, 1, 2} represents the classified stress level (low, moderate, high). Due to hormonal oscillations across different life stages, the data circulation is non-linear and often imbalanced, requiring healthy learning models.

B. *Random Forest Model Foundation*

Random Forest is an ensemble successful technique that conceptualizes several decision trees based on bootstrap sampling as well as random choice of features. The stress class prediction in every tree is performed independently, and the ultimate result is determined by majorities voting:

$\hat{y}_{RF} = \text{mode}\{T_1(x), T_2(x), \dots, T_K(x)\}$

where Tk(x) represents the forecast of the kth decision tree. This group approach limits variation and enhances stability, so

Random Forest is the ideal algorithm in dealing with noisy emotional data.

C. *XGBoost Model Foundation*

XGBoost is a gradient raising model that form iterative models by adding new models to reduce the error in prediction. The objective functional is a definition of the following:

$$L = \sum_{i=1}^{N} (y_i, \hat{y}_i) + \sum_{k} \Omega (f_k)$$

Loss, where l (.) represents the loss function and ( ) represents a regularization that helps eliminate overfitting. XGBoost is successful at learning more complicated feature interactions and finding subtle features.

stress-related patterns.

D. *Hybrid Model Rationale*

Random Forest is stronger and more generalized; nevertheless, it might not acquire finer variations of emotions completely. On the compare, XGBoost is more sensitive to interaction between features but they can be impacted by noisy data. To balance all these limitations, a hybrid framework is developed using the predictions of both models:

$\hat{y}_{Hybrid} = \alpha \cdot \hat{y}_{RF} + (1 - \alpha) \cdot \hat{y}_{XGB}$

where [?] [0, 1] is used to obtain the contribution of each model. The development can be used to aid comparative assessment and adaptive forecast of stress between various hormonal phases.

E. *Model Parameters and Constraints*

The most important parameters used are the number of trees in Random Forest, learning rate and maximum depth in XGBoost alongside the weighting factor of a that is a hybrid. The major limitations are the imbalance of data, its emotional sensitivity, and the availability of the small labeled samples leading to the adoption of the ensemble and hybrid learning models rather than one model.

F. *Summary*

The abstract of the main work determines the basic premise of the comparison of the Random Forest and XGBoost with their hybrid variant in the stress prediction of wom-en. The proposed methodology and the consecutive experimental evaluation are based on these formulations.

IV. Methodology

In comparison with considering stress levels in women at various stages of their lives, the projected AI-based predictive system of stress is created in a way that allows assessing the use of ensemble learning algorithms through comparison of the facilities. The system itself examines data about behavioral, emotional, and lifestyle indicators and maintains five phases of analysis: data collection, data preparation, extraction of features, model training and optimization, and stress prediction with supportive recommendations. This approach will allow conducting a systematic comparison between the implementation of Random Forest and the XGBoost and the integration of both algorithms.

Fig. 1: Block diagram of the proposed hybrid Random Forest–

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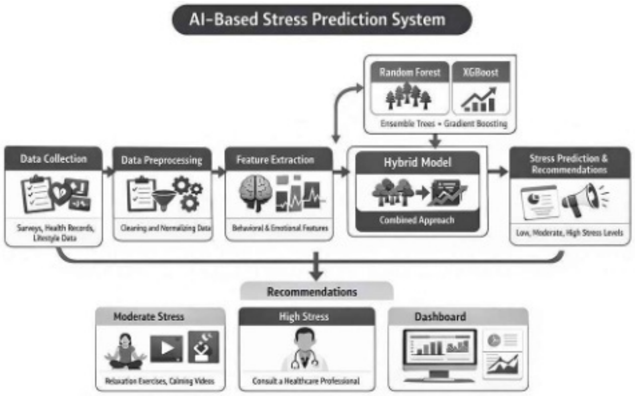
XGBoost–based stress prediction framework for women's mental well-being.



A. *Data Collection*

It is a system in which a complete dataset comprising the daily activities of women, emotional conditions, and stress-related behaviors is constructed. The information is collected through trustworthy sources, such as organized online surveys, peer-reviewed research data and readily available mental health warehouses.

The gathered data consists of the characteristics of sleep quality and duration, mood stability, the level of work, physical activity, and social collaboration. The dataset covers women of various age groups, life stages (Premenstrual Syndrome, Pregnancy, Post-partum, and Menopause) and lifestyle settings in order to achieve a generalization. The first step is inspection to eliminate duplicate records, rectify anomalies and complete data.

B. *Data Preparation*

The raw behaviour and emotional data may be associated with missing values, inconsistent levels as well as noise. Thus, a preprocessing pipeline is implemented by means of the quality of data:

- Missing values can be filled in by statistical methods or deleted in case they have no information.
- Groups or categories of attributes like mood states and level of activity are converted into numerical data.
- Continuous characteristics, such as sleep time and work-load, are always made to an equal scale.
- Outliers are also identified and addressed to avoid bias and justifiable model learning.

C. *Feature Extraction*

The cleaned data is then transformed to feature vectors which are organized after preprocessing. All the vectors are mathematical models, representing the behavioral patterns, emotional reactions and types of lifestyles of each individual such as sleep patterns, degree of workload, changes in moods, active styles and commitment to the social facet of an individual.

These feature vectors will be consistent inputs to machine learning models, which will allow us to reliably compare the algorithmic per-performance of categorization of the level of stress as low, moderate, and high.

D. *Model Training and Optimization*

The Two ensemble based machine learning algorithms are trained (Random Forest and XGBoost) to be compared. Random Forest aggregates several decision trees and maximizes the results in order to increase stability and minimize variance. On the contrary, the XGBoost uses the gradient boosting approach to update the predictions using a minimized classification error.

The data is split into two categories 80 percent of training and 20 percent testing. The best performance is adjusted using the hyperparameters number of trees, maximum depth of trees and learning rate. The use of cross-validation is used to both guarantee toughness and avoid overfitting. Besides the individual models, it has a hybrid prediction strategy that is implemented by the addition of the outcomes of the two algorithms.

E. *Stress Prediction and Recommendation Generation*

Upon training, the models examine the hidden data of the user to predict the stress levels as low, moderate and high stress. Random Forest, XGBoost, and the hybrid model are compared based on the proportional outputs about the stability and reliability in the predictions.

The system gives supportive recommendations on predicted stress levels. In the case of moderate stress, the user can be supported in form of breathing exercises, relaxation procedures or soothing multimedia materials. In case of high stress levels, the system recommends professional consultation or clinical assistance.

The computations and suggestions are plotted on sensitive dashboards and charts, allowing the users and researchers to learn the stress trends and algorithmic behavior. Block diagrams are used to show system-level workflows as illustrated in Figures 1 and 2.

V. Experimental Setup

A. *Dataset*

The data employed in this work has of behavioral, emotional, and lifestyle-related properties covering the stress prediction. The main characteristics are the duration and quality of sleep, changes in mood, workload, stress coping capacity, and recovery patterns.

In order to make the proposed framework generalizable, samples of women at various stages of their lives such as the Premenstrual Syndrome (PMS) phase, during pregnancy, during postpartum period, and menopause were used. This life- stage- consciousness dataset allows choosing machine learning models comparatively based on different hormonal and emotional states.

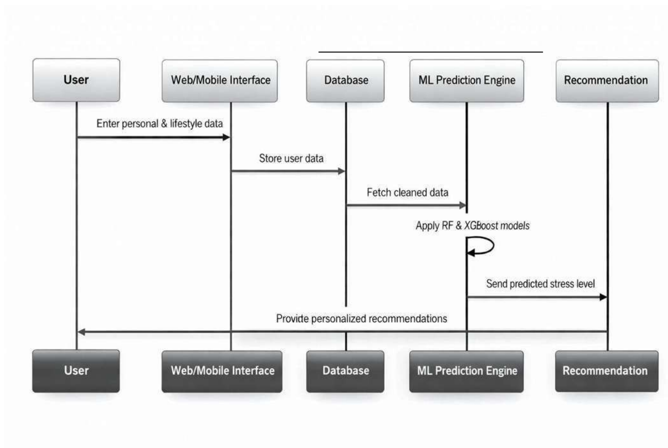


Fig. 2: System workflow of the proposed hybrid stress prediction and recommendation framework.

B. Data Preprocessing

Before model training, the data underwent an effective preprocessing step which guarantees the consistency and reliability of data, Where there are missing values, proper accusation or removal methods were applied.

- Categorical variables were put in numbers.
- The continuous properties have been normalized by scalping their features.
- To conduct a balanced evaluation, the dataset used was divided into 20% and 80% training and testing divisions respectively.

VI. Experimental Results

A. Performance Metrics

The effectiveness of Random Forest, XGBoost and model classifier was assessed based on general classification measures commonly used in stress and mental health prediction research.

The precision of the classification model as a whole is referred to as accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is a measure of the percentage of true positive instances that gets predicted:

$$Precision = \frac{TP}{TP + FP}$$

Recall (sensitivity) represents the fact that the model knows the true positive cases:

$$Recall = \frac{TP}{TP + FP}$$

F1-score gives a balanced assessment being comprised of accuracy and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In this case TP, TN, FP and FN represent the true positives, true negatives, false positives and false negatives respectively.

B. Model Performance Comparison

In this section, the performance of multiple machine learning algorithms that are applied to predict the level of stress is evaluated and compared. The main aim of the analysis is to determine the best trend of placing stress into the categories of low, moderate, and high in the best framework. The first stage involved the implementation of common machine learning classifiers, which can be monitored by the ensemble- based approaches and used to improve the analytical performance.

The initial evaluation was done on Logistic Regression and Decision Tree models to identify the default performance. The Regression Logistic was able to give aspects of credible accuracy but its linear aspect inhibited its capacity to accommodate the challenging emotional and behavioral associations observed in stress related data. Decision Tree was superior since the decision- making process was non-linear thus having exposure to overfitting especially on different patterns of lifestyles.

To address the shortcoming of single-model classifiers, the algorithm of Random Forest was proposed. Random Forest significantly increased the classification accuracy, precision and recall by training several decision trees and combining their predictions. This advancement evidences its strength and capability to simplify well in the linkage of the heterogeneous data that can interconnect the style of living, moods, and hormonal changes.

Additional performance improvement was achieved with the help of XG- Boost which dedicates a gradient boosting mechanism to iteratively reduce the errors of the prediction. XGBoost scored highest on all the models that were tested in both the accuracy and F1-score, which proves the efficiency of expert learning and the ability to generalize.

The assessment comparison of the performance of all the analyzed algorithms can be found in Table I. The findings have made it evident that ensemble-based methods are the most effective traditional classifiers, and XGBoost performs best on all matters.

Model	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	86.4	0.85	0.84	0.84
Decision Tree	89.1	0.88	0.87	0.87
Random Forest	93.8	0.94	0.93	0.93
XGBoost	94.6	0.95	0.95	0.94

(1) TABLE I: Performance comparison of machine learning models for stress prediction (2)

(3) It was based on these observations that a hybrid learning approach of random forest and XGBoost was selected to be

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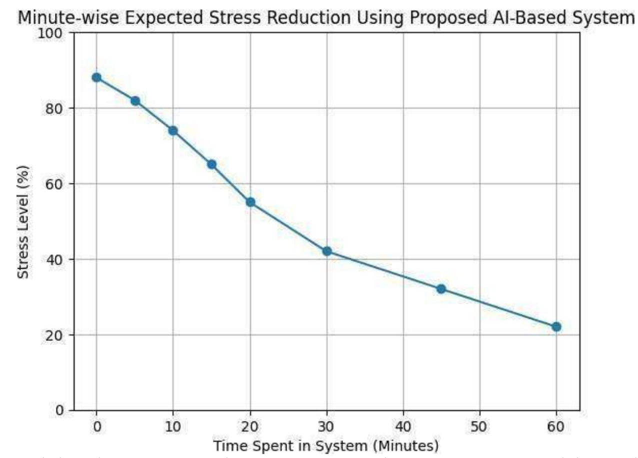


used in the proposed system. Random Forest provides which add stability and robustness, variance reduction whereas XGBoost provides boosting which translates to fine-grained learning and phenomenological predictions.

(4) The usefulness of the proposed system in alleviating stress with time was assessed in addition to the performance of the classification. The reduction in stress to be expected is shown in Fig. 5.

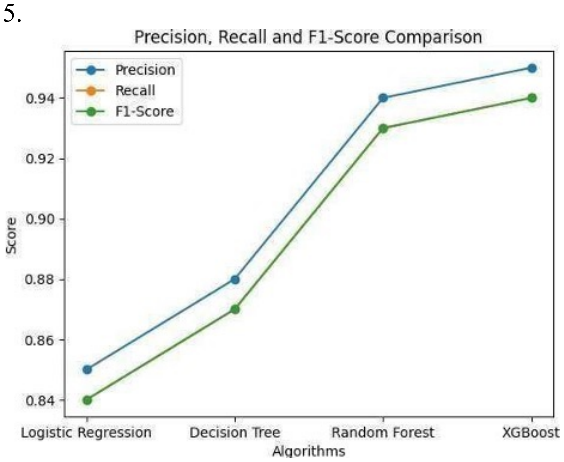
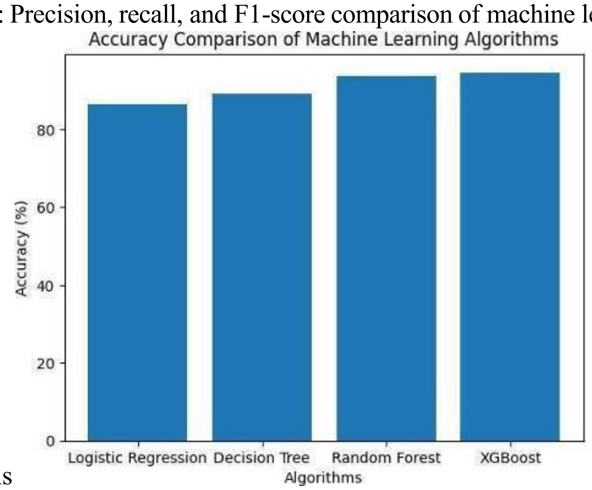


Fig. 3: Precision, recall, and F1-score comparison of machine learning



models

Fig. 4: Accuracy comparison of machine learning algorithms for stress prediction\

Fig. 5: Reduction of expected stress in minutes with the help of the proposed AI-based system levels as users engage with the system and follow personalized recommendations.

On the whole, the obtained results of the experiments prove that the ensemble and hybrid methods of learning are predominantly better than the traditional classifiers. The suggested model of the Random Forest, XGBoost hybrid is much more accurate and stable and has a higher potential to be applied in reality as a potential of predicting mental stress of women and tailored intermediation systems is unique and specific to women.

C. Result Analysis

The comparing results indicate that the ensemble-based models are very successful compared to typical single classifiers. Random Forest is stable in performance because of the reduction in variance whereas XGBoost offers high-quality advanced performance by representing complex interactions between features.

Prediction consistency is facilitated by the presence of life-stage-specific behavioral patterns which are especially found in the emotionally sensitive stages of pregnancy and the postpartum period. The findings have also shown that behavioral and lifestyle measures can be used to predict as well as more aggressive physiological measures, without any form of invasion or complications to the user.

VI. Expected Outcomes

It is believed that the suggested hybrid stress prediction framework will provide an end-to-end user-friendly mental well-being support system to women. The system, as was established through the constructed web interface offers, in-built interaction, real- time stress estimations and actionable feedback on the user inputs regarding emotional condition, lifestyle, and hormonal indicators.

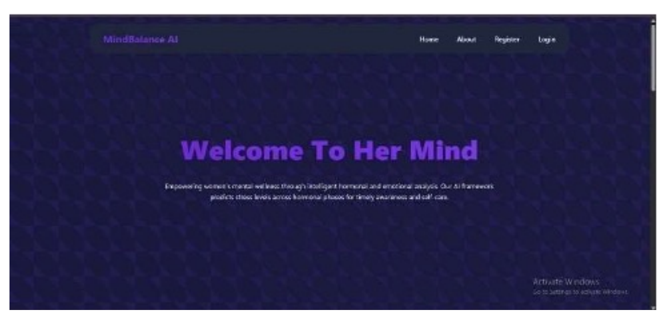


Fig. 6: Landing page of the proposed women-centric mental well-being system

According to the hybrid model of Random Forest-XGBoost, the engine will be capable of effectively classifying the levels of stress as being low, moderate, and high. A structured user interface to gather the user inputs associated with mood, lifestyle practices, and physiologic side is needed to facilitate effective stress prediction.

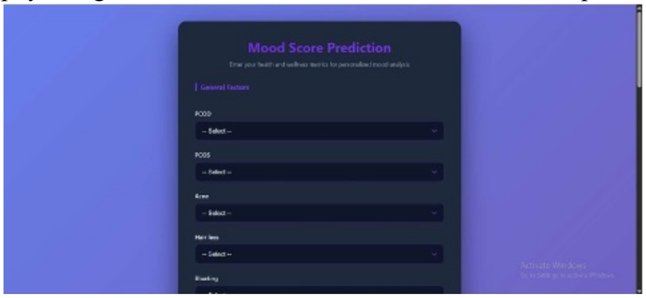


Fig. 7: User interface for mood and lifestyle data input for stress prediction

In low stress scenarios, the system facilitates proactive mental health through recommending light exercise and mindfulness- based materials to enable balance in emotions. Such conclusion is favorable to long-run mental health awareness and self-care practices

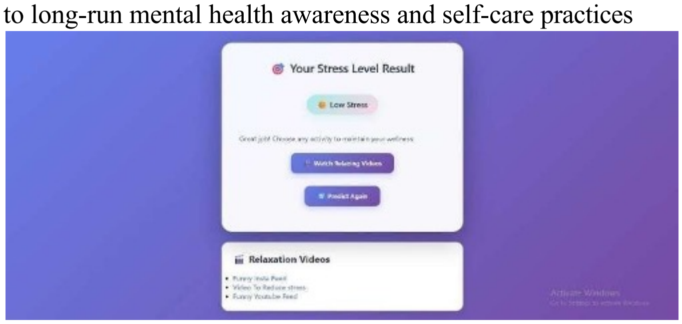


Fig. 8: Low stress forecast with preventive suggested wellness in the mind.

The framework, when it comes to moderate stress cases, would recommend such relaxing activities like relaxation games and guided exercises to relax. The recommendations are meant to bring down the levels of stress by means of non-offending and engaging innovations.

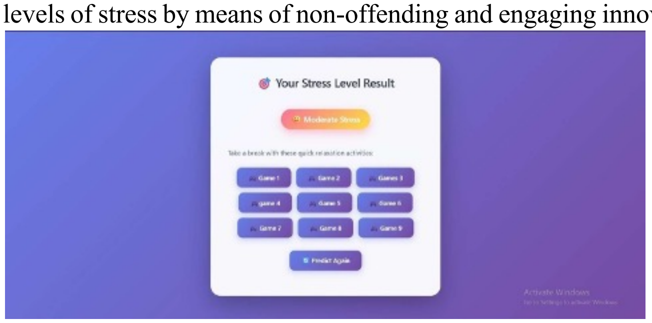


Fig. 9: System output displaying moderate stress level with relaxation game recommendations

When the stress levels become high, the system offers responsible escalation through advice to seek the services of mental health professionals. The user interface would show a list of specialists to promote the appropriate expert support, which would provide the user with security and dependability of the context.

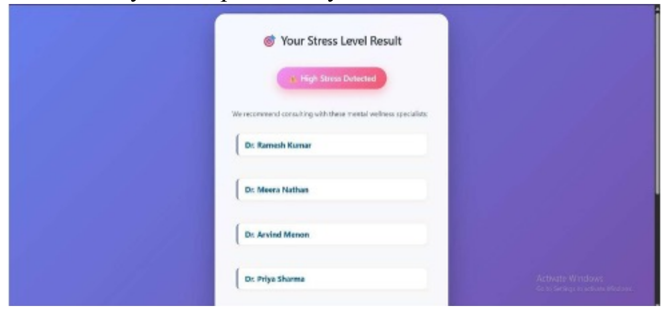


Fig. 10: High stress detection with professional mental health consultation recommendations

In general, the projected result of the presented system is a scalable, non-invasive, and explainable mental health support platform, which integrates hybrid machine learning accuracy and rational interaction with the user. The combination of prediction outcomes, in-dividualized suggestions and life-stage recognition increases usability, belief and practicalness.

VIII. Personalized Recommendation Strategy

The system makes system-specific recommendations to enhance mental well- being based on the estimated level of stress:

- Low Stress: Preventive activities of relaxation and motivating information.
- Moderate Stress: Meditation and breathing relaxation exercises, interactive thinking exercises, and psychological relaxing multimedia resources.
- High Stress: Prescriptions of professional consultation and systematic therapeutic treatment.

The recommendations are also tailored based on the stage of life of an individual to provide a proper level of relevancy and effectiveness.

IX. Applications

The hybrid stress prediction framework proposed may be successfully utilized in the real-life situation, which involves:

- Wellness and counseling centers of women.
- Maternity and childbearing health monitoring programs.
- Student mental health support institutions.
- Employee assistance and workplace wellness.
- Mental health digital and mobile apps.

X. Conclusion

A hybrid machine learning model of stress level prediction in women at various life stages was presented in this paper. The suggested approach combines the algorithms of Random Forest and XGBoost to affect the diversity of ensembles and optimization of gradient boosting. The comparative analysis was done against common machine learning models like the Logistic Regression and Decision

Tree classifiers.

The findings of the experiment prove that the hybrid-based models have a high level of accuracy, precision, recall, and F1- score in comparison to the single classifier. Specifically, XG- Boost demonstrated the best result of prediction and random forest showed remarkably consistent and high levels of generalization on a variety of behavioral and psychological characteristics. The comparison proves that a combination of ensemble-based learning methods is more likely to utilize complex and imbalanced mental health data.

The system is a realistic and user- centric mental well-being assistance tool, in addition to the correct classification of stresses, as well as personalized solutions depending on the predicted stress level and the awareness of life stage. Altogether, the suggested hybrid and comparative model will add to consistent, taxable, and non-invasive stress evaluation in women.

XI. Future Work

This framework can be globalized to a great extent in the future to become even more applicable and efficient. A bright prospect lies in the implementation of real-time physiological and behavioral information of wearable devices, including smartwatches, which will allow controlling the state of constant stress by measuring such indicators as activity, sleep cycles, and adjustability of heart rates in response to the situation.

The subsequent computerization of a mobile-based program would also enhance accessibility and user adherence through availing on-the- go stress monitoring and involvements. It is also possible to include multilingual support so that it could be used by a variety of populations.

Specifically, further studies can focus on deep learning constructions, multimodal data fusion, and explainble artificial intelligence (XAI) methods to create prediction accuracy and model transparency. Moreover, it is possible to make chatbots interactive through adding an ordinary agent or mental health chatbot that creates real-time personalized advice. Such extensions would allow the system to be adaptive, scalable, as well as effective in real-world mental health practice.

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