Developing Predictive Models for Future Stress Likelihood and Recovery Time Using Behavioral and Emotional Data.

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***Abstract*— Stress has a serious impact on mental and physical well-being, but treatments as usual are often unavailable and not effective over the long term. The AyurAura application combines imaginative Ayurvedic therapies with modern AI techniques to deliver customized stress reduction by way of Mandala art and music. This research develops two predictive models for the application. In its first model, the stress prediction probability is estimated from users' behavior in a questionnaire and the result can be used to proactively intervene. The second model forecasts time needed for recovery into a stress-free state by using the changes in daily emotional state and participation in app activities. Machine learning algorithms are used to prepare behavioral and emotional data for improved prediction performance. Trained on multi-institution datasets, both models delivered 90-95% accuracy, enabling the user to detect behavior eliciting stress and the degree needed for recovery. These results highlight the possibility of combining conventional therapeutics with contemporary tech for ongoing, affordable stress relief interventions with personalized needs in mind.**

***Keywords*—Ayurvedic Therapy, Behavioral Data Analysis, Logistic Regression, Random Forest, Recovery Time Estimation.**

I. Introduction

Stress is an inescapable aspect of modern life, affecting mental and physical well-being; today's life is filled with challenges and different situations which can put a considerable load on one's mind. In comparison to an illness, stress can be said to be broader as it can emerge from factors daily which can affect productivity. Unfortunately, treatment for it such as yoga or medicine is not completely efficient while passive devices have overly progressed but remain incapable of adapting to us as individuals. The only solution that an individual has for overcoming stress is the very broad yet stimulating brainwork.

The Mandala painting and music app, like the other available ones, centers around single tasks with no way to track how stressed out a person is, and as a result, these do not offer stress management therapy. They ignore several important elements, including the cause of anxiety and the time it takes to recover, making them difficult to use.

AyurAura is a fresh application that aims to tackle the concept of machine learning by integrating creativity into the mix to build self-care applications that promote stress management in day-to-day life, who use Ayurveda interventions like music filled with AI based intelligence which aims to set a personalized approach towards stress management in order to alleviate its effects. Unlike existing mental health predictive models, this work focuses specifically on managing daily stress and advancing the state of the art by combining data-driven insights with empirically supported creative interventions.

II. Literature Review

Elevated levels of stress have resulted in a massive amount of research on the causes (e.g., sleep, physical activity, work, social interaction). Even with advances, stress prediction in the future, from behavioral and emotional data, is still limited. Recent studies may use wearable devices, which are not always available, suggesting a more inclusive approach. For example, research conducted on the LEMURS project and published in Nature and the IEEE International Conference on Healthcare Informatics has shown how wearable recordings (e.g., sophisticated measures of sleep, heart rate variability) can be used to predict stress. But such devices are not accessible to all people, creating a possibility to build stress prediction based on behavioral patterns and emotional state which is not necessarily based on wearables [1][2][3]. Traditional stress management methods, like Ayurveda, offer holistic solutions including yoga and meditation, but they lack time efficiency for modern users. In contrast, owing to the application of AI and machine learning (ML), digital technologies for the stress monitoring of health and wellbeing have been developed, but these tend to ignore the integrative perspective of Ayurveda [8][9]. The Ayur Aura system fills the gap by combining Ayurvedic tenets with AI/ML and creates a dynamic personalized platform for stress management. By combining creative therapies like mandala art and music, it tracks emotional and behavioral data and

979-8-3315-3098-3/25/$31.00

predicts recovery time. Self-report instruments (e.g., the Discrete Emotions Questionnaire) yield real-time emotional indicators, which can support deeper understanding of emotional status [10]. Predictive algorithms analyze adherence to advised behavior and stress recovery prediction, providing adaptive feedback on the user's input [11][12][13][14].

Conclusively, although wearable technology and current new platforms have a promise for stress prediction, they are usually unaffordable and do not integrate with comprehensive treatments. Ayur Aura fills these voids both by integrating Ayurvedic applications with Artificial Intelligence/Machine Learning (AI/ML), offering an affordable, individualized, and efficient platform for stress intervention that tracks emotional and behavioral data, estimates stress risk, and computes recovery periods. This integrated platform has the potential to change the way stress is controlled by providing increased access and participation to a large population of users.

III. METHODOLOGY

In this study, we developed and trained machine learning models that will predict the likelihood of stress and recovery time from behavioral and emotional variables. Data was collected from a nationally representative sample of the general population, to be representative of the population at large. As shown in Fig. 1., users entered their behavioral information into the AyurAura app. The AyurAura app applied Random Forest and K-Nearest Neighbors (KNN) algorithm to predict the probability of stress. Using activity completion rates and emotional states tracked through a daily questionnaire, users are presented with an individual stress recovery timeline, which is estimated by logit regression and Random Forest. This complete system offers precise prediction and personalized stress management.

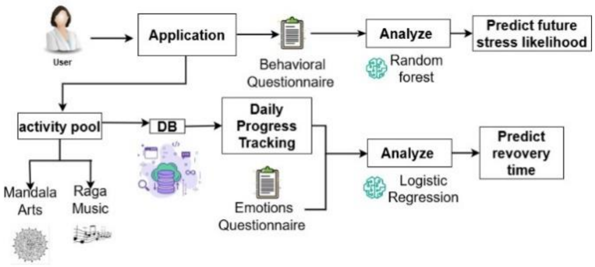

Fig. 1. Overall system diagram of the proposed solution

A. *Prediction of Future Stress Likelihood*

In this work, we designed a machine learning approach to forecast future stress risk via a range of behavioral and lifestyle indicators as demonstrated in Fig. 2. The system evaluates the influence of variables such as sleep, physical exercise, job, electronic media usage, social activity, nutrition, smoking, alcohol, and leisure. Data was collected by surveys and interviews on daily activities. Random Forest and k-Nearest Neighbors (KNN) algorithms were applied for training—Random Forest for complex relationships and imbalanced data and KNN for local patterns. This method allows high stress risk prediction, which helps users to modify behaviors to decrease the stress.

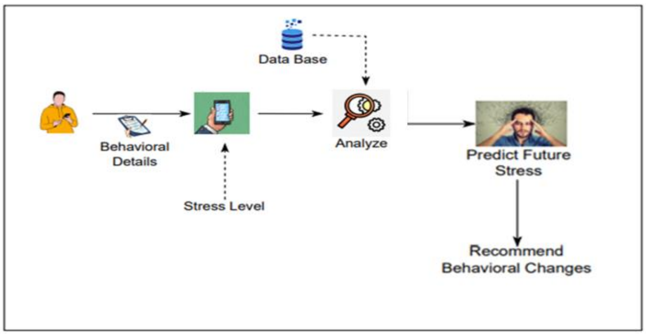

Fig. 2. Flow of Prediction of Future Stress Likelihood

1) Features and Target Variable

As per the details provided, the prediction data regarding stress probability emergence was derived from one thousand individuals, consisting of numbers of cases which were low and high stress likelihood. 519 case subjects were labelled 0 for low stress while 481 were considered high stress and were labelled 1. Data collection was achieved through an online survey as well as interviews which were also undergone through categorization by an expert to ensure data integrity. Random sampling was utilized for the general population aged 18 or above and antecedent behavior reporting was done regarding sleep duration, exercise details, occupational hours, screen time details, socializing frequency, diet, smoking, alcohol consumption and other leisure activities. Stress likelihood prediction involvement by a field expert is one of the key strengths. Personal bias in categorization of this information constitutes a potential limitation, albeit this may be remedied by allowing for experts to consult. Such a categorization or segmentation makes it possible to ascertain with precision whether certain activities if continued in the present circumstances may lead to stress and enables clear advice to be given as to how to act to improve the balance between work and family life, sleep, exercise, and other activities.

2) Data Preprocessing

Data preprocessing was crucial to formulate behavioral data for model training. From Google Forms and interviews, the data included aspects such as sleep, exercise, work hours, and socialization. Columns that were not informative (e.g., user IDs) were eliminated, and categorical variables (e.g., diet, social interactions) were numericized. Data was standardized by using StandardScaler to normalize features and accelerate convergence of models. Data was partitioned ninety percent for training and ten percent for testing to assess the generalization ability of the model to unseen data.

3) Model Development

Pseudocode for Stress Likelihood Prediction Model

Input: Behavioral data (e.g., sleep hours, screen time, exercise, work)
Output: Likelihood of stress
BEGIN

1. Import necessary libraries (pandas, sklearn, RandomForestClassifier, KNeighborsClassifier).
2. Load the dataset containing behavioral features.

3. Preprocess the data:
    - Remove irrelevant columns.
    - Encode categorical features.
    - Standardize numerical features.
4. Split the dataset into training (80%) and testing (20%) sets.
5. Initialize a Random Forest Classifier/ KNN Classifier.
6. Train the model on the training data.
7. Optimize hyperparameters using GridSearchCV.
8. Evaluate the model:
    - Predict on the test data.
    - Calculate accuracy, precision, recall, and F1-score.
    - Plot the confusion matrix.
9. Extract and rank feature importance from the model.
10. Save the trained model and scaler for future use.
11. Output predictions and key influencing features. **END**

The Random Forest algorithm was chosen for its ability to handle both categorical and continuous features, providing accurate predictions. The preprocessed data was split into 80% for training and 20% for testing. Model performance was evaluated using metrics like accuracy and classification reports. Hyperparameter tuning was done via GridSearchCV, optimizing parameters like the number of estimators and maximum depth for better accuracy.

Additionally, the k-Nearest Neighbors (KNN) algorithm was tested and compared with Random Forest. Model performance was assessed using confusion matrices, classification reports, and precision-recall curves. The final Random Forest model and its scaler were saved using .joblib for future deployment in the Ayur Aura app.

B. Prediction of Recovery Time to Stress-Free State

The fig. 3. offers a view of a machine learning prediction system that is embedded in the AyurAura app and provides psychological recovery times. Users of the mobile app are required to enter details of daily feelings/states (e.g. calm, happiness, stress etc.) and energy levels along with task completion details. Such information is accumulated into a central storage unit and then processed using machine learning solutions. The emotional sensor together with the activity sensor allows for the calculation of unique, real time recovery times. Users are given reliable estimations, which they can use together with stress augmenting activities to visualize their recovery goals and strategies. This stress management framework is adaptive and is centered around the user.

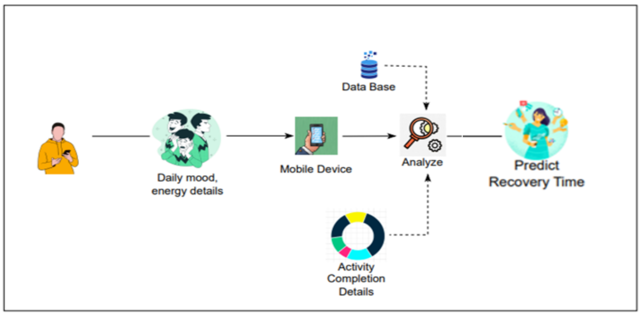

Fig. 3. Flow of Prediction of Recovery Time to Stress-Free State

1) Features and Target Variable

The subjects were selected randomly from the general population of age 18 years or above, wherein an Ayur Aura app tracked the daily emotional levels such as happiness, calmness, and stress levels of the subject and completion rate of the assigned stress-relieving activities such as Mandala art and music therapy. The following dataset was developed by collecting data from 200 individuals of different age groups. Data from each user is taken for a total duration of 14 continuous days to capture diversified patterns and gives, in total, 2,800 data points.

$$\text{Final Recovery Days} = \text{Base Recovery Days} \times (1 - \text{Activity Multiplier}) \quad (1)$$

By using equation (1) Recovery days were classified according to the opinions of an Ayurvedic doctor on the relation between stress levels and emotional well-being. According to the starting level of stress, categorization was done in the following manner. For Base Recovery Days:

- ≥4: 5 days
- <4: 10 days

To enhance the accuracy of the recovery days to the real recovery activities performed by the user, an adjustment parameter was used, which was in terms of activity completion rate:

- 90%: 0.8
- 80%-90%: 0.4
- 60%-80%: 0.2
- <30%: -0.2

Significant in this data is the collection among the same users for several days on the pattern of the emotional states of activity participation. This provides very useful insights toward modeling. At the same time, a major shortcoming in the present dataset is that only 200 individuals were sampled, probably restricting generalizability of findings. Certainly, a proper model would call for an increase in the sampling population to include a wider range of demographic groups.

2) Data Preprocessing

In preprocessing, columns of irrelevant information (e.g., user ID) as well as categorical (e.g., gender) variables were excluded and binarized, respectively. Percentage features (e.g., completion rates) were transformed into decimals. Missing values were replaced by mean imputation and numerical features were standardized to provide equal importance to features across differing ranges. Such steps were critical for data preparation and model performance optimization.

3) Model Development

Pseudocode for Recovery Days Prediction Model

Input: Emotional data (daily stress, calmness, energy, happiness levels) and activity completion rates.
Output: Predicted recovery days
BEGIN

1. Import necessary libraries (e.g., pandas, sklearn, RandomForestRegressor).

2. Load the dataset with emotional data and activity rates.
3. Preprocess the data:
    - Remove irrelevant columns.
    - Encode categorical variables.
    - Standardize numerical features.
4. Define the target variable (recovery days):
    - Assign base recovery days
    - Adjust using activity completion rates.
5. Split the dataset into training (80%) and testing (20%) sets.
6. Initialize a Random Forest Regressor/ Logistic Regression.
7. Train the model on the training data.
8. Evaluate the model:
    - Predict recovery days on the test data.
    - Calculate metrics like Mean Absolute Error and R-squared.
9. Save the trained model and scaler for future use.
10. Output predicted recovery days

END

For their capacity to model categorical and numerical features, logistic regression and random forest were selected to provide alternative strengths for global analysis. Logistic regression was employed for continuous outcomes and random forest for complex, nonlinear relationships. Both models were trained on a 80% split of the data, and then tested on the remaining 20%, making sure to evaluate unseen data. Missing values were imputed using the mean strategy. Hyperparameter tuning was conducted to reach the highest accuracy so that the models could generalize effectively and return robust predictions relying on emotional, activity, and demographic features.

IV. RESULTS AND DISCUSSION

1) Prediction of Future Stress Likelihood model evaluation.

Model performance was assessed by several metrics to maintain accuracy and reliability in predicting stress probabilities. Key metrics included accuracy, precision, recall, F1-score, and confusion matrices. Further, precision-recall curves were applied to evaluate the performance of models at different thresholds.

The Random Forest model initially exhibited strong performance, with accuracy, precision, and recall of 94% as presented in Fig. 4. These measures suggested the robustness of the model for accurately predicting future stress probability from behavioral data. Fig.5. showed an equal number of correct and incorrect classifications between stress and non-stress categories.

```
Optimized Model Accuracy: 94.00%
Optimized Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.92      0.94        99
           1       0.92      0.96      0.94       101

    accuracy                           0.94       200
   macro avg       0.94      0.94      0.94       200
weighted avg       0.94      0.94      0.94       200
```

Fig. 4. classification report of random forest model

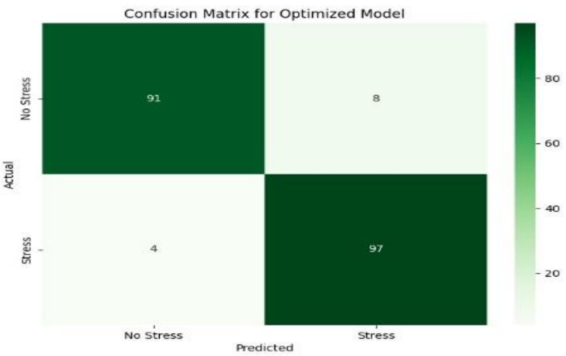

Fig. 5. confusion matrix for random forest

Using k-Nearest Neighbors (KNN) as a replacement for Random Forest was applied to the model and tested. It achieved an accuracy of 92.5% and performed well across precision, recall, and F1-score metrics as shown in Fig. 6. Yet, the KNN model exhibited a slightly lower performance than Random Forest especially in achieving a vicious tradeoff between precision and recall.

```
KNN Model Accuracy: 92.50%
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.93      0.92        99
           1       0.93      0.92      0.93       101

    accuracy                           0.93       200
   macro avg       0.93      0.93      0.92       200
weighted avg       0.93      0.93      0.93       200
```

Fig. 6. Classification repot of KNN model

Although the KNN model showed good performance as illustrated in Fig.7., the Random Forest model performed better than the KNN model in most of the evaluation measures, especially in accuracy (94% vs. 92.5% and classification balance. Thus, Random Forest was chosen as the main algorithm to be implemented in the Ayur Aura application.

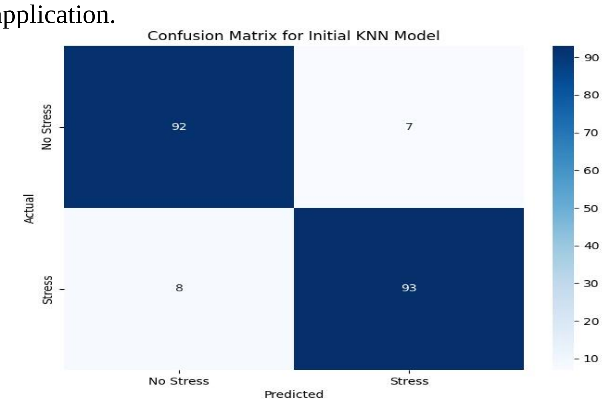

Fig. 7. confusion matrix for KNN model

2) Prediction of Recovery Time to Stress-Free State model evaluation

Model performance was assessed by metrics of accuracy, a classification report, and a confusion matrix to determine the recovery day predictions and to aid in interpretation of the emotional data. Accuracy, a performance criterion, gives the percentage of correctly predicted number of recovery days, i.e., how accurate the model is in predicting recovery days. An accurate score of the model indicates that it generalizes well to different recovery day categories, and this gives clues to future improvement. The classification report gives an overview of statistics such as precision, recall, and F1-score for every recovery day class. Precision quantifies how precise the model's positive class predictions are as per class. Recall assesses the model's capacity to select all class instances that are actually relevant

The accuracy was very high for the Random Forest model, i.e., 99.64%.as shown in Fig. 8. This indicated that the model performed excellently overall. Nevertheless, some performance differences for each class were observed, especially for small classes with marginal samples. The Logistic Regression model, while still good, showed a lower accuracy of 91.96%, suggesting that it struggled with certain classes, especially those with fewer data points as in Fig. 9.

```
Initial Accuracy: 0.9964285714285714

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        13
           1       1.00      0.98      0.99        53
           2       1.00      0.67      0.80         3
           3       1.00      1.00      1.00        96
           4       0.99      1.00      0.99        83
           5       1.00      1.00      1.00        39
           6       0.93      1.00      0.97        14
           8       1.00      1.00      1.00        82
          10       1.00      1.00      1.00       105
          12       1.00      1.00      1.00        72

    accuracy                           1.00       560
   macro avg       0.99      0.96      0.98       560
weighted avg       1.00      1.00      1.00       560
```

Fig. 8 classification report for random forest

```
Initial Accuracy: 0.9196428571428571

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.46      0.63        13
           1       0.88      0.98      0.93        53
           2       0.00      0.00      0.00         3
           3       0.98      0.98      0.98        96
           4       0.88      0.96      0.92        83
           5       0.81      0.77      0.79        39
           6       0.50      0.07      0.12        14
           8       0.87      0.98      0.92        82
          10       0.97      0.97      0.97       105
          12       0.97      0.97      0.97        72

    accuracy                           0.92       560
   macro avg       0.79      0.71      0.72       560
weighted avg       0.91      0.92      0.91       560
```

Fig. 9. Classification report for logistic regression.

For Random Forest, the matrix revealed that the model generally made correct predictions across the majority of classes, with the diagonal values being predominantly high as in Fig 10. However, for some classes, such as recovery day "1", there was difficulty distinguishing. This may be caused by the lack of balanced dataset or insufficient samples for some of the recovery day categories.

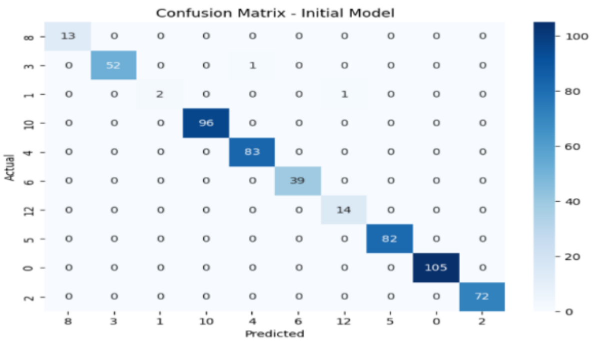

Fig. 10. confusion matrix for random forest model

For Logistic Regression, the confusion matrix highlighted that the model struggled with predicting certain classes, particularly "6", where many instances were misclassified. The off-diagonal values suggested that the model had difficulty distinguishing between some recovery day categories, such as "1" and "12" as shown below in fig 11.

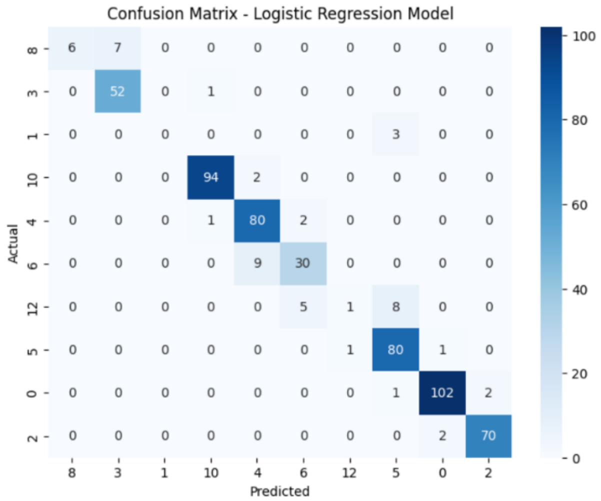

Fig. 11. confusion matrix for logistic regression

The Random Forest model outperformed the Logistic Regression model with an accuracy of 99.64%, compared to 91.96% for Logistic Regression. Random Forest showed superior performance across and for majority classes, whereas Logistic Regression exhibited its difficulties with imbalanced data, specifically in categories of small recovery days such as "6" and "2" where both precision and recall were worse. This finding hints at greater Random Forest appropriateness for the task. As an extension of Logistic Regression, resampling, class weighting and hyperparameter tuning can be used to mitigate the bias caused by the imbalance of the dataset and improve the model performance.

V. CONCLUSION AND FUTURE WORK

Future work can address the study's limitations and explore incorporating additional behavioral dimensions such as work-life balance, financial stress, and hobbies to enhance prediction performance. Expanding the dataset to include participants from diverse demographic groups will improve the generalizability of the models. Integrating real-time sensor data from wearables (e.g., heart-rate monitors) and sleep trackers may enable more objective and accurate analyses. Advanced algorithms, such as gradient boosting or deep learning, could also be investigated to manage complex datasets and further optimize performance. These findings underscore the importance of early behavioral modifications and sustained engagement in stress-reducing behaviors to promote mental health and reduce the duration of stress responses. The AyurAura application, currently under development, holds significant potential for empowering users to manage their mental health more effectively. By embedding these predictive models, AyurAura can provide real-time, personalized stress prevention plans, leveraging user behaviors, wearable data, and emotional trajectories. This data-driven approach represents a transformative step toward delivering accessible, individualized mental health support.

VI. ACKNOWLEDGMENT

We would also like to thank Dr. M. Kooragoda, an expert in this field and an Ayurvedic doctor herself, for his guidance and support in validating the dataset collected from the public by partnering with us. That itself assured the credibility of the data and their relevance according to Ayurveda. We are grateful to all respondents who participated in this study and were aged 18 years and above. Informed consent about data privacy was sought from respondents before their participation in the study. Further, we applied for and await approval from the Ethical Review Committee that standards of ethical consideration and observance of data privacy have been followed.

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