AYURAURA - PERSONALIZED STRESS MANAGEMENT APPLICATION USING AYURVEDIC CREATIVE THERAPIES.

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Declaration

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Abstract

Stress is a widespread issue affecting mental and physical health, contributing to anxiety, depression, cardiovascular diseases, and weakened immunity. Traditional stress management methods, such as yoga, meditation, and Ayurveda, have been practiced for centuries but often lack personalization and real-time tracking. In contrast, modern AI-driven solutions provide data insights but fail to integrate holistic healing. This disconnects results in fragmented, ineffective stress management strategies. To address this gap, *AyurAura* integrates Ayurvedic principles with AI and ML to create a dynamic, user-centric stress management system. The system visualizes progress, predicts recovery timelines, and provides personalized feedback. Predictive algorithms estimate the time needed to achieve a stress-free state based on adherence to therapeutic activities and lifestyle modifications. Key features include mood and energy tracking, progress analytics, and AI-driven recommendations. AyurAura's AI models analyze user data from questionnaires, eye-blinking rates, music therapy engagement, and daily emotional tracking to refine stress predictions and anticipate future stress likelihood based on behavioral patterns. A user-friendly interface enables seamless data reporting and visualization.

By combining holistic healing with AI-driven insights, AyurAura offers an adaptive stress management approach. This study presents the conceptual framework, design, and methodology of AyurAura, aiming to revolutionize stress management through personalized, data-driven strategies that empower users to regain mental well-being.

Keywords: Stress Management, Ayurveda, Artificial Intelligence, Machine Learning, Personalized Feedback.

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List Of Abbreviations

Abbreviation	**Description**
AI	Artificial Intelligence
ML	Machine Learning
PSS	Perceived Stress Scale
HRV	Heart Rate Variability
GSR	Galvanic Skin Response
CNN	Convolutional Neural Networks
I/O	Input/Output
VGG	Visual Geometry Group
KNN	K-Nearest Neighbors
SVM	Support Vector Machine
RMSE	Root Mean Square Error
API	Application Programming Interface
RNNs	Recurrent Neural Networks
NLP	Natural Language Processing

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1.Introduction

Stress management is more important than ever in today's fast-paced world, where the pressures of daily life continue to intensify, significantly impacting both physical health and mental well-being. With the increasing demands of work, personal responsibilities, financial pressures, and societal expectations, individuals often find themselves struggling to cope with persistent stress. Chronic stress, which arises from prolonged exposure to these challenges, has been linked to numerous serious health issues, including heart disease, high blood pressure, weakened immune function, digestive disorders, and various mental health conditions such as anxiety and depression.

Despite the growing awareness of stress-related health risks, many people find it difficult to access or commit to traditional stress management methods such as therapy, counseling, or medication. These conventional approaches, while effective, are often limited by factors such as cost, time constraints, stigma, and personal preferences. Many individuals hesitate to seek professional help due to financial barriers, busy schedules, or concerns about privacy and confidentiality. Furthermore, some may be reluctant to rely on pharmaceutical solutions due to potential side effects or a desire for more natural interventions.

As a result, there is a growing need for alternative stress management solutions that are effective, easily accessible, and discreet. Innovative approaches that incorporate digital technology, personalized wellness strategies, and creative therapies are emerging as viable options to help individuals manage stress in a way that aligns with their unique lifestyles. Techniques such as mindfulness applications, guided meditation, stress-tracking tools, and holistic interventions like art therapy, music therapy, and breathing exercises are gaining popularity as practical and user-friendly solutions. These methods not only provide individuals with greater control over their stress levels but also offer a sense of empowerment by allowing them to engage in self-care at their own pace and convenience.

Given the far-reaching impact of chronic stress on society, prioritizing accessible and effective stress management solutions is essential. Whether through innovative technological advancements or holistic self-care practices, finding sustainable ways to reduce stress can lead to improved overall well-being, enhanced productivity, and a better quality of life for individuals across all walks of life.

Stress can be identified and managed through a combination of physiological testing and self-reported measurements, allowing for a more comprehensive understanding of an individual's mental state. Traditional psychological surveys, such as the PSS and other self-assessment tools, continue to be valuable in measuring stress levels and emotional well-being. However, advancements in technology have introduced new methods for stress detection, including physiological indicators such as HRV, skin conductance, and eye-tracking tests. These objective measures provide deeper insights into stress responses, complementing self-reported data and offering a more accurate assessment of an individual’s stress levels.

Eye-tracking technology, in particular, has emerged as a promising tool in stress detection. [1] Research has shown that subtle variations in pupillary response, gaze direction, and blink rates are closely linked to stress and cognitive load. When an individual experiences stress, their eye movement patterns often change, reflecting shifts in attention, heightened vigilance, or cognitive fatigue. This scientific understanding has led to the growing adoption of eye-tracking tests in psychological and neurological studies, enabling more precise stress assessments beyond traditional survey methods. By integrating these physiological signals with psychological assessments, stress identification becomes more reliable and data-driven, paving the way for improved intervention strategies.

In addition to modern technological advancements, ancient healing systems like Ayurveda provide valuable insights into stress management by addressing both mental and physical health. Ayurveda, a traditional medicinal system practiced for thousands of years, takes a holistic approach to well-being by incorporating lifestyle adjustments, personalized nutrition, herbal remedies, and emotional balance into its stress management treatments. Unlike conventional Western medicine, which often focuses on symptom relief, Ayurveda emphasizes preventive care and the harmonization of mind and body through natural and therapeutic practices. By evaluating stress through an Ayurvedic lens, individuals can benefit from personalized wellness strategies that promote long-term resilience against stress-related disorders.

This work presents a novel approach to stress regulation by merging Ayurvedic principles with modern machine learning (ML) techniques, implemented through a smartphone application. The proposed system leverages ML algorithms to analyze both self-reported emotional states and physiological indicators, such as eye movement patterns and blinking frequency, to provide real-time stress detection. By continuously monitoring and analyzing these inputs, the system can dynamically assess an individual's stress levels and provide personalized recommendations tailored to their unique stress profile.

To enhance mental and emotional well-being, the platform integrates creative therapy techniques, which align with Ayurvedic principles of holistic healing. These include music therapy, which has been scientifically proven to reduce stress by influencing brain wave activity and promoting relaxation, as well as mandala drawing, a meditative art practice that fosters mindfulness and emotional expression. By offering customized therapeutic interventions, the system not only helps individuals recognize their stress triggers but also equips them with effective tools to manage and reduce stress over time.

By combining the wisdom of Ayurveda with state-of-the-art machine learning techniques, this innovative approach seeks to transform stress management into a personalized and accessible experience. The integration of physiological monitoring, self-reported assessments, and creative therapy interventions allows individuals to take proactive steps in improving their mental health. This holistic system has the potential to revolutionize stress management, making it more precise, effective, and adaptable to the diverse needs of individuals in today’s fast-paced and stress-prone world.

This research focuses on not only detecting stress in real-time but also predicting future stress based on behavioral patterns such as sleep quality, screen time, dietary habits, and social interactions etc. By incorporating ML algorithms, the system can analyze an individual's behavioral habits and identify potential stressors before they escalate into chronic stress. This predictive capability allows for early intervention, enabling users to take preventive measures and make lifestyle adjustments that can mitigate the negative effects of stress. Unlike traditional stress management techniques that often address stress after it has already taken a toll, this approach shifts the focus towards proactive prevention, making stress management more effective and sustainable.

Machine learning plays a crucial role in this predictive model by identifying subtle correlations between various behavioral factors and stress levels. For instance, irregular sleep patterns, excessive screen exposure, and unhealthy eating habits have been linked to increased stress and anxiety. Similarly, lack of social interactions or constant smoking and drinking can significantly impact mental well-being. By analyzing data from multiple factors, the system can detect deviations from healthy routines and provide early warnings about potential stress accumulation. The integration of these predictive models empowers individuals to take control of their mental health by receiving timely alerts and actionable insights tailored to their specific needs.

Furthermore, addressing stress-related issues is often hindered by the reluctance or difficulty in seeking help. Many individuals struggle to express their feelings or hesitate to approach mental health professionals due to stigma, privacy concerns, or social barriers. To overcome this challenge, this research incorporates a chatbot that serves as a confidential and accessible support system. This chatbot provides a private channel for users to articulate their emotions, receive immediate guidance, and access relevant stress-relief techniques. By offering a non-judgmental space for users to share their concerns, the chatbot reduces the barriers to seeking help and encourages more people to prioritize their mental health.

Another significant aspect of this study is the creation of prediction models that estimate the time required for an individual to recover from stress. By analyzing user participation in stress-relieving activities—such as meditation, exercise, journaling, and creative therapies—the system can predict how long it may take for a person to regain emotional balance. These recovery models take into account multiple factors, including stress severity, engagement levels in relaxation techniques, and historical behavioral trends. Users can visualize their progress over time, making stress management a more structured and measurable process.

The integration of AI and ML with traditional Ayurvedic principles makes this project a comprehensive and easily accessible stress management solution. Ayurveda emphasizes holistic well-being by addressing mental, physical, and emotional health in unison. By incorporating Ayurvedic wisdom—such as mindfulness, breathwork, and dietary recommendations—alongside modern AI-driven interventions, the system offers a unique and personalized approach to stress management. Unlike one-size-fits-all solutions, this framework adapts to each individual's unique stress profile, providing tailored interventions based on both scientific insights and ancient healing practices.

Technology has significantly enhanced the accuracy and efficiency of stress detection by integrating behavioral and physiological data. AI and ML techniques have enabled researchers to create sophisticated models that analyze complex patterns in human behavior, making stress management more data-driven and precise. By leveraging smartphone sensors, and self-reported inputs, this system can provide real-time feedback and long-term stress projections, allowing users to make informed decisions about their mental well-being.

The substantial impact of stress on mental health and overall quality of life has made it a critical area of research, prompting the development of innovative solutions that go beyond traditional coping mechanisms. Chronic stress not only affects mental well-being but also contributes to severe physical health conditions, including cardiovascular diseases, weakened immune function, and metabolic disorders. Given the increasing prevalence of stress-related illnesses, researchers are now exploring new methodologies that integrate advanced technology with holistic healing approaches to create effective stress management solutions.

This project aims to revolutionize stress management by combining the predictive power of AI with the holistic healing principles of Ayurveda, developing a durable, personalized, and effective method for identifying, tracking, and alleviating stress. Unlike conventional stress management techniques that focus primarily on reactive treatments, this research introduces a proactive system that enables individuals to anticipate and mitigate stress before it escalates. By leveraging AI-driven insights, real-time physiological monitoring, and Ayurvedic interventions, this model provides users with an adaptive stress management framework that aligns with their unique behavioral patterns and lifestyle preferences.

Furthermore, thorough evaluation of stress levels is made possible through multi-modal methods, such as integrating psychological surveys with physiological indicators like heart rate variability (HRV). HRV is a well-established biomarker of stress, as fluctuations in heart rate patterns reflect autonomic nervous system activity and provide valuable insights into an individual's emotional state [2]. When combined with psychological self-assessments, HRV measurements offer a more comprehensive and objective evaluation of stress levels, enhancing the accuracy of detection and intervention strategies.

In addition to HRV, eye-tracking technology has emerged as a valuable tool in stress detection, as numerous studies have shown a correlation between stress levels and changes in pupil expansion, gaze patterns, and eye movement behaviors [1]. Under stressful conditions, individuals tend to exhibit altered eye movements, including increased blink rates and reduced saccadic activity. These changes can be effectively captured using AI-powered eye-tracking systems, which provide real-time, non-intrusive monitoring of behavioral stress indicators. By integrating eye-tracking with other physiological markers, stress detection becomes more precise, allowing for early intervention and tailored management approaches.

The predictive capabilities of stress detection algorithms have significantly improved due to extensive research on eye-tracking measures, including pupil dilation, gaze direction, and blink rates [3]. These parameters offer valuable insights into cognitive load and emotional distress, enabling AI models to recognize stress patterns with high accuracy. Moreover, real-time behavioral monitoring through eye-tracking technology allows for continuous assessment without requiring active user input, making stress management more seamless and accessible.

In addition to eye-tracking and HRV analysis, foundational research indexed on PubMed highlights the importance of integrating multiple behavioral and physiological indicators to enhance stress detection methods. These include skin conductivity, heart rate fluctuations, and psychological assessments, which together provide a multidimensional view of an individual's stress profile[4]. Skin conductance, also known as GSR, reflects changes in sweat gland activity that occur due to emotional arousal. Combined with HRV and eye-tracking data, GSR contributes to a more accurate stress assessment, helping users gain deeper insights into their physiological responses to stress.

By incorporating these scientifically validated techniques, our application integrates eye analysis and standard ayurvedic questionnaires to deliver real-time stress evaluation. This multi-faceted approach allows for a precise classification of stress into four levels: mild, moderate, severe, and critical. Understanding these levels enables users to take appropriate actions based on their stress intensity, whether it involves guided breathing exercises, mindfulness techniques, creative therapy interventions, or Ayurvedic lifestyle adjustments.

Furthermore, by providing users with access to personalized recommendations, AI-driven insights, and a structured framework for stress management, this project contributes to a healthier and more resilient society where mental well-being is prioritized and accessible to all. Through the seamless integration of advanced AI technologies and holistic healing principles, this research paves the way for a revolutionary approach to stress management that is not only durable and effective but also adaptable to the evolving needs of individuals in today's high-pressure world.

Because of its impact on the mind and body, stress reduction is still a key area of study in mental health. Stress-reduction effects from music therapy have been scientifically shown, especially when Hindustani ragas are used. These musical structures encourage emotional well-being and relaxation by evoking particular emotional reactions. Research on the "MusiHeal" app confirms that certain ragas can successfully lower stress levels [5]. Mandala art therapy, which has long been utilized for emotional balance and awareness, has also become an efficient stress-relieving tool. With the use of digital innovations, mandala therapies become more widely available via mobile applications and internet platforms, maintaining its conventional advantages while addressing a broader population [6]. Digital mandala therapy is a successful modern adaptation of a centuries-old technique that improves stress management by encouraging awareness and participation, according to studies. Additionally, using mandalas for meditative coloring has become popular as a stress-reduction method that encourages concentration and calm. Free mandala patterns are offered by websites like "Domestika", guaranteeing accessibility for anybody seeking ways to relax aesthetically [7].

Current studies on stress prediction focus an extreme value on identifying factors and developing predictive models. Studies show that stress levels are greatly influenced by lifestyle decisions such social contacts, physical activity, sleep patterns, and work habits. However, accessibility is limited because the majority of prediction models rely on wearable technology [8]. A study that was published in the Journal of Medical Internet Research revealed a strong relationship between stress levels and sleep patterns, showing that while a higher resting heart rate increases the risk of stress, a longer sleep duration decreases it [9]. By examining physiological data, such as heart rate variability and sleep parameters, another study published in Nature demonstrated how well machine learning models predict stress [10]. IEEE International Conference investigation has confirmed that integrating several data sources, including skin conductance and heart rate, improves predictive accuracy [11].

A major predictive factor of stress, sleep loss makes individuals more susceptible to psychological distress [12]. Regular exercise has been shown to reduce stress, and studies conducted in Madrid have confirmed that it is beneficial for working professionals [13]. Furthermore, dietary practices have an impact on stress regulation, depending on age and gender, high-fat diets have varying effects on neuronal function and redox stress [14]. Studies from Finnish universities have shown a strong correlation between a lack of social connections and elevated stress and depressive symptoms [15], further demonstrating the importance of social contacts in stress management. Research conducted by the University of Peradeniya during COVID-19 also showed that higher levels of stress are linked to more screen time [16]. Recreational activities have also been shown to improve wellbeing, considerably lower stress, and minimize harmful strategies for coping like consumption of alcohol and smoking [17] [18].

Because everyday stress is becoming more common, comprehensive and individualized stress management solutions are needed. Even if contemporary AI-powered tools and conventional techniques like Ayurveda have advantages, their efficacy is sometimes limited by their lack of integration. Ayurveda promotes holistic health via herbal remedies, meditation, and lifestyle changes [19], but it is still difficult to access in digital media. On other hand, whereas AI and ML technologies make it easier to monitor and predict stress, they frequently fall short of offering the level of individualized treatment that is essential to Ayurvedic principles [20]. In order to close this gap, the suggested system combines AI and ML with Ayurveda to produce a dynamic stress management tool that monitors health indicators, shows development, and forecasts recovery times [21] [22]. One important aspect of this system is its self-reporting method, which uses measures like the discrete emotions questionnaire to capture how you feel in real time [23]. Based on user adherence, predictive algorithms calculate stress recovery, improving motivation with transparent progress visualization [24].

This system offers data-driven, versatile predictions that are customized to each consumer's requirements, in contrast to traditional methods that provide static feedback [25]. And a user-centric, holistic approach that not only tracks stress but also actively advises users toward long-term well-being by fusing AI-driven precision with Ayurvedic wisdom is offered. This expansive and technologically advanced approach makes stress management products more efficient, interesting, and available to a wide range of users.

1.1. Research gap

Current studies on stress prediction focus on identifying factors and developing predictive models. Studies show that stress levels are greatly influenced by lifestyle decisions such as social contacts, physical activity, sleep patterns, and work habits. However, accessibility is limited because the majority of prediction models rely on wearable technology. Research has demonstrated that sleep patterns, heart rate variability, and behavioral data can accurately predict stress. However, most existing solutions lack integration with traditional healing techniques such as Ayurveda. While AI and ML models provide precision in stress tracking, they often fail to offer personalized intervention strategies aligned with holistic wellness practices.

Moreover, many AI-based stress detection tools focus on real-time assessment but do not offer proactive measures for preventing future stress. Predictive analytics in stress management remains underdeveloped, limiting early interventions. Additionally, while Ayurvedic practices emphasize long-term stress recovery through personalized recommendations, most digital stress management solutions provide generalized interventions that lack adaptability to individual needs.

Stress-relief techniques such as music therapy and Mandala art therapy have been scientifically validated for their effectiveness, yet they remain underutilized in digital platforms. Most existing applications that incorporate these therapies do not integrate real-time stress analysis, making it difficult to measure their impact dynamically. Furthermore, the lack of adaptive feedback mechanisms in stress management applications limits user engagement and motivation. There is a growing need for an integrated approach that combines advanced technology with traditional stress management strategies to enhance accessibility, personalization, and long-term effectiveness.

1.2. Research Problem

The increasing prevalence of stress-related illnesses highlights the necessity for an accessible, effective, and personalized stress management solution. Traditional techniques such as counseling and medication may not be viable for everyone due to financial, geographical, or personal barriers. Existing AI-powered stress detection tools primarily focus on tracking stress levels but lack proactive intervention mechanisms, holistic wellness approaches, and the ability to accurately predict stress before it occurs. This gap limits the potential for early intervention and highlights the need for systems that not only monitor but also anticipate stress to empower timely action.

Ayurvedic principles provide a time-tested method for stress relief, but their adoption in modern digital health solutions is minimal. Current predictive models mainly rely on physiological data from wearable devices, limiting their accessibility. Moreover, stress recovery times are rarely considered, leading to a lack of personalized recommendations for long-term well-being. This study seeks to bridge these gaps by integrating AI-driven biometric analysis with Ayurvedic stress management techniques, creating a solution that is proactive, predictive, and holistic.

In addition, while numerous digital platforms offer stress assessment, they often lack multi-modal approaches that combine physiological and behavioral indicators. Many applications do not consider stress variability across different individuals, leading to generalized rather than personalized interventions. Furthermore, predictive models that account for user engagement in stress-reducing activities and provide adaptive guidance for stress management are underdeveloped. Addressing these limitations requires a holistic system that integrates AI precision with Ayurvedic wisdom, ensuring a personalized and dynamic stress management experience.

1.3.Research Objectives.

The primary objective of this study is to develop a stress management system that integrates Ayurvedic principles with machine learning models for real-time stress detection and personalized interventions.

To achieve this broad goal, the study focuses on the following specific objectives:

1. To analyze the effectiveness of eye-tracking measures and standard ayurvedic questionnaires in stress prediction and classification.
2. To implement and evaluate stress based on stress-relief therapies such as Mandala art therapy and music therapy within a mobile application.
3. To develop predictive models capable of forecasting future stress based on behavioral patterns.
4. To design an interactive chatbot that offers real-time emotional support and guidance for stress reduction.
5. To create a recovery time prediction model based on user adherence to stress-relieving activities, providing personalized feedback and motivation.
6. To enhance accessibility and user engagement through interactive progress visualization, allowing individuals to track their stress levels and improvement over time.
7. To integrate adaptive feedback mechanisms that adjust intervention strategies based on user responses, improving the effectiveness of stress management techniques.
8. To establish a multi-modal stress assessment framework that combines Ayurvedic principles with AI-driven stress tracking for a holistic approach to well-being.
9. To explore the impact of creative therapies on stress recovery and develop AI-based models to optimize therapy recommendations based on individual user responses.

2.Methodology

Through a smartphone application, users can enter answers to a daily survey and get positive reinforcement. Blink patterns are identified as a sign of stress through eye movement analysis, and daily routines and user behavior are tracked to predict future stress. The current stress level of the user is classified into moderate, medium, severe, or critical based on the analysis of the recorded data. Based on this, a group of customized stress-relief activities such as Raga music therapy and Mandala drawing is suggested. To maximize treatments, work schedules and users' development are taken into account as well. After forecasting of the recovery time, the system creates customized program of activity and progress reports for users so that they can observe their improvement along the line of time.

2.1. Integrating eye movements and questionnaire analysis for real-time stress level detection

This research uses mobile data and deep learning-based analysis to analyze eye-blinking pattern identification and questionnaire answers to detect stress levels. The method records 300 participants over the age of 18 under different lighting conditions using 10-second selfie videos and their normal questionnaire answers. The goal is to have an Ayurvedic expert analyze blinking frequency and compare it with established indicators of stress. Normal blinking happens two to three times in ten seconds; any deviation from this standard may indicate varying levels of stress. Deep learning techniques are used to improve accuracy to allow for automatic prediction of stress after preprocessing and labeling of data obtained into stress levels. Deep learning allows effective feature extraction from eye movements to ease generalization over many subjects and environments. Fig.1. demonstrates an overview of integrating eye movement and questionnaire analysis for real-time stress level monitoring.

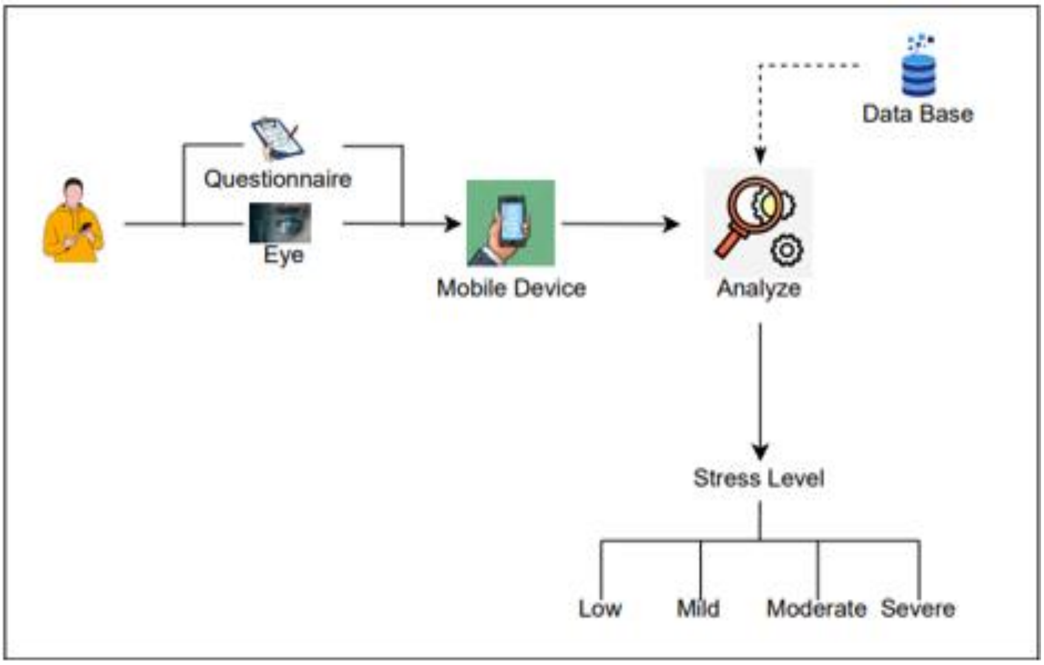

Fig. 1. Overview diagram for initial stress detection

a) Features and Target Variable

The database combines behavioral and physiological characteristics in a bid to maximize the accuracy of stress levels classification. Blink rate is a vital physiological parameter which can be measured over 10-second films. Discrepancies from the baseline standard of two to three blinks for ten seconds indicate differing degrees of stress. Controlled lighting provides high-quality data of consistent quality in all contexts.

Moreover, age group data is supportive of measuring stress variances across groups, and standardized stress questionnaires quantify self-reported stress. An Ayurvedic specialist validates the target variable categorization of stress into four levels:

- **Level 1:** High stress, >6 blinks.
- **Level 2:** Moderate stress, 4-6 blinks.
- **Level 3:** Normal, 2-3 blinks.
- **Level 4:** Low blink rate, 0-1 blink

This multi-dimensional framework combines eye movement data and self-assessments to enhance classification accuracy and reliability.

b) Data Preprocessing

The data used in this study contains four levels of video clips under different stresses, which were stored in four folders labeled from Level 1 to Level 4. There was preprocessing applied to every video clip by capturing up to 100 frames from each and resampling each frame into the same resolution size of 224x224 pixels for the purpose of matching the size requirement for inputs required by pre-trained CNNs. All pixel values were normalized between [0,1] by a division of 255 for improved numerical stability and model convergence. The stress level labels were one-hot encoded with a LabelBinarizer, transforming the categorical labels into binary vectors for multi-class classification. The dataset was split into training and test sets, 80% for training and 20% for testing, with balanced evaluation. For more efficient computation and data management while training, the preprocessed frames and labels were saved in.npy format to be read via memory mapped I/O. The end-to-end preprocessing pipeline thus furnished homogenous data across videos and improved the model's generalizability across stress levels.

c) Model Development

Pseudocode for Stress Level Detection Model.

Input: Video files categorized by stress levels (Levels 1-4)

Output: Predicted stress levels and model performance metric.

BEGIN

1. Import Libraries (TensorFlow, OpenCV, sklearn, matplotlib, seaborn, etc.)
2. Load and Preprocess Data
    - Extract up to 100 frames (resize to 224x224).
    - Normalize pixel values (0 to 1).
    - Assign labels from folder names (Level 1 to Level 4).
  - Encode labels using one-hot encoding.
  - Split into training (80%) and testing (20%) sets.
  - Save preprocessed frames and labels to .npy files.

3. Build Model
    - Load pre-trained VGG16 (without top layers) for feature extraction.
    - Add custom layers:
        - Flatten layer.
        - Dense layer (128 neurons, ReLU).
        - Dropout layer (50%).
        - Output Dense layer (4 neurons, softmax for 4 stress levels).
    - Compile model (Adam optimizer, categorical crossentropy loss, accuracy metric).
4. Train Model
    - Train for 10 epochs with batch size 32.
    - Use 20% of training data for validation.
5. Evaluate the Model
    - Predict stress levels for test data.
    - Generate classification report (precision, recall, F1-score).
    - Plot confusion matrix for visual analysis.
6. Hyperparameter Tuning (Optional)
    - Adjust learning rate, epochs, or batch size.
    - Retrain with updated parameters.
7. Save Model
    - Save trained model in HDF5 format for future use.
8. Visualization
    - Plot confusion matrix with seaborn.

END

The initial stress detection Model is based on pre-trained CNN models, VGG16 and RestNet50, to learn the spatial features of frames in a video. The frame can be viewed as an individual sample image, and the model must classify the frame into one of the four stress levels. The VGG16 model was selected for further enhancement based on its performance.

2.2. Predicting Future Stress Likelihood and a Motivational Chatbot.

The Fig. 2. is a description of the stress prediction system integrated in the AyurAura app. Users input their behavioral information, which is analyzed using a Random Forest model to determine the likelihood of them experiencing stress. For the identified users who are at risk, the system recommends behavioral changes to help them stay stress-free. Apart from that, the app generates a personalized activity schedule based on the stress level and includes a chatbot to which users can speak when they are stressed. This adaptive system provides accurate predictions of stress and customized support to enhance overall well-being.

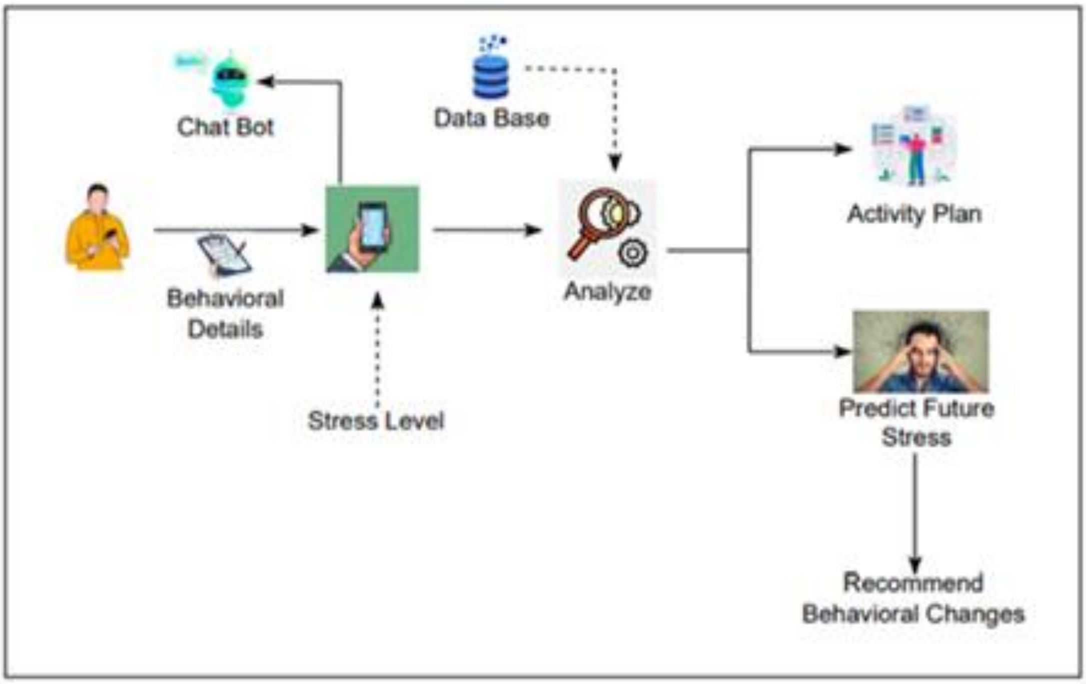

Fig. 2. Prediction of future stress likelihood flow.

a) Features and Target Variable

Data was collected from 1,000 participants through Google Forms and in-person surveys, noting the primary behavioral determinants that influence stress levels. The behaviors noted were sleeping habits, frequency of exercise, working hours, screen time, social interaction quality, healthiness of diet, smoking and drinking, and engagement in leisure activities.

After data collection, a doctor categorized individuals into two distinct groups: those who have a possibility of experiencing stress and those who are not, based on their behaviors. A number of research studies have yielded strong correlations between these behavioral determinants and the levels of stress, thereby increasing the validity of this classification approach.

This categorization was utilized as the machine learning model's target variable. The data set had a wide variety of behavioral patterns in such a way that significant conclusions could be made on stress prediction. However, while the sample size of 1,000 individuals provides a good baseline, expanding the data set to represent a wider range of demographics could serve to enhance the accuracy of the model further.

b) Data Preprocessing.

During preprocessing, rows with missing data were dropped to maintain data integrity. Duplicate values were also identified and dropped to prevent data redundancy. Column names were also renamed for readability. Numerical features were also standardized to ensure consistency in varying scales. These preprocessing steps helped in purifying the dataset and optimizing model performance.

c) Model Development

Pseudocode for Stress Likelihood Prediction Model

Input: Behavioral data. (sleep, exercise, work hours, screen time, social interaction quality, healthiness of diet, drinking and smoking, recreational activities)

Output: Predicted likelihood of stress (Stress / No Stress).

BEGIN

1. Import necessary libraries (e.g., pandas, sklearn, RandomForestClassifier, joblib, seaborn, matplotlibt).
2. Load the dataset containing behavioral data and stress probability.

3. Preprocess the data:
    - Remove incomplete data rows.
    - Rename column names for better readability.
    - Remove duplicate rows.
4. Define the target variable (stress_probability).
5. Split the dataset into training (80%) and testing (20%) sets.
6. Initialize a Random Forest Regressor/ KNN Classifier.
7. Train the model using the training data.
8. Evaluate the model:
    - Predict stress probability on the test data.
    - Calculate accuracy, classification report, and confusion matrix.
9. Save the trained model and scaler for future use.
10. Output predicted stress probability

END

Random Forest Classifier was employed since it can handle both numerical and categorical inputs as well as handle missing values and outliers robustly. The model was trained on 80% of the data, and 20% of the data was utilized to test the model's generalization ability to new data. Standardization was utilized to assign equal weightage to features. Missing values were treated through imputation, and records with duplication were removed to maintain data integrity. Hyperparameter was tuned to enhance model accuracy and achieve the optimum generalization of stress probability estimation.

2.3. Activity creation and predicting stress level based on activity performance.

In this research, as shown in Fig. 3. we created a machine learning approach which utilizes activity performance data to estimate the current level of stress for an individual. Apart from demographic characteristics including age and gender, the system analyzes the impact of different engagement factors, including mandala pattern type, color patterns, duration spent doing the activity, music track nature selected, and the time spent listening. Real-time observation of the public was employed to gather data through observing them interacting in activities.

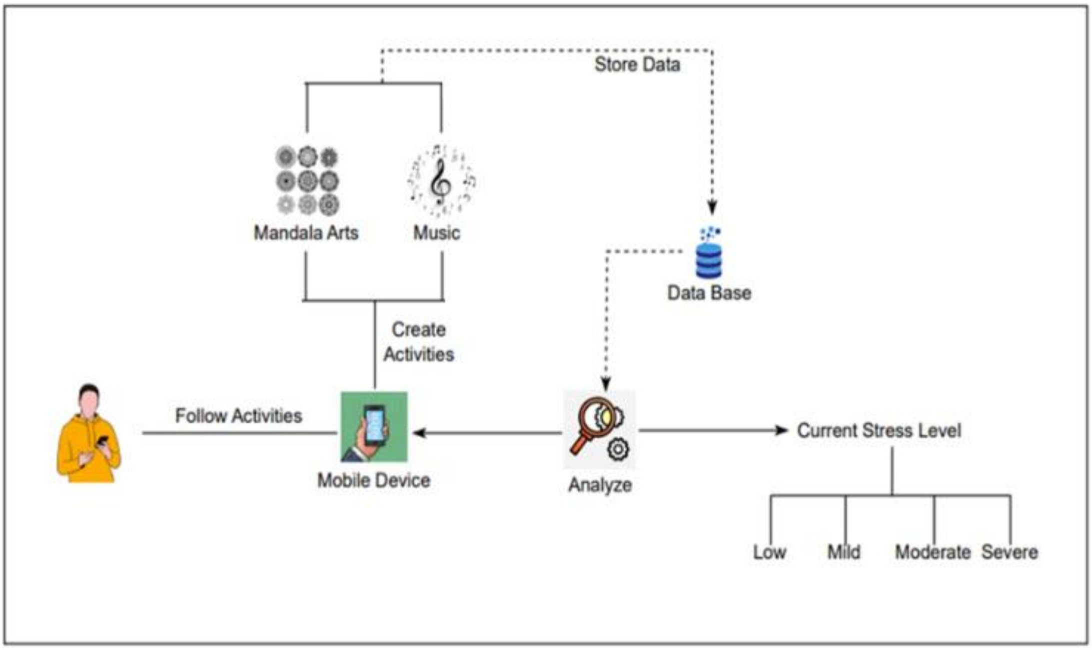

Fig. 3.Flow of Prediction of Current Stress based on activity engagement.

a) Features and Target Variable

The data has been collected through data from more than 1,000 participants in the research study. Stress levels have been ranked into four different categories as Critical (1), Severe (2), Mild (3), and Low (4). In order to make the sample representative of people, aged 18 years or older, participants were randomly selected from the total population. A dynamic analysis of the elements responsible for stress was facilitated by gathering real-time data while individuals engaged in various activities. Mandala pattern designs, color palettes, the amount of time spent on the activity, the nature of the music track chosen, and the amount of time spent listening were all included in these exercises. To examine their impact upon stress variances, demographic indicators like gender and age were included.

An expert-monitored classification method was used for ensuring reliability and consistency in labeling the stress level. Behavioral analysis and psychology professionals monitored segmentation and classification of stress levels, which minimized inconsistencies and maximized prediction accuracy. To successfully search for behavioral patterns that produce stress variations, model structures data with clearly defined engagement factors and stress classes.

The primary objective of this research is the predicted level of stress (1-4) that signifies an individual's current level of stress due to his/her interaction with different tasks.

The model learns patterns from data that result in very accurate predictions of the level of stress through machine learning algorithms like Random Forest and SVM. With the help of this classification system, people can evaluate their existing stress levels and decide whether or not to engage in different activities that will help them manage their stress effectively.

b) Data Preprocessing

Data preprocessing was done in preparation for model training to organize behavioral data. Individuals painted mandalas and listened to music for data collection. Mandala design patterns, colors used, time taken to do the task, type of music track, listening time, and demographic data like age and gender were all measured. Column entries (such as user IDs) that yielded no useful data were trimmed down to have a cleaner dataset. For model clarity improvement, categorical features such as mandala pattern designs, selected color themes, and types of music tracks were converted to numerical values. The StandardScaler was utilized for normalizing the dataset so that there would be a normalized distribution of features and accelerating model convergence to improve model training efficiency. The data was then split into a 90% training set and a 10% test set so that the model's capacity to generalize to unseen data can be tested. To test the model's capacity to generalize to unknown data, the data was then split into a 90% training set and a 10% test set.

c) Model Development

Pseudocode for Stress Level Prediction Model

Input: Activity engagement data (e.g., mandala design, color choices, time spent, music preferences)

Output: Predicted stress level**.**

BEGIN

1. Import necessary libraries (pandas, sklearn, RandomForestRegressor, SVM, StandardScaler).
2. Load the dataset containing engagement features.
3. Preprocess the data:
   - Remove irrelevant columns.
   - Encode categorical features (mandala design, color palettes, music type).
   - Standardize numerical features.

4. Split the dataset into training (90%) and testing (10%) sets.
5. Initialize the Random Forest Regressor and SVM Regressor.
6. Train both models on the training data.
7. Optimize hyperparameters using GridSearchCV.
8. Evaluate the models:
   - Predict on the test data.
   - Compute RMSE and R^2 score.
   - Compare model performance and select the best one.

9. Extract and rank feature importance from the trained Random Forest model.
10. Save the trained model and scaler for future use.
11. Output predictions and key influencing features.

END

The Random Forest Regressor was used since it can handle imbalanced data and model complicated relationships, making it a good choice for predicting stress from a broad set of engagement variables. The SVM Regressor was used to improve the precision of prediction, especially in regression-based predictions where modeling small changes in the stress level matters.

2.4. After prediction: predictive analytics for achieving a stress-free state.

A machine learning prediction model deployed within the AyurAura app and yielding stress recovery durations is shown in fig. 4. As part of task completion information, users need to input their daily emotions and states (such as stress, happiness, or relaxation) and energy levels. Once gathered within a central storage facility, machine learning algorithms are utilized for data processing. Individual, in-time recovery times may be computed via the correlation of the activity and mood sensors. Along with stress-relief exercises, the users can utilize the accurate estimates provided in an attempt to visualize their rehabilitation targets and methods. This form of stress management practice is user-adaptive and center.

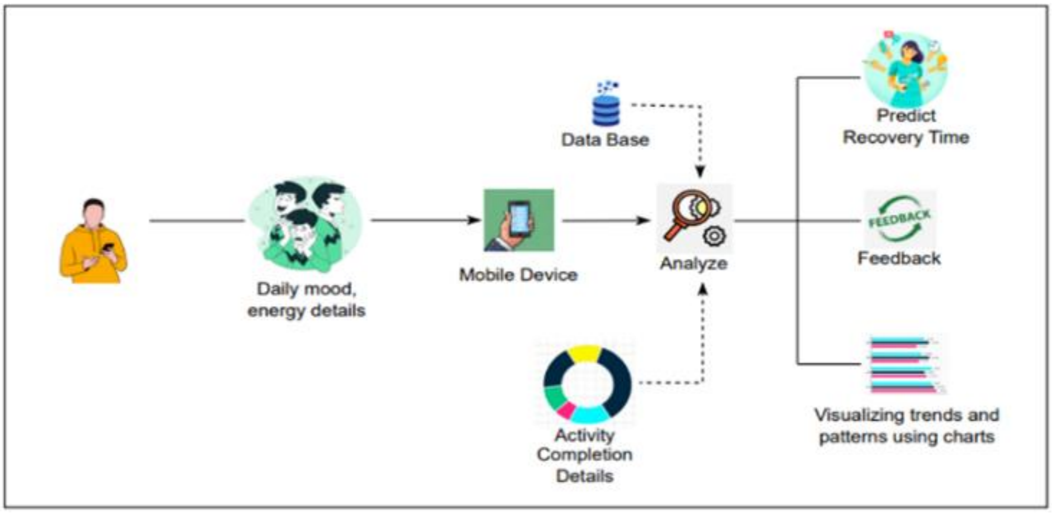

Fig. 4. Flow of Prediction of Recovery Time to Stress-Free State

a) *Features and Target Variable*

Feature engineering played a crucial role in enhancing the predictive power of the model, and it involved a thoughtful process of transforming raw data into meaningful features that could better inform the model's predictions. One of the most impactful and thoughtfully engineered features in this study is the Recovery Days metric. This feature was introduced with the primary intention of estimating the duration a user may require to recover from a state of stress, taking into account both their daily reported psychological well-being and the extent of their engagement in therapeutic activities. Unlike static indicators that might only reflect a snapshot of emotional status, the Recovery Days metric was designed to be dynamic—adapting to fluctuations in the user's mental state and their behavioral involvement in self-care routines. The creation of this feature was done in close consultation with a healthcare professional (a medical doctor), to ensure that the logic behind the metric reflected a clinically relevant understanding of the stress recovery process.

The calculation of the Recovery Days metric begins with the assessment of two key categories of user data collected on a daily basis: well-being metrics and engagement metrics. The well-being category consists of four daily self-reported scores—Stress Level, Energy Level, Happiness Level, and Calmness Level. Each of these was evaluated in terms of its deviation from an ideal, healthy baseline. Higher stress levels, or lower levels of energy, happiness, and calmness, were all seen as signals that a user was in greater need of recovery. To reflect this, each metric was translated into a 'need score'—a numerical representation of how far the user's reported value was from the desired norm. For example, if a user reported feeling very stressed and low in energy, they would be assigned a higher need score, indicating a larger gap between their current and optimal state.

Parallel to this, user engagement in therapeutic practices was also quantified. Two aspects were captured here: the Overall Activity Completion Rate (%), and the Duration of Participation (measured in minutes) in therapeutic activities such as Mandala art coloring and music therapy. The underlying rationale was that greater participation in these activities generally correlates with a quicker recovery, while minimal engagement might suggest a lack of progress or a potential need for intervention. As such, specific thresholds were set. For activity completion rates, a percentage below 40% was interpreted as high need, while percentages above 95% reflected low need, with gradations in between (e.g., 40-60%, 60-80%, 80-95%). Similarly, for participation duration, durations under 20 minutes reflected high need, while those over 50 minutes reflected minimal need, with intermediate bands in between. These structured intervals allowed the system to consistently quantify user engagement in a way that could be compared across individuals and over time.

Once all individual need scores were determined from both well-being and engagement domains, they were aggregated into a single Total Need Score. This composite score provided a holistic, one-number summary of how much support or recovery effort a user may require on a given day. Importantly, this score captured the interplay between mental state and behavioral patterns—someone feeling emotionally low but also highly engaged in therapeutic practices would generate a different score than someone with the same mood but who was disengaged, thereby offering a more personalized representation of the user's condition.

The final step in the process involved translating the Total Need Score into an actual Recovery Days value. This was achieved through mathematical scaling and transformation procedures, including rounding, boundary enforcement (to avoid unrealistic values), and proportional adjustment based on clinical insights. This transformation ensured that the output would represent a realistic number of days expected for recovery, rather than an abstract score. By doing this during the data preparation phase—before any model training—the Recovery Days metric acted as a rich, ready-to-use label or feature for supervised machine learning tasks, improving the predictive strength of the models built later on.

Ultimately, the introduction of the Recovery Days metric brought immense value to the dataset. It allowed for a deeper, more contextual understanding of user journeys through the stress recovery process. Unlike a simple measure of stress level or therapy completion, this metric synthesized multiple dimensions of user data into a single, clinically-informed estimation of how long recovery might take. This allowed the system to respond more intelligently, offering tailored predictions and insights that are both psychologically and behaviorally grounded. Even though the Recovery Days calculation was executed outside the modeling algorithms—during data preprocessing—it laid a foundation for building more adaptive, meaningful, and human-centered AI models. It also positioned the overall system as one that not only tracks mental wellness but actively interprets it in ways that support proactive and personalized mental health care.

b) Data Preprocessing

Reprocessing involved binary conversion of categorical variables like gender and removal of irrelevant features like user IDs. Completion rates and other percentage features were also converted to decimal values. For equal weighting for various scales, numerical features were standardized and mean imputation was used for handling missing data. Proper preparation of data and optimization of model performance required all these steps.

c) Model Development

Pseudocode for Recovery Days Prediction Model.

Input: Daily emotional data (stress, calmness, energy, happiness levels) and activity completion rates.

Output: Estimated recovery days

BEGIN

1. Import required libraries (e.g., pandas, sklearn, RandomForestRegressor).
2. Load the dataset containing emotional metrics and activity completion rates.
3. Perform data preprocessing:
    - Remove unnecessary columns.
    - Convert categorical variables into numerical format.
    - Standardize numerical features for uniformity.
4. Define the target variable (recovery days):
    - Establish base recovery days.
    - Modify based on activity completion rates.
5. Divide the dataset into training (80%) and testing (20%) subsets.
6. Initialize the chosen model (Random Forest Regressor or Logistic Regression).
7. Train the model using the training data.

8. Assess model performance:
    - Predict recovery days using test data.
    - Compute evaluation metrics such as Mean Absolute Error and R-squared.
9. Store the trained model and data scaler for later use.
10. Return the predicted recovery days.

END

As they could handle both categorical and numerical features, logistic regression and random forest were selected as balancing techniques for further investigation. The random forest identified complex, nonlinear patterns while the logistic regression handled continuous responses. In order to make it feasible for the model to be tested against unseen data, the dataset was divided, 80% for training and 20% for testing. Missing values were filled with mean imputation, and hyperparameter tuning was carried out to obtain best accuracy. This helped the models generalize efficiently and provide accurate predictions based on demographics, mood, and activity participation.

2.5. Testing

The overall performance of the application was evaluated through rigorous testing across all four core components of the powered stress management solution. Each component was tested individually as well as in an integrated environment to ensure reliability, consistency, and alignment with expected outcomes. The testing process considered both backend performance and user-facing functionality across different deployment settings development environment, local server using FastAPI, and prototype mobile interfaces.

2.5.1. Test Plan & Test Strategy for Real-Time Stress Detection Using Eye Movement and Questionnaire Analysis

This component detects stress levels in real-time using eye movement tracking and responses from the Perceived Stress Scale (PSS) questionnaire. The model analyzes both eye blink rate and PSS scores to assess the user’s current stress level. Both inputs are utilized simultaneously before the model predicts the stress level.

Test Case ID	Scenario	Input	Expected Output	Status
1	Ensure eye movement data is captured and logged correctly	video feed for 15 seconds	Eye blinks extracted and saved	Pass
2	Verify PSS responses are scored and logged correctly	Responses to the 10-item PSS form	PSS score generated and normalized for model input	Pass
3	Ensure both eye movement and PSS score are processed together for accurate stress prediction	Eye: High blink rate; PSS score: 28	Stress Level: "Severe"	Pass

Table 1. Test plan of Real-Time Stress Detection Using Eye Movement and Questionnaire Analysis

2.5.2. Test Plan & Test Strategy for Future Stress Prediction and Chatbot Integration

This component predicts future stress based on behavioral data input by the user. Additionally, there is a chatbot to help users manage their stress.

Test Case ID	Scenario	Input	Expected Output	Status
4	Validate if the model predicts future stress	Behavioral data	Predict stress likelihood(Stress or no stress).	Pass
5	Ensure the chatbot processes and responds to stress-related queries correctly	"I feel overwhelmed today"	Response: "Would you like to try a calming activity?"	Pass
6	Recommend behavior changes for users to stary stress free if they are likely to be stressed.	Behavioral data	Behavior modification recommendations	Pass

Table 2. Test plan of Future Stress Prediction and Chatbot Integration

2.5.3. Test Plan & Test Strategy for Current Stress Level Prediction Using Mandala Art and Music Therapy

This component predicts the user's current stress level based on engagement with mandala art and Hindustani raga-based music therapy, along with demographic details such as age and gender. No biometric data is involved.

Test Case ID	Scenario	Input	Expected Output	Status
7	Ensure correct logging of mandala activity details (design, color, time)	Design: "Complex", Colors: "1st palette", Duration: 20 min	Data stored and available for prediction	Pass
8	Ensure music type and duration are accurately logged	Music type: "Deep sleep", Duration: 15 min	Data logged and available for prediction	Pass
9	Validate stress prediction based on mandala activity alone	Design: "Simple", Colors: "7th palette", Time: 20 min, Age: 22, Gender: Female	Stress Level: "Moderate"	Pass
10	Validate prediction using combined mandala and music data	Design: "Medium", Colors: "8th palette", Time: 10 min, Music track: "Du flu", Duration: 15 min, Age: 28, Gender: Male	Stress Level: "Low"	Pass

Table 3.Test plan of Current Stress Level Prediction Using Mandala Art and Music Therapy

2.5.4. Test Plan & Test Strategy for Recovery Time Prediction Using "Recovery Days" Metric

This component predicts the number of days required for a user to recover from their current stress level, based on emotional trends and therapy engagement records.

Test Case ID	Scenario	Input	Expected Output	Status
12	Verify that activity and emotion logs are processed into a format suitable for the model	7-day log of stress and activity data	Sequence data properly formatted	Pass
13	Validate recovery prediction for a user with moderate stress history	Past mood and stress data showing gradual improvement	Predicted Recovery Time: 3 Days	Pass
14	Ensure recovery time is displayed clearly on the UI	Predicted Recovery Days: 5	Display: “Estimated Recovery Time: 5 Days”	Pass

Table 4. Recovery Time Prediction Using "Recovery Days" Metric

2.6. Commercialization Aspects of the Product

The proposed AyurAura system showcases strong commercial potential within the rapidly expanding wellness and digital health sectors, effectively merging traditional Ayurvedic principles with advanced AI-driven solutions for stress management. The app's multifaceted commercialization strategy is meticulously crafted to maximize revenue, ensure broad adoption, and enhance user engagement.

- **Monthly Subscription Model:**

AyurAura will implement a freemium model, offering essential features for free, while premium functionalities are accessible through a monthly subscription priced at Rs.300. Premium offerings include advanced mandala art designs and exclusive guided meditation sessions and more. This competitively priced subscription is anticipated to attract a large user base, with the personalized nature of the services driving substantial growth in subscriptions, establishing a consistent revenue stream.

- **Hospital Partnerships:**

Establishing partnerships with hospitals and healthcare providers presents a significant opportunity to integrate AyurAura into conventional healthcare practices. By offering a 50% discount on subscription fees to patients referred by hospitals, the app can be positioned as a key component of holistic post-treatment care, particularly for stress management. This partnership approach not only drives subscription growth but also bolsters the app's credibility within the healthcare sector, leading to a reliable stream of referrals and enhanced patient outcomes.

- **Social Media Commercialization:**

AyurAura's growth strategy will heavily leverage social media platforms to engage users and increase visibility. By curating content that aligns with the interests of wellness communities, the app can foster a loyal following. Strategies such as influencer collaborations, social media challenges, and campaigns promoting user-generated content are designed to boost brand awareness and app downloads. Moreover, targeted social media promotions will highlight the benefits of premium features, aiding in the conversion of free users into paying subscribers.

- **Application Monetization**:

In addition to subscription-based revenue, AyurAura is poised to generate income through in-app purchases, sponsored content, and strategic partnerships with wellness brands. Users will have the option to purchase additional services such as exclusive therapy sessions, custom art therapy kits, or Ayurvedic wellness products directly through the app. Collaborations with wellness brands for sponsored content and integrated offerings will open new revenue channels, while also enriching the user experience with complementary products and services

3.Results & Discussion

3.1. Integrating eye movements and questionnaire analysis for real-time stress level detection

a) Model Evaluations

The training log, as seen in Fig. 5, plots accuracy and loss against 10 epochs of training. The model's accuracy fluctuates at around 32.23%, and validation accuracy fluctuates around this estimate. This reasonably low accuracy indicates that the model fails to generalize well across different levels of stress. The consistent gap between training and validation accuracy hints at potential issues with data complexity, class imbalance, or insufficient feature extraction from video frames.

```
Epoch 1/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 52s 76ms/step - accuracy: 0.3223 - loss: 1.4184
Epoch 2/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 62ms/step - accuracy: 0.3210 - loss: 1.3491
Epoch 3/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 61ms/step - accuracy: 0.3315 - loss: 1.3379
Epoch 4/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 62ms/step - accuracy: 0.3243 - loss: 1.3338
Epoch 5/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 61ms/step - accuracy: 0.3170 - loss: 1.3366
Epoch 6/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 62ms/step - accuracy: 0.3240 - loss: 1.3397
Epoch 7/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 61ms/step - accuracy: 0.3244 - loss: 1.3392
Epoch 8/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 62ms/step - accuracy: 0.3269 - loss: 1.3364
Epoch 9/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 61ms/step - accuracy: 0.3234 - loss: 1.3381
Epoch 10/10
484/484 ━━━━━━━━━━━━━━━━━━━━ 30s 61ms/step - accuracy: 0.3221 - loss: 1.3422
<keras.src.callbacks.history.History at 0x7eaaf2b96c80>
```

Fig. 5. Initial stress detection training log.

In addition, as shown in Fig. 6., the prediction of the model on a test instance is class probability estimates at four levels of stress. The model's highest predicted probability (33.01%) is at Stress Level 3, indicating that the model lacks strong belief in predicting between stress levels. The corresponding probability distribution in indicating no strong prediction of a particular class also represents how challenging it is to predict stress levels.

```
"predicted_class": 3,
"predicted_percentage": 33.01,
"probabilities": [
    0.1306495815515182,
    0.291516751050949l,
    0.3300842940807342S,
    0.2477493733167648З
]
```


Fig. 6. Model output for a test sample.

Low confidence values and training-validation performance without training indicate that current architecture, hyperparameters, and training set have to be re-checked for potential optimization. Increasing dataset by data augmentation, tuning learning rates, or modifying architecture (temporal modeling to videos) would likely assist in better classification outcomes.

b) Mobile Application Development

The mobile application for recording and detecting stress levels was implemented with Firebase as the data store and authentication, Flask as the backend processor, and Flutter for the frontend interface. With the app, users can register, login securely, and view their dashboard. Users can use the device camera within the app to record a 10-second video snippet to determine stress levels. The stress level of the user is displayed on the screen with immediate feedback once the video processing and questionnaire submission are completed. The pre-trained deep learning model predicts the stress level of the user from the frames when the video is uploaded automatically to the backend. To further improve prediction accuracy, the user is requested to complete a brief, standard questionnaire right after the video upload. The users are given a pre-curated list of activities that can reduce stress, like music and mandala arts, based on the level of tension they have selected. The smooth user experience, data security, and real-time interaction between the mobile frontend and the backend processing pipeline are all guaranteed by the use of Flutter, Flask, and Firebase.

3.2. Predicting Future Stress Likelihood and a Motivational Chatbot

a) Model Evaluations

The performance of the model was measured in terms of accuracy, classification report, and confusion matrix to determine the strength of predicting stress likelihood based on behavior patterns. Accuracy measures the number of correct classification instances and the ability of the model to generalize unseen data. A greater accuracy value indicates a more precise prediction system for flagging people likely to face future stress. Classification report also provides important evaluation measures such as precision, recall, and F1-score for no-stress and stress classes. Precision calculates how many of the predicted stress instances are actually correct, while recall examines the model's performance to identify all individuals actually in danger. The confusion matrix further aids in depicting model performance visually by displaying the number of true positives, true negatives, false positives, and false negatives that can be useful for future improvement in stress prediction accuracy.

The Random Forest model had a maximum accuracy rate of 94.00%, with strong predictive ability in stress and non-stress classes, as seen in Fig. 7. From the classification report, precision, recall, and F1-score were high for both classes throughout, with precision being 0.96 for "No Stress" and 0.92 for "Stress", showing that the model makes correct predictions.

```
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. 7. Random forest classification report.

Fig.8. confusion matrix indicates that the overwhelming majority of the classifications were correct, with 91 true positives (correct "No Stress" predictions) and 97 true negatives (correct "Stress" predictions). However, there were some classifications that were incorrect, particularly where the stress indicators overlapped.

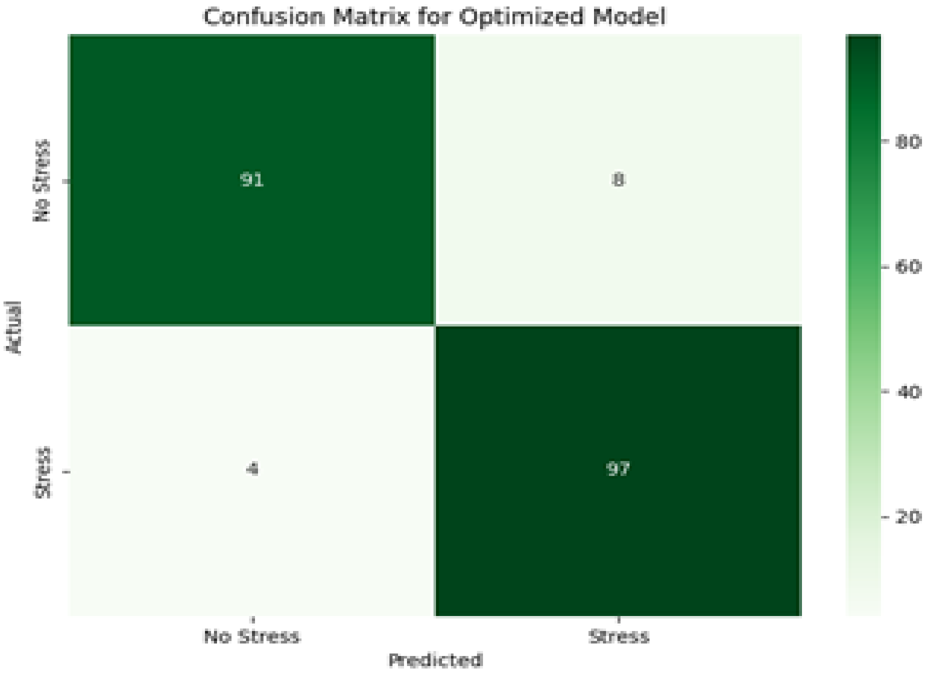

Fig. 8. Confusion matrix for random forest

The KNN model, although still good, gave a slightly worse accuracy of 92.50%, as clear from Fig. 9. The classification report shows that precision and recall were nicely balanced for both classes, with 0.91 precision for "No Stress" and 0.94 for Stress", shows that the model was able to classify most cases correctly but sometimes struggled with margin cases.

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

           0       0.91      0.94      0.93        99
           1       0.94      0.91      0.92       101

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

Fig. 9. Classification report for KNN model.

Fig. 10. The confusion matrix shows that the model was generally accurate but misclassified some "Stress" cases as "No Stress" and vice versa.

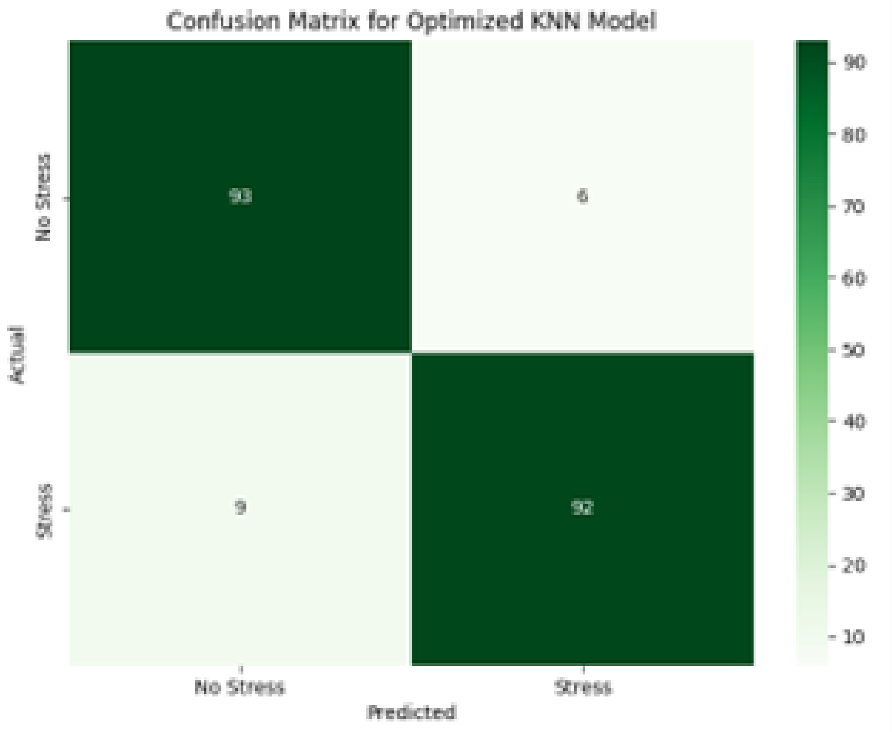

Fig. 10. Confusion matrix for KNN model.

The Random Forest model outperformed the KNN model with an accuracy of 94.00% compared to 92.50%. Random Forest performed better in correctly classifying both stress and non-stress cases, whereas KNN performed slightly worse recall for "No Stress" cases, leading to greater misclassifications. The confusion matrices show that Random Forest misclassified fewer cases and is the superior model to utilize when trying to predict stress.

While performing satisfactorily, Random Forest's margin of misclassification indicates that further adjustments, i.e., balancing the dataset or fine-tuning of hyperparameters, would enhance its efficiency. Similarly, KNN could be enhanced by more effective feature scaling or tuning the number of neighbors for best classification performance. Ensemble techniques or deep learning approaches may be considered in future enhancements to take the predictive capability of stress assessment models to the next level.

b) *Mobile Application Development*

The implementation of the stress prediction and management system was carried out using a mobile application, where the front-end was developed using Flutter and the back-end using Flask. The app provides the user with an interactive interface to assess the likelihood of experiencing stress in the future, receive behavior change suggestions, and engage in stress relaxation activities. Non-stressed users are allowed to input their behaviors so that they can examine their future likelihood of stress occurrence. The system examines their behavioral patterns and provides them with customized advice on how they can remain in a stress-free state. Users receive realistic advice on behavior change for stress avoidance in the future when the model predicts a high likelihood of future stress.

For the already stressed users, the application offers customized stress management methods. Based on the stress level of the user, it recommends stress-reducing activities such as mandala art and music therapy. Additionally, the users can converse with an in-built chatbot, which gives advice and support in real-time during stressful moments. The Flask-powered back-end contains the trained predictive model and manages user interactions. Upon input of behavioral data by the user, the app sends it to the Flask server, where preprocessing is carried out before prediction. The server returns the likelihood of future stress, along with personalized recommendations, which are displayed in the app. By combining predictive analytics, personalized recommendations, and interactive support tools, the mobile app allows users to regulate their stress levels and provide long-term well-being.

3.3. Activity creation and predicting stress level based on activity performance

a) Model Evaluations

SVM as well as the Random Forest method were used here to train our model and measure how accurately our model had forecasted stress levels. We attempted to improve performance of both the models and measure primary evaluation criteria like accuracy, precision, recall, and F1-score by hyperparameter tuning of their models. For meaningful comparison, we ran both the algorithms on a single set of data. This allowed us to examine how every model responds to varying categorizations of stress levels. The identification of the model best approximating the inherent patterns of the data is aided by the findings, which show the strength and weakness of every method.

The complete evaluation of the performance of the SVM algorithm to predict various levels of stress can be seen from the classification report as in the Fig 11. The model had a modest capacity to properly classify stress levels with an overall accuracy of 78%. In the per-class performance analysis, the model excelled at the prediction of stress level 3 because it effectively classifies high-stress instances with precision of 0.84, recall of 0.86, and F1-score of 0.85. It also showed good prediction for stress level 0, with F1-score of 0.79 and recall of 0.81, indicating that the majority of events in this class were correctly labeled. Despite this, the model had more trouble with stress level 2, as evidenced by the recall falling to 0.69, which means that there were some cases of moderate stress that were incorrectly classified into other levels. The 0.78 precision, recall, and F1-score macro and weighted averages indicate that the model is performing consistently across all stress levels. Misclassification rates of SVM model for stress level 2 offer a range of improvement either through feature engineering or through hyperparameter tuning in spite of its balanced classification capability.

	precision	recall	f1-score	support
0	0.78	0.81	0.79	52
1	0.77	0.78	0.77	59
2	0.75	0.69	0.72	48
3	0.84	0.86	0.85	43
accuracy			0.78	202
macro avg	0.78	0.78	0.78	202
weighted avg	0.78	0.78	0.78	202

Fig. 11. SVM model classification report.

The accuracy of classification by the Fig 12. model is exemplified by the confusion matrix generated following the running of the SVM algorithm. The model performed well in classifying Classes 1, 2, and 4, as evident from the diagonal values that reflect correctly classified instances (42, 46, and 37 correct classifications, respectively). Class 3 misclassified more than Class 2, with examples incorrectly assigned to Class 2 (7 examples) and Class 4 (5 examples). There is a significant amount of confusion between similar classes, with Class 2 and Class 3 being confused more than any other classes, despite the model being accurate for the majority of classes. Reducing misclassifications may be attainable through optimal feature selection, changing class weights, or fine-tuning hyperparameters for enhanced performance. Also, if class imbalance exists, data augmentation or class balancing may be beneficial. Although the general performance of the SVM model is encouraging, further improvement may be needed to achieve higher classification accuracy.

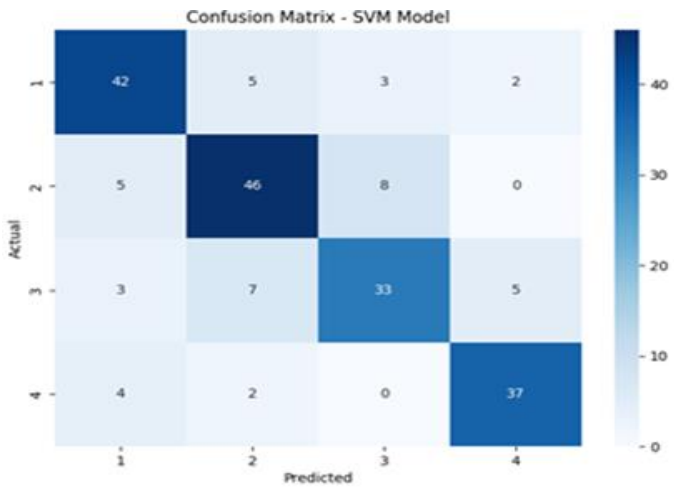

Fig. 12. Confusion matrix for SVM model.

The first image provides the Fig. 13. Random Forest classifier report showing metrics for precision, recall, F1-score, and support of each class. Class 1 performed well since its accuracy and recall values were 0.87 and 0.88, respectively, which made the F1-score 0.88. Class 2 accuracy and recall values were 0.82 and 0.83, respectively, and hence were lower than the first one. Class 3 with an F1-score of 0.74 performed worst, perhaps because it had higher misclassification rates. Class 4, at an F1-score of 0.88, was performing well. With macro and weighted averages of precision, recall, and F1-score both 0.83 and overall accuracy of 83%, the model is observed to be well balanced and performs as well in classifying all classes.

	precision	recall	f1-score	support
1	0.87	0.88	0.88	52
2	0.82	0.83	0.82	59
3	0.76	0.73	0.74	48
4	0.88	0.88	0.88	43
accuracy			0.83	202
macro avg	0.83	0.83	0.83	202
weighted avg	0.83	0.83	0.83	202

Fig. 13. Random forest classification report.

The same confusion matrix of Random Forest model reveals the classification performance graphically in Fig.14., with true projections along the diagonal and false classifications off-diagonal areas. The model correctly classified 46 samples of Class 1, 49 samples of Class 2, 35 samples of Class 3, and 38 samples of Class 4. There are some misclassifications in the errors, however, with Class 3 having 7 misclassifications to Class 2 and 4 misclassifications to Class 4, and Class 2 having 8 misclassifications to Class 3. These misclassifications suggest that there may be overlaps in the features between these classes. Overall, the confusion matrix shows a good but slightly unbalanced performance with scope for improvement in separating Classes 2 and 3.

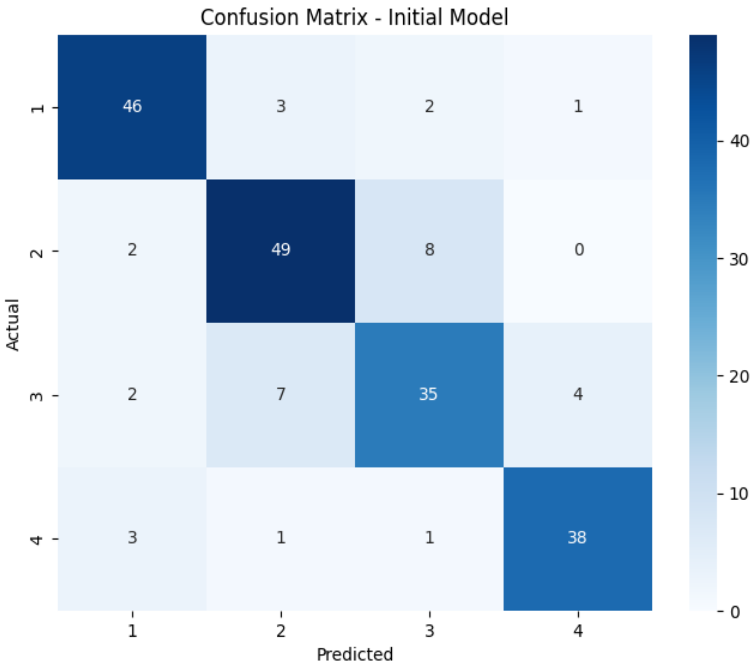

Fig. 14. Confusion matrix for random forest model.

Based on stress level prediction performance, Random Forest is the ideal because it classifies better than SVM. Random Forest has a balanced and more consistent classification across all stress levels at 83% overall accuracy than SVM with an accuracy of 78%. Less misclassifications in the confusion matrix show that the model does the more difficult Classes 2 and 3 better than SVM, and can also accurately classify Classes 1 and 4 with good precision and recall. Higher misclassification rates were generated by SVM because it faced severe difficulties with Stress Level 2, although it had a great predicting score for Stress Level 3. Furthermore, Random Forest is a robust and consistent model since it has higher macro and weighted average scores in precision, recall, and F1-score. Although there are areas for improvement in both models, Random Forest is the better option for precise stress level prediction since it provides better overall performance, reduced error rates, and more consistent classification for various stress levels.

b) Mobile Application Development

The front-end user interface of the mobile app was developed using Flutter, the backend processing using Flask, and user authentication, data storage, and performance monitoring using Firebase. The app offers users a personalized stress management platform where they can select from three types of Mandala art patterns based on their interests. Once a mandala type has been selected, there are eight palettes that can be selected and colored instantly using the interactive canvas interface in the app. User behavior such as patterns chosen, color selections, and how long spent, are all tracked and stored to analyze. Aside from Mandala coloring, the users are capable of viewing a music library comprising different genres, and listen to any song of their choice.

Each user's performance in these activities is tracked, and their stress level after activity is calculated based on the performance metrics such as type of music, duration, completion rates. The stress level after activity is displayed to the user, and they can view how their stress level is now. The application's history feature records all the past activities and their corresponding stress levels, enabling users to monitor their progress and identify the activities that work best for their stress relief. The seamless combination of Flutter, Flask, and Firebase offers the user continuity of experience, real-time data storage, and analysis efficiency in terms of performance, thus rendering the application an effective stress management system.

3.4. After prediction: predictive analytics for achieving a stress-free state

a) Model Evaluations

Random Forest model performed greatly overall with an impressive accuracy rate of 99.64%. There were slight differences in performances between classes though, especially on smaller classes where there were fewer samples. Logistic Regression model still performed well though with an overall accuracy of 91.96%, but its performance was greatly affected by several classes, especially those with fewer data points.

In Fig. 15, the Random Forest model's confusion matrix showed it could predict correctly most of the classes with their diagonal values all having high numbers. It was more difficult, however, to distinguish between certain classes, say recovery day "1". Maybe the imbalance in the dataset or not having sufficient samples for particular recovery day classes was the explanation behind this challenge.

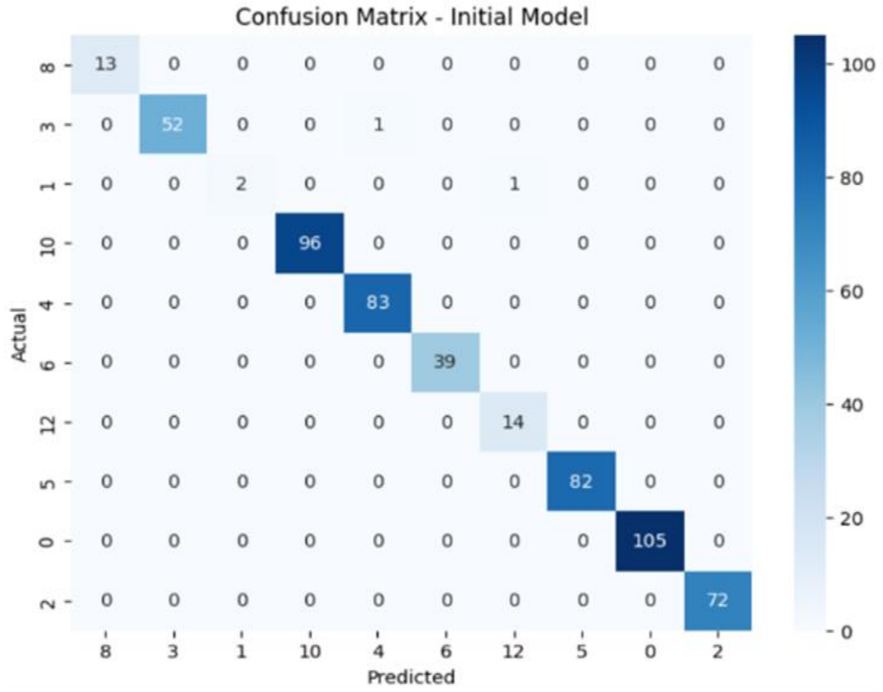

Fig.15. Confusion matrix for random forest model

The Logistic Regression model's confusion matrix in Fig. 16. showed that it was struggling to predict certain classes, namely "6," where a high proportion of the cases were being misclassified. The model was struggling to differentiate between some recovery day groups, like "1" and "12," from the off-diagonal data.

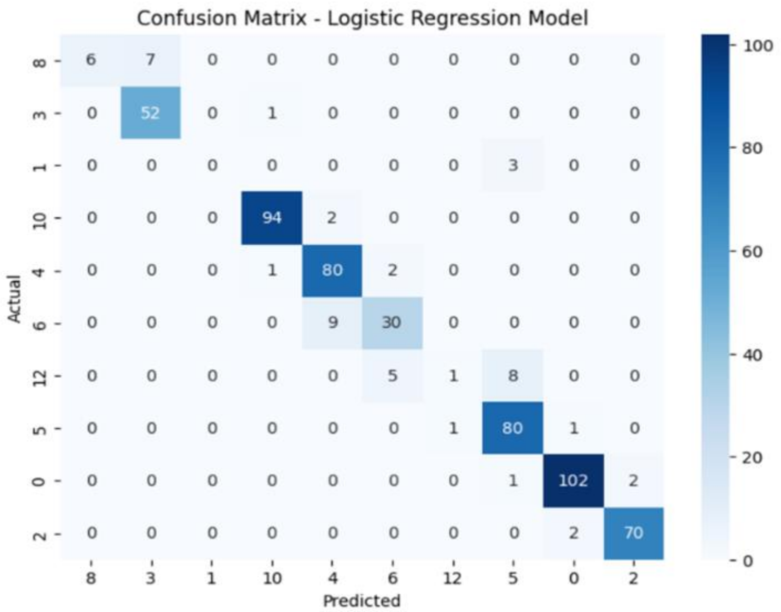

Fig.16. confusion matrix for logistic regression

The Random Forest model was more accurate with 99.64% compared to the Logistic Regression model, with an accuracy of only 91.96%. While Logistic Regression was bad with unbalanced data, especially in small recovery day groups like "6" and "2," where precision and recall were inferior, Random Forest was overall superior and also in most of the classes. That would make Random Forest more appropriate for this task. Techniques like resampling, class weighting, and hyperparameter tuning can be used to balance the imbalance in the data and minimize the bias to improve the performance of logistic regression.

b) Mobile Application Development

Implementation of the stress recovery prediction model was done by incorporating it within a mobile app created using Flutter for the client-side and Flask as the back-end. The app is an interactive portal where users can check their stress level and observe how they recover through the predictions achieved through the Logistic Regression model. The mobile application prompts users with five questions daily to gauge their emotional state and activity completion levels. The users can set reminders for the questionnaires to ensure consistency in the data gathered. The responses are processed and sent to the back-end based on Flask, where the Logistic Regression model computes the estimated number of recovery days required for the user to be stress-free.

To enhance the user experience, the app also features a dashboard that displays real-time predictions and history. Through interactive graphs, users can visualize how they have improved over time, with trends in their emotional responses, activity completion rates, and estimated recovery times. Visualizations enable the users to identify patterns in their stress recovery process and make informed decisions about their well-being.

The trained Logistic Regression model is implemented on Flask, which serves as the API for the mobile application. When the user provides an answer, the app sends the data to the Flask server where preprocessing is carried out prior to prediction. The predicted recovery days are then sent by the Flask API, which is displayed on the user side.

To encourage user engagement, the app has timed notifications to remind the users to complete their daily questionnaire. This offers data consistency and improves the accuracy of the model with a steady flow of user inputs.

4.Summary of Each Student's contribution

<table>
<tr><th>Member Name</th><th>Contribution</th></tr>
<tr><td>Wickramasinghe
B.G.W.M.C.R.
IT21279652</td><td>

Dataset Collection & Preprocessing:
a) Curated and labeled a dataset of 300 participants under different lighting conditions, ensuring diversity in data.
Model Development & Training:
Full-Stack Mobile Application Development
a) Frontend (Flutter): Developed a cross-platform user interface with Flutter, ensuring a smooth and interactive experience for users across iOS and Android devices.
b) Backend (Flask): Implemented Flask as the backend to handle video processing, stress prediction, and user activity recommendations.
c) Database & Authentication (Firebase): Utilized Firebase for secure user authentication and real-time data storage of stress levels, activity engagement, and recovery tracking.
Stress Detection & Prediction Model Integration
a) Integrated a pre-trained deep learning model to analyze facial expressions from a 10-second video snippet and detect stress levels.
b) Questionnaire-based augmentation system to enhance accuracy, ensuring that both behavioral data and video-based predictions contribute to the final stress level assessment.
Real-Time User Experience & Recommendations
a) Implemented a dashboard where users can view their detected stress level and track their historical stress patterns.
b) Developed a personalized stress-relief recommendation engine that suggests activities (e.g., music therapy, Mandala drawing) based on the detected stress level.
Security & Performance Optimization
a) Ensured secure user authentication with Firebase Authentication, protecting sensitive user data.
b) Optimized video processing efficiency to minimize latency in stress detection and provide users with real-time results.
c) Integrated Flutter's native camera access to allow in-app video recording, enhancing user convenience.

</td></tr>
</table>

Jayathunge K.A.D.T.R. IT21162732	• Data Collection & Processing: a) Collected and curated activity engagement data from over 1,000 participants, ensuring a diverse sample set. • Feature Engineering & Preprocessing: • Model Development & Optimization: • Frontend Development (Flutter) - Engaging User Interface a) Developed a visually appealing and interactive UI using Flutter, ensuring smooth user experience and real-time responsiveness. b) Designed a Mandala coloring interface, allowing users to choose from three Mandala art patterns and eight customizable color palettes to enhance their relaxation process. c) Implemented a dynamic music library, enabling users to browse, select, and listen to various music genres as part of their stress-relief activities. d) Built the history feature, allowing users to track their past activities and corresponding stress levels for personalized insights. • Backend Development (Flask) - Stress Analysis & Tracking a) Developed Flask-based backend processing, stress level calculations, and activity performance tracking. b) Implemented real-time analytics, processing Mandala art patterns, color choices, time spent on activities, and music listening habits to determine stress relief effectiveness. • Firebase Integration - Secure Data Handling & Performance Monitoring a) Integrated Firebase for user authentication, enabling secure login and account management. b) Developed real-time data storage, ensuring seamless tracking of user behaviors and stress history for long-term progress monitoring. c) Implemented performance monitoring to ensure efficient app performance, quick data retrieval, and enhanced scalability. • AI-Driven Personalized Stress Management a) Designed a data-driven approach where activity completion rates, time spent, and engagement levels influence stress reduction predictions. b) Ensured that users receive personalized recommendations based on their preferred activities, effectiveness of stress relief methods, and tracked progress over time.

Gunasekera H.D.P.M. IT21161674	• Data Collection & Preparation: a) Designed and conducted a large-scale survey with 1,000 participants via Google Forms and in-person surveys to collect behavioral data influencing stress. • Model Development & Implementation: • Evaluation & Optimization: • Frontend Development (Flutter) - Interactive User Experience a) Designed and developed an engaging and user-friendly interface using Flutter, ensuring smooth navigation and real-time updates. b) Implemented a dynamic questionnaire and behavior input system, allowing users to log behaviors for future stress prediction. c) Created a personalized recommendation dashboard, where users receive customized suggestions to change behaviors to stay stress free. d) Development of a motivational chatbot to offer real-time guidance and emotional support to users experiencing stress. • Backend Development (Flask) - Stress Prediction a) Developed and integrated a Flask-based backend, handling data processing, model execution, and user request management. b) Connected the mobile application to a machine learning predictive model, allowing users to assess their likelihood of future stress. c) Implemented a real-time API that takes behavioral inputs, processes them, and returns stress likelihood scores with personalized behavior change suggestions. • Stress Management & Real-Time Assistance a) Integrated an in-app chatbot, offering real-time emotional support and stress management guidance. • Predictive Analytics for Future Stress Prevention a) Developed customized guidance features, ensuring that users receive personalized and actionable insights to maintain a stress-free state. • Scalable, Secure & Efficient System Architecture a) Ensured secure communication between the mobile frontend and backend using efficient API handling. b) Optimized Flask server performance to minimize response times for real-time predictions. Designed a scalable architecture, making it future-proof for additional features and user expansion.

Weerasinghe W.P.D.J.N. IT21162664	• Data Collection & Analysis a) Designed and implemented a structured data collection process involving 200 participants for 14 days, resulting in 2,800 data points tracking daily emotional states and activity completion rates. • Feature Engineering & Data Preprocessing • Model Development & Optimization. • Frontend Development (Flutter) – Intuitive User Experience a) Developed a user-friendly mobile interface using Flutter, ensuring smooth navigation and real-time responsiveness. b) Implemented daily questionnaires with timed notifications, ensuring consistent data collection to improve prediction accuracy. c) Built visualization tools, including interactive graphs to display trends in emotional states, activity completion rates, and estimated recovery days. • Backend Development (Flask) – Predictive Model Integration a) Developed the Flask-based backend, handling data preprocessing and interaction with the trained Logistic Regression model. b) Implemented a secure API that processes user responses and returns estimated recovery days based on the stress recovery prediction model. c) Designed real-time data handling, ensuring that every user input is instantly analyzed and displayed on their dashboard. • Data Management & Consistency a) Integrated timed notifications to encourage consistent questionnaire completion, improving the quality of data collected. b) Ensured seamless data flow between the Flutter frontend and Flask backend, maintaining a steady stream of input for accurate predictions. • AI-Driven Stress Recovery Prediction a) Successfully integrated the Logistic Regression model into the application for predicting recovery days based on emotional state and activity completion. b) Implemented preprocessing pipelines to clean, format, and structure user inputs before prediction, ensuring higher model accuracy. c) Designed the app to give users real-time feedback, helping them make informed decisions about their well-being.

5.Conclusion

This research presents AyurAura, a comprehensive mobile application designed to empower individuals in self-managing stress through an innovative blend of AI-driven biometric analysis and the holistic principles of Ayurveda. Stress is a growing concern in modern society, significantly impacting mental and physical well-being. Despite the availability of traditional stress management techniques such as therapy and medication, accessibility, affordability, and personal preference often limit their widespread adoption. AyurAura addresses these challenges by providing an integrated, data-driven, and personalized approach to stress management that is both accessible and effective.

The core functionality of AyurAura revolves around multi-modal stress detection and intervention strategies. By leveraging cutting-edge technologies such as eye tracking, self-reported questionnaires, mandala art therapy, music therapy, behavior based stress likelihood predictions, and recovery tracking, the application offers users a holistic platform for stress relief. Machine learning algorithms play a crucial role in analyzing user data to detect stress levels, predict future stress, and estimate recovery times. By providing users with real-time insights, AyurAura helps them understand their stress triggers, monitor their emotional well-being, and implement effective coping mechanisms.

The system architecture of AyurAura is designed to ensure seamless user experience and efficient processing of stress-related data. The frontend is developed using Flutter, a versatile cross-platform framework that ensures a smooth and interactive user interface. The backend, built with Flask, efficiently handles data processing, model execution, and communication between components. This combination allows for real-time stress assessments, ensuring that users receive instant feedback and recommendations tailored to their specific needs.

Although the preliminary outcomes of AyurAura are highly promising, there are certain limitations that future research and development can address to enhance the app’s effectiveness and accuracy. One key limitation is the size of the dataset used to train the machine learning models. A larger and more diverse dataset would improve the generalizability of the models, leading to greater accuracy in stress detection and prediction. By incorporating data from a broader demographic with varying lifestyles and stress triggers, the application can become more adaptable to different user profiles.

Additionally, the accuracy of stress assessments can be improved by incorporating expert validation from multiple medical professionals. Currently, self-reported stress evaluations and physiological data serve as the primary inputs for the AI models. However, including assessments from mental health practitioners, psychologists, and Ayurvedic specialists would reduce potential biases and enhance the reliability of stress classification. Expert feedback could refine the stress detection algorithms, ensuring that the model captures subtle indicators that might be overlooked in purely data-driven approaches.

Future development efforts can also explore the use of more advanced machine learning techniques, such as ensemble methods and deep learning, to improve the predictive accuracy of stress detection and recovery time estimation. Ensemble learning techniques, such as random forests and gradient boosting, can combine multiple models to enhance robustness and reduce overfitting. Additionally, deep learning models, particularly RNNs and transformers, could be leveraged to analyze sequential behavioral data, identifying complex stress patterns over time.

Expanding the range of behavioral factors considered in future stress prediction would further enhance the model's effectiveness. While the current approach primarily focuses on sleep patterns, screen time, and dietary habits etc, additional factors such as financial stress, work-life balance, interpersonal relationships, and social interactions could be incorporated. These factors play a crucial role in shaping an individual's overall stress levels and could improve the model's ability to anticipate potential stressors.

Another significant enhancement would involve the use of NLP for chatbot functionalities. Currently, the chatbot provides a confidential and accessible platform for users to express their emotions and receive guidance. However, applying NLP advancements such as sentiment analysis, contextual understanding, and personalized response generation would make the chatbot more interactive, supportive, and effective in stress mitigation. By analyzing the tone and content of user inputs, the chatbot could provide tailored recommendations, suggest relaxation techniques, and even detect early signs of emotional distress.

To further enrich the user experience, AyurAura can be expanded by integrating additional stress-reduction exercises beyond mandala art and music therapy. While creative therapies have shown promising results in alleviating stress, incorporating practices such as guided relaxation, deep breathing exercises, progressive muscle relaxation, yoga, and meditation would provide users with a diverse set of coping strategies. Offering personalized recommendations based on user preferences and stress profiles ensures that individuals can choose the techniques that work best for them, increasing adherence and engagement with the app.

By continually evolving and incorporating such innovations, AyurAura is poised to redefine digital stress management, offering users real-time, evidence-based interventions tailored to their unique needs. By expanding the dataset, refining predictive models, enhancing chatbot capabilities, and integrating wearable technology, AyurAura can become an even more powerful tool for proactive mental wellness management.

This research not only contributes to the field of AI-driven stress detection but also bridges the gap between technology and traditional Ayurvedic wisdom, creating a holistic, personalized, and scientifically-backed approach to stress management. With continuous improvements, AyurAura has the potential to revolutionize mental wellness, empowering individuals to take charge of their emotional well-being in a fast-paced, stress-inducing world.

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7. Appendices

Appendix - A

Appendix - B

Perceived Stress Scale

A more precise measure of personal stress can be determined by using a variety of instruments that have been designed to help measure individual stress levels. The first of these is called the **Perceived Stress Scale**.

The Perceived Stress Scale (PSS) is a classic stress assessment instrument. The tool, while originally developed in 1983, remains a popular choice for helping us understand how different situations affect our feelings and our perceived stress. The questions in this scale ask about your feelings and thoughts during the last month. In each case, you will be asked to indicate how often you felt or thought a certain way. Although some of the questions are similar, there are differences between them and you should treat each one as a separate question. The best approach is to answer fairly quickly. That is, don't try to count up the number of times you felt a particular way; rather indicate the alternative that seems like a reasonable estimate.

For each question choose from the following alternatives:
0 - never 1 - almost never 2 - sometimes 3 - fairly often 4 - very often

________ 1. In the last month, how often have you been upset because of something that happened unexpectedly?

________ 2. In the last month, how often have you felt that you were unable to control the important things in your life?

________ 3. In the last month, how often have you felt nervous and stressed?

________ 4. In the last month, how often have you felt confident about your ability to handle your personal problems?

________ 5. In the last month, how often have you felt that things were going your way?

________ 6. In the last month, how often have you found that you could not cope with all the things that you had to do?

________ 7. In the last month, how often have you been able to control irritations in your life?

________ 8. In the last month, how often have you felt that you were on top of things?

________ 9. In the last month, how often have you been angered because of things that happened that were outside of your control?

________ 10. In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?

Appendix - C

To Whom It May Concern,

As an external supervisor and expert in the domain of stress management and Ayurvedic practices, I affirm that the data for this research study should be collected from the general public. After discussing with the research team about the research requirements, it has been concluded that stress is a common experience affecting people in their daily lives and is not classified as a specific illness.

To achieve a comprehensive understanding of stress management, data should be gathered through various methods:

- **Videos and Voice Recordings:** To capture real-time stress responses and assess the effectiveness of stress management techniques.
- **Questionnaire Results:** To collect structured feedback on participants' stress levels, mood, and engagement in the activities.
- **Activity Completion Observations:** To track participants' adherence to recommended activities and their impact on stress management.
- **Daily Surveys:** To monitor ongoing stress levels and overall progress over time.

Collecting data from the general public ensures that the study results are representative of a diverse population, enhancing the validity and applicability of the research findings in managing everyday stress effectively.

External Supervisor's Name: Dr. M. Kooragoda

Signature: ______________________

Date: 2024/09/25

Dr. Maneesha Kooragoda
BAMS (University of Colombo)
MEDHINI AYURVEDA
Malabe - 074 360 7868

To Whom It May Concern,

<u>Confirmation of Dataset Validation and Collection</u>

This is to confirm that the dataset provided by Team AyurAura has been validated and meets the required standards for accuracy and reliability. I actively supported and participated in collecting this data, ensuring it aligns with the necessary protocols and methodologies.

If you have any questions or need further clarification, please feel free to reach me.

AyurAura Team Members:
Weerasinghe W. P. D. J. N.
Jayathunge K. A. D. T. R.
Gunasekera H. D. P. M.
Wickaramasinghe B. G. W. M. C. R.

Sincerely,

Dr. Maneesha Kooragoda
BAMS (University of Colombo)
MEDHINI AYURVEDA
Malabe - 074 360 7868

Appendix - D

Informed Consent for Participation in Research Study

Title of Study: AyurAura: Personalized Stress Management Plan Using Ayurvedic Practices and Creative Therapies

Research Team:

Student ID	Name	Signature
IT21162664	Weerasinghe W.P.D.J.N.	
IT21162732	Jayathunge K. A. D. T. R.	
IT21161674	Gunasekera H. D. P. M.	
IT21279652	Wickramasinghe B.G.W.M.C.R.	

Purpose of the Study:
You are invited to participate in a research study that aims to develop and evaluate a personalized stress management plan using Ayurvedic practices and creative therapies. The goal of this study is to assess the effectiveness of our approach in managing stress and improving mental health.

What Participation Involves:
As part of this study, you will be asked to participate in activities designed to collect data on stress management. This will include providing information about your stress levels, mood, and participation in recommended activities.

Recording and Data Collection:
For research purposes, we will be recording videos and audio during the study. These recordings are essential for analyzing how well the stress management techniques are working and for improving the study's outcomes. Please be assured that:

- All recordings and collected data will be securely stored.
- Access to the data will be limited to authorized research personnel only.
- Your personal information and identity will be kept confidential.

Confidentiality and Data Security:
Your data will be protected in accordance with data protection regulations. We will take all necessary steps to ensure that your personal information remains private and is not disclosed to unauthorized individuals.

Voluntary Participation:
Your participation in this study is completely voluntary. You are free to withdraw from the study at any time without any negative consequences.

Consent:
By reading above, you acknowledge that you have been informed about the study, the use of recordings, and the measures in place to protect your data. You agree to participate in the study and provide consent for the use of your recordings as described.

Contact Information:
If you have any questions about the study or your participation, please contact

Name	Contact no.
Weerasinghe W.P.D.J.N.	0713007363
Jayathunge K. A. D. T. R.	0763121956
Gunasekera H. D. P. M.	0771529404
Wickramasinghe B.G.W.M.C.R.	0766958557

Permission from External Supervisor:
As an external supervisor and an expert in the domain of stress management and Ayurvedic practices, I hereby grant permission for this research study to proceed and for data to be collected from participants.

External Supervisor's Name: Dr.M.Kooragoda

Signature: ____________________

Dr. Maneesha Kooragoda
BAMS(University of Colombo)
MEDHINI AYURVEDA
Malabe - 074 360 7868

Date: 25/09/2024

Thank you for your participation and support in this research study.