AYURAURA - PERSONALIZED STRESS MANAGEMENT APPLICATION USING AYURVEDIC CREATIVE THERAPIES.

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Abstract

Stress negatively impacts mental and physical health, yet traditional stress management techniques often struggle with accessibility and long-term effectiveness. Ayurveda, an ancient Indian medical system, promotes mind-body balance for stress relief. However, its adoption is limited due to the availability of practitioners, accessibility challenges, and scientific skepticism. AyurAura addresses these limitations by integrating ayurvedic principles with ai-driven biometric analysis, offering an accessible and personalized stress management solution. The AyurAura application uses biometric data, including eye-blinking rates, along with the perceived stress scale to assess stress levels. It recommends non-pharmaceutical therapies such as mandala art and music therapy, accessible via smartphones. Predictive analytics enhances user experience by forecasting future stress levels based on behavioral patterns, enabling proactive intervention. The platform includes a progress tracker with daily updates on mood, energy levels, and activity engagement, generating visual reports and personalized feedback. A chatbot provides real-time support and motivation, ensuring user adherence. The methodology involves training machine learning models on user-generated biometric and self-reported emotional data to predict stress levels and recovery time. Testing includes cross-validation and performance evaluation using accuracy, precision, and recall metrics. Preliminary results show a strong correlation between biometric data patterns and stress fluctuations, validating the app’s effectiveness. In conclusion, AyurAura offers an innovative, evidence-based approach to stress management by integrating ayurvedic principles with ai-driven insights. It enhances accessibility, personalization, and effectiveness in stress relief. Future research should focus on expanding datasets and integrating additional biomarkers for improved accuracy. The findings support ai-enhanced ayurvedic interventions as a transformative approach to stress management.

Keywords: Stress management, Ayurveda, AI-driven analysis, Biometric monitoring, Predictive analytics

Table Of Contents

Table Of Figurses

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
VGG16 / VGG19	Visual Geometry Group
KNN	K-Nearest Neighbors
LSTM	Long Short-Term Memory
SMOTE	Synthetic Minority Over-sampling Technique
API	Application Programming Interface
DASS	Depression Anxiety Stress Scales
TCN	Temporal Convolutional Network
GRU	Gated Recurrent Unit
.npy	NumPy file format
UI	User Interface

List Of Appendices

1.Introduction

1.1.Background

In today's fast-paced and constantly evolving world, managing stress has become more crucial than ever. The demands of modern life—ranging from intense work schedules, academic pressures, and financial responsibilities to the challenges of maintaining personal relationships—have created an environment where individuals are constantly under pressure. This relentless pace of life can lead to the accumulation of stress over time, resulting in a state of chronic stress that negatively affects both mental and physical well-being.

Chronic stress is not merely an emotional experience; it has been scientifically linked to a range of serious health problems. Prolonged exposure to stress hormones such as cortisol can impair cardiovascular health, contribute to the development of hypertension, and increase the risk of heart attacks and strokes. Additionally, stress compromises the immune system, making the body more susceptible to infections and illnesses. On the psychological front, individuals experiencing long-term stress are more prone to developing anxiety disorders, depression, burnout, and even cognitive decline [1]. The connection between stress and these health complications highlights the urgency of identifying and adopting effective stress management strategies.

As stress becomes an increasingly pervasive concern across all age groups and demographics, the importance of finding accessible, personalized, and holistic methods for managing it cannot be overstated. Traditional techniques such as meditation, physical exercise, and therapy have shown great promise, but in many cases, they require time, resources, or professional support that may not be readily available to everyone. Therefore, there is a growing need for innovative solutions that are both evidence-based and easily integrated into everyday life. These solutions can empower individuals to take control of their mental health, monitor their stress levels proactively, and adopt preventative strategies before stress escalates into more serious health concerns. In this context, technological advancements, including mobile health apps, wearable devices, and artificial intelligence-powered interventions, offer promising avenues to make stress management more personalized, efficient, and widely accessible [1].

Figure 1 shows the results of a survey question asking participants whether they would like to assess their stress levels. Out of 29 respondents, an overwhelming majority—86.2%—answered Yes, while only 13.8% responded No. This strong positive response highlights a significant interest among individuals in monitoring and understanding their stress levels. The findings suggest that most people are not only aware of their stress but are also willing to engage in self-assessment if accessible tools or platforms are made available. Such data underscores the potential demand for user-friendly, non-intrusive methods to evaluate stress, paving the way for the development of innovative solutions such as mobile applications, wearable technology, or creative therapy-based assessments.

Figure 1 Users interest to access stress level

One of the most significant challenges individuals face in effectively overcoming stress is the difficulty of accessing timely and appropriate support. In an era where time has become a scarce resource, many people struggle to prioritize their mental health amidst the demands of work, education, and family life. Regular visits to healthcare professionals often require not only time but also financial resources, both of which may be limited for many. As a result, individuals tend to delay seeking help until their stress levels have significantly escalated, reducing the effectiveness of interventions. Moreover, there remains a persistent social stigma surrounding mental health, which discourages open conversations about stress and emotional well-being. This stigma, along with personal discomfort in expressing vulnerability, often prevents individuals from reaching out for help [2].

In addition to these societal and logistical barriers, another layer of complexity arises from people's hesitance to rely on pharmaceutical solutions. Although medications can provide relief from symptoms associated with chronic stress, many individuals are cautious about using them due to potential side effects, dependency concerns, or personal beliefs rooted in natural or holistic lifestyles [3]. These apprehensions can lead to individuals avoiding treatment altogether, further contributing to the negative health consequences of unmanaged stress.

These widespread obstacles highlight the urgent need for alternative stress management methods that are not only effective but also accessible, private, and easy to integrate into daily life. Solutions that allow for self-guided, non-invasive, and enjoyable stress relief methods can bridge the gap left by conventional approaches. Among these alternatives, the incorporation of creative activities—such as art, music, journaling, dance, or guided breathing and meditation—has gained attention for its therapeutic potential. Such activities offer individuals a means of expressing and processing emotions in a safe, personal space, without the fear of judgment or the pressure of clinical environments.

Figure 2 illustrates the ratings of various challenges individuals encounter when attempting to manage stress, including the lack of time, fear of stigma, cost barriers, and reluctance toward medication. These findings demonstrate the widespread struggle many people face with traditional stress relief approaches and emphasize the value of integrating creative therapies as viable alternatives. By offering flexibility, engagement, and a sense of personal empowerment, creative interventions can play a critical role in promoting long-term stress resilience and emotional well-being.

Figure 2 challenges in managing stress

Various methods are employed to identify and assess stress, ranging from subjective self-reports to more objective physiological measurements. Traditional approaches, particularly psychological questionnaires and self-assessment scales, remain widely used due to their ease of administration and ability to capture an individual's perceived emotional and mental state. These tools allow individuals to reflect on their feelings, behaviors, and coping mechanisms over time, often offering critical insights into the nature and severity of their stress. Instruments like the Perceived Stress Scale (PSS), Depression Anxiety Stress Scales (DASS), and others have been validated across diverse populations and are instrumental in both clinical and research settings.

However, while subjective reports are valuable, they can sometimes be influenced by bias, underreporting, or difficulty in articulating emotional experiences. To overcome these limitations, researchers and healthcare providers have increasingly turned toward physiological indicators, which offer a more objective and real-time understanding of the body's response to stress. These indicators include heart rate variability, skin conductance, hormonal levels (such as cortisol), breathing patterns, and eye movements, among others.

Among these, eye tracking has emerged as a promising non-invasive technique for stress detection. Eye movement data can reveal subtle changes in gaze behavior, saccadic velocity, and pupil dilation—factors that are closely linked to cognitive load and emotional arousal [4], [5]. Under stress, individuals may exhibit rapid or erratic eye movements, longer fixation durations, and increased pupil size due to the activation of the autonomic nervous system. These metrics can be recorded unobtrusively using eye-tracking hardware, making them suitable for integration into daily environments and digital interfaces.

Ayurveda, an ancient and holistic system of medicine that originated in India over 5,000 years ago, provides a rich and comprehensive perspective on stress management. Unlike conventional approaches that often isolate physical symptoms from emotional and mental well-being, Ayurveda emphasizes the interconnectedness of the mind, body, and spirit. According to Ayurvedic philosophy, health is achieved through the balance of three fundamental bio-energies, or doshas—Vata, Pitta, and

Kapha. Each individual has a unique constitution or Prakriti, which determines their physical and psychological tendencies, including their responses to stress [6].

In the context of stress identification, Ayurveda goes beyond the modern physiological metrics and incorporates more nuanced diagnostic techniques. Eye analysis is one such method, wherein practitioners observe subtle cues such as eye color, brightness, dryness, and movement to determine imbalances in the doshas. For instance, dull or sunken eyes may be associated with an aggravated Vata, while redness and irritation could suggest an imbalance in Pitta. These visual assessments are considered key indicators of internal disharmony, reflecting how stress is manifesting within the body and mind.

In addition to observational techniques, Ayurvedic questionnaires are used to evaluate an individual's lifestyle, emotional tendencies, sleep quality, dietary habits, and daily routines. These assessments help build a holistic profile of the person’s current state and identify the root causes of stress. Unlike standardized psychological surveys, Ayurvedic questionnaires are deeply personalized and designed to align with an individual's doshic constitution. Through this individualized assessment, Ayurvedic practitioners aim to restore balance in the doshas, thereby addressing stress not just as a symptom but as a manifestation of deeper systemic imbalances [6].

Overall, Ayurveda offers a deeply integrative and personalized approach to stress identification and management. By combining traditional wisdom with modern tools, there is a growing potential to enhance stress detection and treatment strategies, particularly in systems that value holistic health and preventive care.

The integration of traditional and modern stress management practices into a mobile application represents a transformative and highly promising solution for addressing stress in today’s fast-paced world. With the widespread adoption of smartphones and increasing interest in health technology, mobile apps have emerged as powerful tools for delivering accessible, personalized, and real-time support. By merging advanced technologies, such as eye movement analysis, with the holistic principles of Ayurveda, a mobile application can bridge the gap between modern science and ancient wisdom to provide a well-rounded approach to stress detection and relief.

In tandem with these physiological techniques, the app can include Ayurvedic diagnostic tools, such as dosha-based questionnaires, lifestyle assessments, and symptom tracking interfaces. Users could input information about their sleep, diet, mood, daily activities, and emotional state, which the app could then use to generate a personalized stress profile rooted in Ayurvedic theory [6]. The app may also utilize visual diagnostic methods, prompting users to capture a selfie or short video clip of their eyes or face for holistic analysis, mimicking traditional Ayurvedic practices such as eye observation.

The real strength of such an integrated application lies in its ability to personalize recommendations. Based on both biometric inputs and subjective self-assessments, the app could offer curated suggestions for stress relief tailored to the user's constitution and current state. These might include breathing exercises (pranayama), guided meditation, herbal tea recipes, mindfulness activities, or specific lifestyle tips derived from Ayurvedic guidelines [6]. Moreover, the app could incorporate progress tracking features, allowing users to visualize trends in their stress levels over time and recognize triggers and patterns that may be contributing to chronic stress.

This multi-modal approach not only makes stress management more accessible to a broader audience but also respects user privacy and autonomy. Individuals can engage with the app in the comfort of their own space, without the need for clinical visits or social exposure. This is especially important considering that many people are reluctant to seek help due to stigma or time constraints [2], [3]. By enabling self-monitoring and self-regulation through a user-friendly digital platform, such an app empowers individuals to take proactive steps toward mental well-being on their own terms.

In summary, the fusion of cutting-edge physiological monitoring and ancient Ayurvedic insights within a mobile application creates a comprehensive, culturally informed, and user-centric model for stress detection and management—an approach that is not only scalable but also deeply attuned to individual needs and preferences.

Overall, the proposed system aspires to set a new and innovative standard in the field of stress management by effectively blending state-of-the-art machine learning techniques with the time-tested wisdom of traditional Ayurvedic practices. In a world where mental health concerns are rapidly escalating and access to personalized care is often limited, this hybrid approach offers a compelling, forward-thinking solution. By capitalizing on the strengths of both modern artificial intelligence (AI) and holistic medicine, the system seeks to not only detect stress with high accuracy but also to provide tailored interventions that resonate with users' physiological and emotional needs [7], [8]

At the core of the system is a user-friendly mobile application that delivers real-time stress assessments based on a variety of data inputs, including biometric indicators such as eye movement patterns and ayurvedic questionnaire. Through continuous data collection and pattern recognition powered by machine learning algorithms, the system can adapt to individual behavioral changes over time, improving its predictive accuracy and responsiveness. These technologies allow the app to offer immediate feedback, helping users recognize and respond to their stress triggers proactively, rather than reactively [7]

Simultaneously, the integration of Ayurvedic principles provides a deeply personalized and holistic dimension to the application. Instead of offering one-size-fits-all recommendations, the app evaluates users’ doshic imbalances, lifestyle patterns, and environmental factors to generate insights rooted in Ayurvedic diagnostics. This includes suggestions for diet, sleep, physical activity and mindfulness practices that are specifically aligned with each user’s constitution (Prakriti) and current imbalances. These culturally rooted, non-pharmaceutical interventions are not only effective but also accessible and sustainable, aligning with a growing public preference for natural and self-guided healing modalities [8].

One of the most significant contributions of the proposed system is its potential to overcome the limitations of conventional stress management methods. Many traditional approaches require clinical visits, time-consuming therapy sessions, or medication regimens, which may not be feasible or appealing for everyone. Barriers such as time constraints, social stigma, reluctance to use medication due to side effects, and lack of privacy often prevent individuals from seeking help [2], [3] By contrast, the mobile app empowers users with autonomous, real-time self-care in a private and non-judgmental environment, enhancing accessibility across different demographics, including students, professionals, and caregivers [9].

In addition, the system's scalability and data-driven adaptability make it suitable for long-term use and broad implementation in health and wellness ecosystems. With continuous updates and feedback loops, the system can refine its models to better understand diverse user populations and evolving stress patterns, ultimately contributing to more inclusive and effective digital health solutions.

In summary, this novel integration of AI-powered analytics and Ayurvedic wisdom presents a paradigm shift in how stress can be understood, tracked, and managed. The proposed application stands as a comprehensive, intelligent, and culturally resonant platform, tailored for modern lifestyles. It not only bridges the gap between ancient knowledge and digital innovation but also offers a personalized, real-time support system that aligns with contemporary health preferences and technological possibilities [7], [8], [9].

1.2 Literature Review

Stress detection has emerged as a critical and rapidly evolving field of research, fueled by the increasing global awareness of stress as a major contributor to a wide array of mental, emotional, and physical health challenges. Chronic stress has been scientifically linked to numerous health conditions, including depression, anxiety disorders, cardiovascular disease, weakened immune response, and digestive issues. As modern life continues to impose growing pressures—from academic and workplace demands to personal and societal expectations—identifying stress accurately and promptly has become more important than ever for preserving overall well-being.

The growing recognition of stress's pervasive effects has prompted researchers to explore innovative ways to detect and manage it, particularly through non-invasive, continuous monitoring systems. Traditional methods, such as psychological surveys and self-reported assessments, though valuable, often suffer from limitations including subjectivity, recall bias, and lack of real-time feedback. These shortcomings have catalyzed a shift toward objective, data-driven approaches that utilize measurable physiological and behavioral signals as indicators of stress.

Thanks to advances in technology and machine learning, researchers can now leverage powerful tools to track and interpret stress markers with greater accuracy and efficiency. Machine learning models have demonstrated exceptional capability in identifying complex patterns within large datasets, enabling the detection of subtle changes in an individual's physical or emotional state. These models can be trained to recognize stress by analyzing features such as heart rate variability, skin conductance, eye movement patterns, facial expressions, speech patterns, and breathing rates, often in combination to enhance prediction reliability.

Moreover, the proliferation of wearable devices and smartphone sensors has made it possible to collect this physiological data in real time, outside clinical settings, making stress monitoring more practical and scalable. For instance, wearable fitness trackers can continuously monitor heart rate and skin temperature, while smartphone cameras and microphones can gather data on facial cues and vocal tones—each offering a window into the user's current stress level. These inputs can be analyzed by embedded AI algorithms to detect stress episodes as they happen, potentially alerting the user and recommending interventions before the stress escalates.

Behavioral signals are also gaining traction in this field. Subtle shifts in daily activities, sleep patterns, productivity, or social interactions—often logged passively through mobile apps—can serve as additional data points for stress detection. When combined with machine learning, these behavioral cues can help paint a comprehensive picture of a user's mental state, allowing for more personalized and proactive interventions.

In summary, the field of stress detection is becoming increasingly interdisciplinary, blending psychology, neuroscience, computer science, and biomedical engineering to create robust systems capable of identifying stress in diverse populations and contexts. These advances not only promise better stress management tools but also pave the way for preventive mental health care, where individuals are empowered with insights about their well-being before problems become severe. As the research continues to evolve, integrating stress detection into everyday technology—such as mobile apps and wearable health platforms—will be key to making mental health support more accessible, timely, and impactful.

Recent research underscores the growing effectiveness of integrating multiple data sources to improve the accuracy and reliability of stress detection systems. Unlike traditional single-modality approaches that may rely solely on either subjective or physiological metrics, multi-modal stress detection frameworks combine diverse forms of data to capture a richer, more holistic picture of an individual's mental and emotional state. This integration significantly enhances the robustness and sensitivity of stress assessments, allowing for more personalized and context-aware detection.

For instance, studies have demonstrated that combining physiological signals, such as heart rate variability (HRV), skin conductance, and respiration patterns, with self-reported psychological questionnaires leads to marked improvements in the accuracy of stress recognition models [1]. HRV, a widely recognized biomarker of autonomic nervous system activity, provides objective insights into a person's physical stress response, while questionnaires capture the subjective experience of stress, including thoughts, feelings, and perceptions. When used together, these data sources can validate and complement each other, reducing false positives and improving predictive confidence.

The multi-modal approach also addresses one of the major limitations of stress detection: the individual variability in stress responses. Different people may exhibit different physiological or behavioral indicators under stress, and these responses may vary depending on the situation, time of day, or even cultural background. By incorporating multiple channels of information, including facial expression analysis, speech tone detection, eye-tracking data, breathing rhythm analysis, and behavioral activity logs—researchers and developers can train machine learning models that are more adaptive and personalized. These models learn to recognize subtle, cross-modal patterns that may not be apparent when analyzing a single data stream in isolation.

Moreover, the use of machine learning and deep learning algorithms in multi-modal systems allows for more sophisticated fusion of heterogeneous data. Techniques such as late fusion, early fusion, and hybrid fusion strategies help combine data at various levels of abstraction, ensuring that valuable information is preserved throughout the analysis pipeline. For example, while a neural network might process raw physiological signals to detect stress-related features, another model might analyze questionnaire responses or user interactions, and a third layer might integrate both outputs to make a final, more accurate classification.

Beyond improving accuracy, multi-modal stress detection systems offer additional benefits in terms of real-time monitoring and adaptability. With sensors embedded in smartphones, wearables, and even voice assistants, it becomes possible to continuously gather and interpret signals from multiple modalities throughout the day, offering timely alerts or interventions when stress levels rise. This real-time capability is especially valuable for applications in healthcare, workplace wellness, education, and even human-computer interaction, where early detection of stress can prevent long-term negative outcomes.

In summary, the integration of multiple data sources in stress detection represents a significant advancement in the pursuit of reliable and user-centric mental health technologies. By combining physiological metrics like HRV with psychological assessments and behavioral cues, these systems are better equipped to capture the complexity of stress as it manifests in different individuals and contexts. As more research continues to validate the effectiveness of this approach [1], multi-modal systems are likely to become the gold standard in next-generation stress detection tools.

In addition to physiological measures, eye gaze patterns have been extensively studied as potential indicators of stress. Eye gaze is considered a valuable behavioral marker, as it can provide insights into an individual's emotional state and cognitive processes. Research has demonstrated that variations in specific eye gaze metrics, such as pupil dilation, eye movement patterns, and fixations, can significantly correlate with different levels of stress. These eye gaze indicators offer a non-invasive method for assessing stress, distinguishing them from more traditional physiological measures like heart rate or cortisol levels.

Studies have shown that when individuals experience stress, their pupil dilation tends to increase, a response that is associated with heightened arousal. Similarly, eye movement patterns, such as increased fixations on certain stimuli or erratic gaze shifts, may reflect cognitive load and emotional tension, both of which are influenced by stress. In particular, research has suggested that under stress, individuals may exhibit changes in the smoothness and speed of their eye movements, often making more abrupt or less controlled shifts in gaze. These subtle but consistent changes in eye behavior can serve as reliable indicators of the underlying emotional state of the individual.

Eye-tracking technology has been increasingly utilized to monitor and capture these metrics in real-time. By tracking eye movement and pupil dilation with high precision, this technology allows researchers to obtain valuable data about an individual’s stress response without relying on direct physical measures. In fact, eye-tracking devices are becoming increasingly accessible and are capable of providing continuous, real-time assessments of stress levels, making them a promising tool for stress detection in various contexts.

The non-intrusive nature of eye gaze-based stress detection is particularly beneficial, as it allows individuals to be assessed in naturalistic environments without disrupting their activities or requiring invasive procedures. This approach has been found to be highly suitable for settings where traditional physiological monitoring, such as blood pressure measurement or skin conductivity, may be impractical or uncomfortable for the individual. Moreover, eye gaze metrics can be collected unobtrusively during routine activities like reading, watching videos, or interacting with digital interfaces, further enhancing the practicality of this method for widespread use.

Thus, the use of eye gaze patterns, in conjunction with other physiological measures, presents a promising avenue for improving stress detection and management. With advancements in eye-tracking technology, the ability to capture real-time behavioral indicators of stress continues to evolve, opening up new possibilities for personalized and non-invasive stress monitoring and intervention [4].

Further research into eye-tracking metrics highlights the critical need for evaluating a wide array of parameters to enhance the accuracy and effectiveness of stress detection systems. Eye-tracking technology has evolved significantly in recent years, enabling the collection of more detailed and diverse metrics related to eye movement and behavior. Studies have focused on assessing a broad range of eye-tracking metrics, including pupil dilation, gaze patterns, blink rates, and saccadic eye movements, to better understand how these factors correlate with stress levels. By analyzing these metrics in various combinations, researchers aim to uncover deeper insights into the complex relationship between eye gaze behaviors and emotional states.

Pupil dilation, for example, has long been recognized as a sensitive indicator of arousal and cognitive load. Under stress, pupils tend to dilate as part of the body's fight-or-flight response, driven by increased sympathetic nervous system activity. However, it is not just the size of the pupils that is important but also the rate and pattern of dilation, which can provide valuable insights into the intensity and duration of stress. By continuously monitoring these changes, researchers can track shifts in an individual's stress levels over time, allowing for more precise detection and intervention.

In addition to pupil dilation, gaze patterns play a crucial role in understanding stress responses. During stressful situations, individuals may exhibit alterations in how they direct their gaze, such as fixating on specific areas for longer periods or shifting their attention more rapidly between multiple stimuli. These changes can reflect cognitive overload, distraction, or heightened emotional tension, all of which are associated with stress. Detailed analysis of gaze patterns—such as the frequency and duration of fixations or the direction and speed of saccadic movements—can provide a more comprehensive understanding of the underlying stress response and cognitive processes at play.

Blink rates are another key metric studied in relation to stress detection. Increased blink rates are commonly observed when an individual is under stress or experiencing high cognitive load. This can be attributed to physiological responses such as dry eyes or nervous tension, which can trigger more frequent blinking. By measuring changes in blink frequency and the interval between blinks, researchers can gain additional insights into an individual's emotional state and potential stress levels. Blink rate data, when considered alongside other eye-tracking metrics, can improve the sensitivity of stress detection systems, allowing them to capture a broader spectrum of stress-related behaviors.

This comprehensive analysis of multiple eye-tracking metrics aims to refine the accuracy of stress detection systems by integrating various parameters that, together, provide a fuller and more nuanced picture of an individual's stress state. Rather than relying on a single metric, the combination of multiple eye-tracking measures allows for a more holistic assessment of stress, accounting for both physiological and behavioral aspects of the individual's emotional response. The ability to monitor multiple eye-tracking metrics simultaneously enhances the precision of stress detection, making it possible to identify subtle fluctuations in stress levels that might otherwise go unnoticed.

By considering the interactions between these different metrics—pupil dilation, gaze patterns, blink rates, and saccadic movements—researchers are moving closer to developing more reliable and robust systems for stress detection. This integrated approach offers the potential for creating more personalized and context-aware stress management tools, which could be implemented in various settings such as workplaces, healthcare, or even in everyday life. As eye-tracking technology continues to advance, the ability to assess and understand stress levels in real time will become increasingly valuable in improving both individual well-being and overall productivity [5].

Additionally, foundational studies indexed on PubMed offer a broad and comprehensive overview of various stress detection methods that have been investigated over the years. These studies explore a wide range of physiological and behavioral indicators that can be used to assess stress, including heart rate variability, skin conductance, cortisol levels, and psychological assessments such as self-reported questionnaires and behavioral observations. By compiling and analyzing these diverse stress markers, the research provides a thorough understanding of the complexity of stress and its manifestation in the human body. These foundational studies contribute invaluable insights into the development of effective stress detection tools, enabling researchers and practitioners to refine existing methodologies and create more accurate and accessible systems for monitoring and managing stress.

One of the significant contributions of these studies is the identification of the interplay between physiological and psychological indicators of stress. For example, heart rate and skin conductance are often used as direct measures of autonomic nervous system responses, which can provide real-time information about an individual's stress level. When combined with psychological assessments that capture emotional and cognitive experiences, these physiological markers offer a holistic approach to stress detection. Furthermore, these studies also emphasize the importance of considering individual variability, as stress responses can differ significantly between people due to factors such as genetics, personality, and environmental influences. This highlights the need for personalized approaches to stress management, which can be better achieved through the integration of multiple indicators.

The synthesis of findings from these research studies underscores the value of a multi-faceted approach to stress detection. This approach moves beyond relying solely on one type of measurement, such as physiological data or self-reported emotions, to incorporate a variety of stress indicators that provide a more comprehensive and nuanced understanding of an individual's stress state. Our application embodies this multi-faceted approach by integrating both physiological assessments and psychological evaluations. Specifically, the app combines eye analysis assessments—such as pupil dilation, gaze patterns, and blink rates—with a series of carefully designed questionnaires that track emotional and cognitive states throughout the day. This dual methodology allows for real-time, in-depth evaluations of stress, providing users with an ongoing understanding of their stress levels and the underlying factors contributing to them.

Moreover, the app categorizes stress into four distinct levels—Mild, Moderate, Severe, and Critical—enabling users to easily assess their current state and recognize the severity of their stress. By incorporating these levels, the app offers users a more granular and accurate understanding of their emotional and physiological state. The clear categorization allows for early intervention and proactive stress management strategies, which are critical for preventing the escalation of stress to more severe levels that could lead to negative health outcomes. Furthermore, the app equips users with personalized tools and recommendations for managing stress, including relaxation techniques, activity suggestions, and coping mechanisms tailored to their specific needs.

This comprehensive methodology not only reflects the latest advancements in stress research and technology but also ensures that the app provides a sophisticated, reliable, and user-friendly tool for managing stress. By combining cutting-edge research on stress detection with innovative technology, our application offers users a unique solution to monitor, assess, and manage stress in real-time. This approach supports the promotion of overall well-being by empowering users with the knowledge and resources needed to understand and mitigate their stress. As stress continues to be a pervasive challenge in modern life, applications like this one hold great promise for improving mental health and enhancing the quality of life for users across diverse contexts .

1.3.Research gap

Despite notable advancements in modern stress detection methodologies, there remains a significant and persistent gap in the development of holistic, integrated solutions capable of delivering highly accurate, real-time stress assessments in a practical and accessible manner. While individual techniques such as heart rate variability (HRV) analysis, electrodermal activity monitoring, facial emotion recognition, or self-reported psychological questionnaires have each demonstrated value in identifying stress markers, the vast majority of existing research and systems tend to employ these approaches in isolation. This fragmented approach, though valuable in controlled environments, often fails to capture the multifaceted nature of stress as it manifests differently across physiological, emotional, and cognitive domains. The lack of integration among these techniques ultimately limits the overall effectiveness and generalizability of such systems when applied to real-world scenarios.

One of the most glaring issues evident in the comparison table is the consistent omission of combined methodologies—specifically, the integration of both eye analysis and Ayurvedic questionnaire-based diagnostics—within a unified framework powered by machine learning. These two components, while impactful on their own, offer distinct and complementary strengths: eye tracking and blink analysis provide objective, real-time physiological signals linked to emotional and cognitive stress responses, while structured questionnaires grounded in Ayurvedic principles bring culturally informed, subjective insights into an individual's mental and physical well-being. However, current literature and existing systems rarely explore the synergistic potential of combining these two rich data sources. This oversight represents a missed opportunity to substantially improve the reliability, precision, and contextual relevance of stress detection systems.

Moreover, a majority of current solutions remain confined to laboratory environments or depend heavily on manual processes and external hardware—such as specialized sensors, EEG headsets, or clinical-grade cameras—thus posing significant barriers to scalability, usability, and adoption. In contrast, mobile platforms offer an unparalleled opportunity for continuous, on-the-go monitoring and intervention, making them ideal for stress detection tools. However, few systems have successfully transitioned into fully automated mobile applications that are both scientifically robust and user-friendly. Existing mobile apps often rely solely on self-reported data or rudimentary analytics, which may be insufficient for real-time and accurate stress evaluation. This lack of automation and dependence on active user input reduces the practicality and reliability of such tools in everyday life, especially for users experiencing high stress levels who may not be able to engage deeply with the app.

A particularly underexplored area is the incorporation of Ayurvedic health diagnostics into real-time mobile-based stress assessment. Ayurveda, with its holistic approach to health, emphasizes lifestyle balance, mental clarity, and physiological harmony. It offers a rich framework for evaluating stress-related symptoms through time-tested diagnostic techniques like structured questionnaires. When combined with objective indicators like eye blink analysis, which captures involuntary ocular responses such as blink rate variability, duration, and eye fatigue—often influenced by mental strain—there emerges a powerful dual-modality assessment method that is both culturally inclusive and empirically measurable.

The proposed solution aims to bridge these existing gaps by developing a fully integrated, automated stress detection system that harmoniously blends eye blink analysis and Ayurvedic questionnaire-based assessment into a cohesive mobile application. At the core of this approach lies the use of machine learning algorithms capable of processing both physiological and subjective data, extracting meaningful patterns, and delivering real-time stress level predictions with high precision. By employing convolutional neural networks (CNNs) to analyze short eye videos recorded with a front-facing smartphone camera and combining this with intelligently weighted questionnaire responses, the system categorizes user stress levels into four clear categories: Mild, Moderate, Severe, and Critical.

This comprehensive model not only improves detection accuracy by leveraging the strengths of both data streams but also ensures a user-friendly experience that does not require additional hardware or complex interactions. It is designed with scalability and practicality in mind, ensuring accessibility for a wide range of users across different age groups, cultural backgrounds, and technological literacy levels. The intuitive interface built with Flutter, the reliable backend processing via Flask, and secure cloud storage through Firebase together form a technically sound ecosystem that is efficient, responsive, and easy to maintain.

In summary, while existing stress detection methods have made considerable progress, they still fall short of providing a truly integrated, real-time, mobile-based solution that unifies traditional health insights with modern technology. The proposed system fills this void by offering a novel and inclusive approach that aligns scientific accuracy with cultural relevance. As the comparison of various methods clearly demonstrates the limitations of current systems and the pressing need for a new model that embraces both physiological analytics and traditional wellness frameworks. By combining automated eye blink analysis and Ayurvedic questionnaire insights through the power of machine learning, the application sets a new standard in personal stress monitoring—one that is holistic, accessible, and tailored for the challenges of contemporary life.

1.4. Research Problem

The current state of stress assessment technologies presents a fragmented and piecemeal approach to detecting and measuring stress. Existing systems often focus on isolated methods, such as HRV (Heart Rate Variability) analysis, eye tracking, or subjective questionnaires, without integrating these individual techniques to provide a holistic and more reliable stress evaluation. While each of these methods can offer valuable insights into specific aspects of stress, they each have their limitations and fail to address the broader spectrum of stress responses, resulting in less accurate and comprehensive assessments.

For example, HRV analysis is commonly used to assess autonomic nervous system activity and stress responses, offering insights into the body's physiological state. However, HRV alone does not capture other important facets of stress, such as emotional and cognitive indicators, which are critical for a complete understanding of an individual's stress level. Eye tracking, another widely used technique, can detect signs of stress through gaze patterns, pupil dilation, and blink rates. While it can provide useful data, its effectiveness is often compromised by external factors such as lighting conditions, the user’s environment, and the accuracy of the equipment used. Furthermore, eye tracking might not capture the emotional or cognitive components of stress that can only be understood through the individual's subjective experiences.

Questionnaires, on the other hand, can offer subjective insights into how a person feels and perceives their stress. However, they are often prone to biases, such as social desirability bias or personal misunderstanding of the questions, and may not always capture real-time changes in stress levels. Furthermore, questionnaires rely on the user’s ability to accurately recall and describe their experiences, which can lead to inaccurate results, especially when stress manifests unpredictably or during moments of acute stress.

Existing solutions typically focus on just one or two of these approaches, resulting in a fragmented understanding of stress. As a result, they fail to capture the multifaceted nature of stress—its physical, cognitive, and emotional aspects—limiting their effectiveness. Moreover, many current stress detection systems are designed for specific settings or require manual data input, which can disrupt the real-time monitoring of stress. This makes these systems impractical for individuals who need consistent and real-time insights into their stress levels, especially in a mobile or on-the-go context. Many available systems also do not offer a fully automated solution, meaning users must engage in cumbersome processes for stress assessment, which reduces their overall effectiveness in managing stress throughout the day.

To address these significant gaps in existing stress detection methods, the proposed research aims to develop a more integrated, comprehensive solution that combines eye blink analysis and a standard Ayurvedic questionnaire. This solution will leverage advanced machine learning algorithms to analyze data from both the biometric and subjective sources, allowing for real-time stress detection and classification.

By incorporating both objective biometric data from eye analysis (such as blink rates, eye movements, and pupil dilation patterns) and subjective data from the Ayurvedic questionnaire (which assesses emotional, mental, and physical states based on traditional Ayurvedic principles), the system will offer a more accurate and holistic understanding of stress. The Ayurvedic questionnaire will evaluate the user's emotional and mental states in relation to their doshic balance (Vata, Pitta, and Kapha), offering an additional layer of insight into the root causes of their stress. Combined with the machine learning model, the system will be able to detect subtle stress indicators and provide users with an accurate assessment of their current stress level.

Moreover, this proposed system will be mobile-friendly and fully automated, ensuring users can monitor and manage their stress in real time without the need for manual intervention. It will offer a practical, accessible, and seamless experience, allowing users to record their eye video, complete the Ayurvedic questionnaire, and receive instant feedback on their stress levels, all through an intuitive mobile interface. The use of machine learning algorithms will ensure that the system can continuously learn and adapt to each user's unique stress responses over time, making it highly personalized and effective.

In sum, the proposed solution seeks to bridge the gaps left by current stress detection methods by integrating two key approaches—eye analysis and Ayurvedic diagnostics—into a comprehensive and automated system that is mobile-first and user-centric. This approach not only offers a more accurate and holistic assessment of stress but also empowers users with the tools and insights needed to manage and reduce their stress levels proactively. Whether at home, at work, or on-the-go, users will have the ability to track their stress levels in real time and take informed actions to improve their mental well-being.

1.5.Research Objectives.

1.5.1.General Objective

To create a mobile-based system that accurately assesses an individual's stress levels using advanced techniques such as questionnaires and eye analysis, the primary objective of developing the stress detection component is to offer real-time, accessible, and non-invasive insights into a person’s mental and emotional state. This system integrates the precision of computer vision-based eye analysis with the reflective and subjective depth of structured questionnaires, offering a unique blend of objective and self-reported data. By utilizing the front camera of a smartphone, the application captures a short video of the user’s eyes and processes it using machine learning algorithms to detect stress-related patterns such as abnormal blink rates or movement. At the same time, the user responds to a set of carefully designed questions aimed at evaluating stress-related behaviors and emotional responses. By combining these two sources of information, the system generates a comprehensive stress profile, classifying stress into levels such as mild, moderate, severe, or critical. The mobile platform ensures convenience and encourages regular self-assessment, making stress management more proactive and personalized. Ultimately, this solution aims to empower individuals to monitor and address their stress levels effectively, promoting better mental health and overall well-being.

1.5.2.Specific Objectives

1. **Development of Stress Detection Models:**

Design and implement a CNN-based system using the VGG19 architecture to analyze eye blink count data for stress detection. The system captures 10-second videos of the user’s eyes via a front-facing camera. Eye blink counts are extracted using facial landmark detection tools like MediaPipe or Dlib. These counts are processed and fed into the VGG19 model, trained on a labeled dataset to classify stress levels (e.g., Mild, Moderate, Severe, Critical).

The dataset includes samples annotated with stress labels from questionnaires or expert analysis. Preprocessing includes frame extraction, resizing, and normalization. The model's performance is evaluated using accuracy, precision, recall, and F1-score. This approach provides a non-invasive, real-time stress detection system, ideal for mobile or wearable applications.

2. **Integration of Stress Detection Methods:**

Integrate the outputs from questionnaire analysis and eye movement analysis to provide a comprehensive stress assessment. The questionnaire offers subjective insights into the user's stress levels based on their responses, while the eye movement analysis, focusing on blink count, provides objective physiological data. By combining these two data sources, the system delivers a more accurate and holistic understanding of an individual's stress, enhancing the precision of real-time stress detection for personalized health and wellness monitoring.

3. **Mobile Application Development:**

Develop a user-friendly mobile application that integrates real-time stress detection models. The app combines questionnaire responses and eye movement analysis to assess stress levels accurately. It provides immediate feedback, personalized recommendations, and stress management tools. Designed for ease of use, the app aims to help users monitor and manage their stress levels effectively with seamless interaction and intuitive design.

4. **Validation and User Testing:**

Conduct thorough validation and user testing to ensure the stress detection system's accuracy and reliability. Test the app across diverse user demographics to evaluate its performance in real-world conditions. Gather detailed user feedback regarding functionality, usability, and effectiveness. Use this input to refine and enhance the application, addressing any issues and ensuring it aligns with user needs and expectations. This iterative process will help create a reliable, user-centered solution for stress monitoring and management.

2.Methodology

This research leverages cutting-edge mobile data collection techniques in combination with deep learning algorithms to develop a system capable of analyzing both eye-blinking patterns and questionnaire responses for real-time stress detection. The study involved 300 participants aged 18 or older, who were recorded in various lighting environments to account for potential external influences on the data. Participants were asked to provide 10-second selfie videos focusing on their eyes, which are analyzed for blink frequency. Simultaneously, they completed a standardized questionnaire designed to measure their perceived levels of stress, providing valuable subjective data that complements the objective physiological measurements of eye movement.

The primary aim of this research is to explore the correlation between variations in blink frequency and established stress indicators, as assessed by Ayurvedic professionals. Under normal, stress-free conditions, blinking typically occurs two to three times within a 10-second period. This rate serves as a baseline for what is considered "normal" blinking behavior. Deviations from this standard—whether an increase or decrease in blink rate—could suggest the presence of stress, with higher rates often associated with anxiety and lower rates potentially indicative of fatigue or mental relaxation. By incorporating deep learning techniques, the system is able to automate and scale the process of stress detection, making it faster, more accurate, and efficient.

The collected data undergoes a preprocessing phase, where it is cleaned and labeled according to four levels of stress: mild, moderate, severe, or critical. This labeling is done based on both the frequency of blinks and the responses to the stress questionnaire. By feeding this preprocessed data into deep learning models, the system is able to learn from the input and continuously refine its ability to detect and classify stress levels. Convolutional Neural Networks (CNNs) are used for feature extraction from the eye movement data, as they are especially adept at recognizing patterns in visual data. CNNs work particularly well in this context because they can detect subtle, complex features within eye-blink data that are not immediately obvious to human observers, allowing the model to generalize across a broad range of users and environmental factors.

Deep learning algorithms are highly capable of handling large datasets and can efficiently learn from them, allowing the system to improve its performance with each additional input. As the system receives more data, its predictive accuracy continues to improve, resulting in more reliable and timely stress assessments. This aspect of the system is crucial for real-time applications, where immediate feedback is needed to assist users in managing their stress levels. The ability of deep learning to process and classify data in real-time makes this approach particularly suited for mobile applications, which are capable of providing immediate, actionable insights to users.

In addition to the eye-blink data, the system incorporates subjective information gathered from the questionnaire responses. These reports, which reflect the participant's mental and emotional state, provide essential context that enriches the physiological data. When combined with the objective eye movement analysis, the questionnaire responses allow for a more accurate, nuanced understanding of the user's stress levels. The integration of Ayurvedic expertise further enhances the system's validity. Ayurvedic professionals interpret the eye-blink data and use it in conjunction with traditional stress indicators, helping bridge the gap between modern machine learning methods and ancient practices. This interdisciplinary approach not only enhances the accuracy of the stress classification but also opens the door for new methodologies in stress research and management.

Once the data is processed and labeled, it is fed into the deep learning algorithms for training. The system uses this data to learn how to predict stress levels based on both eye-blink frequency and questionnaire responses. The CNN models enable the system to extract the most relevant features from the eye movement data, making the system more effective at identifying stress patterns. As the system trains, its predictive capabilities become more refined, ensuring that it can handle a wide variety of users and environments.

The integration of both objective and subjective data sources results in a comprehensive model for stress detection. This holistic approach ensures that the system provides not only an accurate classification of stress levels but also actionable feedback for users. For example, if a user’s stress is classified as critical or severe, the system might recommend immediate stress-relief techniques, such as breathing exercises, relaxation activities, or mindfulness practices, tailored to the individual's stress profile. These personalized suggestions are designed to mitigate stress before it escalates, giving users a proactive tool to manage their mental health.

Additionally, the system tracks users' progress over time, offering continuous feedback and generating personalized reports that summarize the individual's stress levels and improvement. This allows users to visualize their progress and understand how their stress levels fluctuate over time, making it easier to identify patterns and triggers. With such detailed tracking and reporting, users can make more informed decisions about their mental health and stress management strategies.

Fig. 1. illustrates an overview of the system's architecture, highlighting how the integration of eye movement analysis and questionnaire responses works together to provide real-time, continuous monitoring of stress levels. The system enables users to track their stress in an intuitive, user-friendly manner, providing real-time feedback and personalized suggestions for stress management. By combining deep learning with mobile data collection, this research offers a unique, data-driven approach to stress detection that is adaptable to a wide range of users and settings.

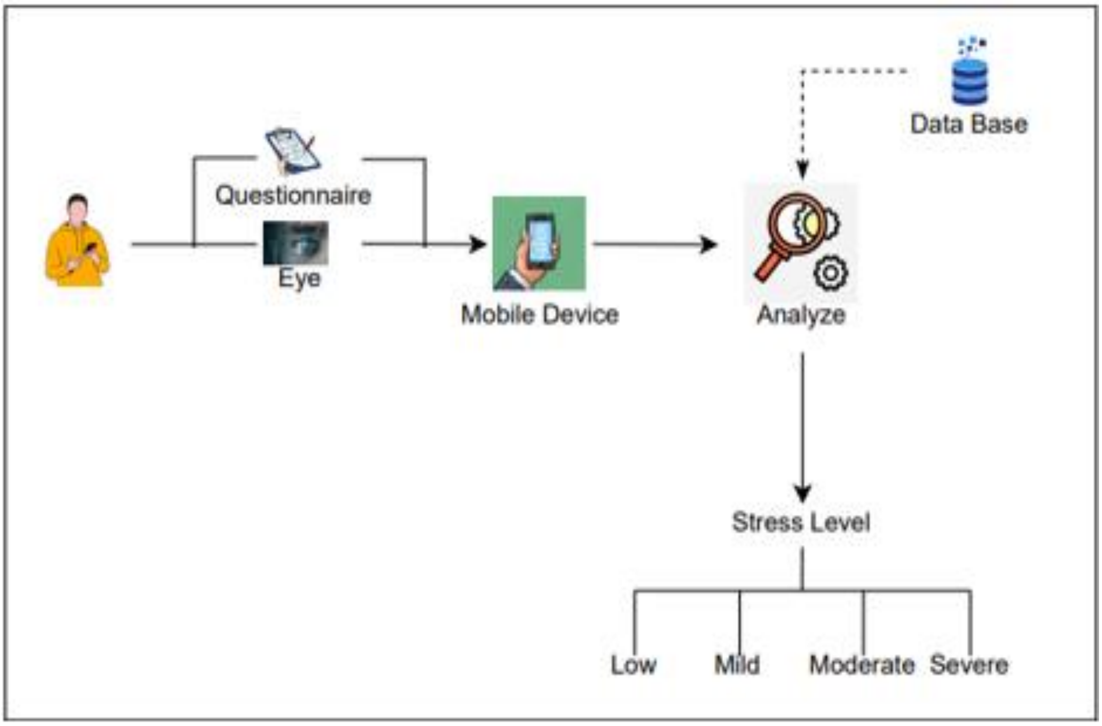

Figure 3. Overview diagram for initial stress detection

In conclusion, this research presents a novel and effective method for detecting and managing stress by combining modern deep learning techniques with traditional Ayurvedic knowledge. By analyzing both physiological data, specifically eye-blink patterns, and subjective stress levels from questionnaires, the system provides an accurate, real-time assessment of stress. The system’s ability to offer personalized recommendations based on these analyses provides users with valuable tools to manage their stress in a proactive and informed way. The combination of deep learning, mobile data collection, and Ayurvedic expertise paves the way for future developments in personalized mental health applications, offering a more holistic and effective approach to stress management. This research holds the potential to significantly impact the field of stress detection and mental health, offering new possibilities for real-time, mobile-based wellness solutions.

2.1.Features and Target Variable

The database used in this research combines both behavioral and physiological characteristics to enhance the accuracy of stress level classification. A key physiological parameter in this process is the blink rate, which is measured over 10-second video recordings of participants. Eye-blink patterns have been found to correlate strongly with stress levels, making blink rate a reliable indicator. Typically, under normal conditions, a person blinks two to three times within a 10-second period. Any deviation from this baseline standard—whether an increase or decrease in blink rate—can indicate varying levels of stress. An increase in blink frequency often correlates with heightened stress or anxiety, while a decrease may signal lower levels of stress or mental fatigue. By observing these discrepancies in blink rate, the system can detect subtle shifts in stress levels in real time.

Controlled lighting conditions are used during the recording of the 10-second films to ensure the highest quality of data and minimize external variables. Consistent and accurate lighting ensures that the data remains reliable and uniform across different contexts and subjects, which is critical for the effectiveness of machine learning algorithms used in stress detection. These controlled conditions provide a high level of consistency, ensuring that the eye-blink data is captured accurately regardless of environmental factors.

In addition to physiological data, the database also includes age group data to account for potential variances in stress levels across different demographics. Stress can manifest differently depending on a person's age, and grouping participants into age brackets helps provide more nuanced insights into how stress affects various groups. This age-related data is useful for training machine learning models that account for demographic variability, improving the robustness of the classification system across different user populations.

Another key component of the database is the inclusion of standardized stress questionnaires, which are used to quantify self-reported stress levels. These questionnaires ask participants to assess their stress on a scale, typically ranging from low to high, and help corroborate the physiological data collected through eye-blink analysis. The self-reported stress levels add a subjective layer to the assessment, offering a more comprehensive understanding of an individual's stress state.

The target variable for the machine learning models is the categorization of stress into four distinct levels, which are validated by an Ayurvedic specialist. The Ayurvedic approach, which has been historically used to assess the mental and physical well-being of individuals, provides an additional layer of expertise and validation to the classification process. The Ayurvedic specialist reviews both the eye-blink data and the questionnaire responses to categorize stress levels according to the following four levels:

- **Level 1: High Stress (More than 6 blinks)** – This category indicates severe stress, where the blink rate is significantly above the normal baseline. This level of stress is often associated with high anxiety, tension, or other intense emotional states.
- **Level 2: Moderate Stress (4-6 blinks)** – This level indicates moderate stress. The blink rate is elevated but not to the extreme level seen in high stress. Individuals in this category may experience feelings of discomfort or unease but may still be able to function normally.
- **Level 3: Normal (2-3 blinks)** – This is the baseline category, representing normal stress levels where the individual exhibits a typical blink rate of two to

three blinks in 10 seconds. This level indicates that the person is in a neutral or relaxed state, without significant emotional or physiological stress.

- **Level 4: Low Stress (0-1 blink)** – This category represents individuals with a very low blink rate, suggesting a state of calm or relaxation. Such individuals are typically in a state of mental tranquility, with minimal signs of stress or anxiety.

This four-tier classification system, combining physiological data (blink rate) and subjective self-assessment (questionnaire responses), offers a multi-dimensional framework for stress classification. The inclusion of age group data further enhances the model's ability to differentiate between various user groups, allowing for more accurate predictions. By integrating both objective and subjective data sources, this framework increases the overall accuracy and reliability of stress level classification, providing a comprehensive tool for real-time stress monitoring.

The combination of eye movement data (blink rate) and questionnaire-based self-reports provides a balanced and holistic approach to stress detection. The use of deep learning techniques allows for efficient processing of these diverse data sources, improving the accuracy of the stress detection system. Additionally, the Ayurvedic expert's validation of the classification ensures that the stress levels are categorized in a clinically relevant and culturally appropriate manner, further refining the reliability of the model. This approach not only enhances the classification process but also contributes to a more personalized and context-aware stress monitoring system.

2.2.Data Preprocessing

The data utilized in this study consists of four categories of video clips, each representing a different level of stress, with the clips stored in folders labeled Level 1 through Level 4. Each video clip corresponds to one of the four stress levels: mild, moderate, severe, or critical. A comprehensive preprocessing pipeline was applied to each video clip to ensure that the data was ready for input into deep learning models, particularly Convolutional Neural Networks (CNNs).

The first step in preprocessing was frame extraction. Each video clip was divided into 100 frames, which were selected to represent the entire video sequence.

This frame extraction allowed for a manageable and uniform amount of data to work with, ensuring that the model receives consistent input. Since CNN models require fixed input dimensions, each frame was resized to a uniform resolution of 224x224 pixels. This resizing step is crucial for ensuring that the data conforms to the input requirements of pre-trained CNN architecture, which are often used in image classification tasks.

After resizing, all pixel values in each frame were normalized to a range of [0,1] by dividing the pixel values by 255. This normalization process is essential for improving numerical stability during model training. By scaling the pixel values, we prevent large values from dominating the gradient calculations, which can cause issues with convergence during training. Normalization also helps with the consistency of data input, making the model more robust and improving its ability to learn.

The next step in the preprocessing pipeline was the encoding of the stress level labels. Since the stress levels are categorical in nature (i.e., each video clip belongs to one of four stress categories), the labels were one-hot encoded using a **LabelBinarizer**. One-hot encoding transforms categorical labels into binary vectors, making them suitable for multi-class classification. In this case, each stress level was represented as a 4-dimensional binary vector, where only the index corresponding to the correct level was set to 1, and the other positions were set to 0.

The data was then divided into two sets: a **training set** and a **test set**. The training set, which accounts for 80% of the data, is used to train the model, while the remaining 20% of the data was designated as the test set to evaluate the model's performance after training. This split ensures that the model can be tested on unseen data, allowing for an unbiased evaluation of its ability to generalize. The dataset was carefully balanced to ensure that each class (stress level) had an equal representation in both the training and test sets, preventing bias in the training process.

To enhance computational efficiency and streamline the data loading process during model training, the preprocessed frames and corresponding labels were saved in **.npy format**. The .npy format is optimized for storing large datasets and allows for fast reading through **memory-mapped I/O** (input/output), enabling the system to access the data directly from memory rather than reading it from the disk every time it is needed. This is particularly important when working with large datasets, as it minimizes the time spent loading data and speeds up the training process.

The preprocessing pipeline also ensured that the data across all video clips was homogeneous in terms of format and structure. This uniformity was crucial for training a CNN model that can generalize well across different levels of stress. By ensuring that each video clip's frames were consistently preprocessed, the model could effectively learn the relationship between eye movement patterns and stress levels, without being biased by inconsistent data inputs.

Moreover, the preprocessing steps were designed to maintain the integrity of the original data while preparing it for efficient training. These steps helped improve the overall **generalizability** of the model by ensuring that the model could effectively learn from a diverse set of video clips, representing various stress levels, without being overfitted to particular types of input or specific lighting conditions.

In summary, the preprocessing pipeline for this research was meticulously designed to handle a large and diverse dataset of video clips and their corresponding stress level labels. The use of frame extraction, resizing, normalization, one-hot encoding, and efficient data storage methods ensured that the dataset was optimized for use with deep learning models. These preprocessing steps, combined with careful data splitting and balancing, laid a solid foundation for training a robust and reliable stress detection model that can generalize effectively across different stress levels and user contexts.

2.3.Model Development

Pseudocode for Stress Level Detection Model.

Input: Video dataset organized into folders based on stress levels (Level 1, Level 2, Level 3, Level 4)

Output: Predicted stress levels and model performance metric Predicted stress levels for test data and model performance metrics.

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 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 development of the Stress Level Detection Model begins with importing the necessary libraries, including TensorFlow for model building, OpenCV for video processing, sklearn for data manipulation, and matplotlib and seaborn for data visualization. These libraries provide a powerful toolkit to handle the complexities of image data and model evaluation.

Once the libraries are imported, the next step is to load and preprocess the data. The dataset consists of video files that are categorized based on four stress levels (Levels 1 to 4). From each video file, up to 100 frames are extracted, resized to 224x224 pixels to ensure consistency in input size, and normalized to have pixel values between 0 and 1. Each video is assigned a label corresponding to its stress level, which is represented using one-hot encoding. The dataset is then split into training and testing sets, with 80% of the data reserved for training and 20% for testing. The preprocessed frames and labels are saved into .npy files for efficient storage and retrieval.

With the data prepared, the model is built using a pre-trained VGG16 architecture. The VGG16 model is widely used for image classification tasks because of its deep structure, which has been proven effective in feature extraction. However, we use VGG16 without its top layers, as the pre-trained weights will help extract relevant features from the images. Afterward, custom layers are added to fine-tune the model for stress level classification. These layers include a flatten layer to reshape the output of the convolutional layers, a dense layer with 128 neurons and ReLU activation to introduce non-linearity, and a dropout layer with 50% dropout rate to prevent overfitting. The final output layer consists of 4 neurons, each corresponding to one of the four stress levels, with a softmax activation function to output the probabilities of each class.

The model is compiled using the Adam optimizer, which is known for its efficiency in training deep learning models, and categorical crossentropy as the loss function, which is appropriate for multi-class classification problems. Accuracy is chosen as the evaluation metric to track the performance of the model during training. The training process is carried out for 10 epochs, with a batch size of 32. To prevent overfitting and monitor the model’s generalization ability, 20% of the training data is used for validation.

After training the model, its performance is evaluated on the test set. The predicted stress levels are compared against the ground truth labels, and a classification report is generated, providing precision, recall, and F1-score metrics for each of the four stress levels. Additionally, a confusion matrix is plotted to provide a visual representation of the model's ability to correctly classify each stress level, highlighting areas of strength and potential improvement.

For further refinement, hyperparameter tuning may be performed. This step involves adjusting parameters such as the learning rate, the number of epochs, or the batch size, to enhance the model's performance. After adjusting the parameters, the model is retrained with the updated settings to determine if improvements are made.

Once the model reaches satisfactory performance, it is saved in the HDF5 format for future use, allowing for easy deployment and reuse without the need to retrain from scratch. Finally, to aid in model evaluation, the confusion matrix is visualized using seaborn, providing a clear and intuitive view of the model's classification results.

This comprehensive development process ensures that the Stress Level Detection Model is robust, accurate, and ready for real-time stress level prediction, offering valuable insights for managing stress based on visual data.

2.4. 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

2.5. Testing

The application's performance was thoroughly tested across all four core components, both individually and in integration, to ensure reliability and accuracy. One key component detects real-time stress by analyzing eye blink rate and PSS questionnaire responses together to predict the user’s current 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

3.Results & Discussion

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

3.1.1.Model Evaluations

The training log, as seen in Fig. 5, plots both training and validation accuracy and loss over the span of 10 epochs. The model's training accuracy stabilizes around 32.23%, while the validation accuracy exhibits a similar fluctuating trend, with no significant improvement across epochs. This consistently low level of performance indicates that the model is not learning meaningful representations from the data, and its ability to generalize across varying stress levels remains limited.

Such performance stagnation points to multiple possible challenges within the model training pipeline. Firstly, the low accuracy and close values between training and validation accuracy imply that the model is not overfitting, but rather underfitting, meaning it has not captured sufficient patterns from the input data to perform effectively even on training samples. This may be attributed to an inadequate model architecture that lacks the depth or complexity necessary to extract high-level features from raw video frames, especially when dealing with subtle indicators like eye blinking frequency and intensity.

Another prominent issue may stem from the limited temporal sensitivity of the current model. Since the dataset comprises 10-second eye videos intended to capture blinking patterns, treating the input frames statically rather than dynamically may result in the loss of crucial time-dependent features. A conventional 2D CNN, although effective for spatial analysis, is often insufficient in isolating temporal dependencies required to distinguish stress-related behaviors. Incorporating temporal models, such as 3D CNNs or LSTM-based architectures, could potentially enhance the model's capacity to capture motion and time-related changes across consecutive frames.

In addition, data quality and distribution play a significant role in determining the learning outcomes. If the dataset suffers from class imbalance, where certain stress levels (e.g., 'Severe' or 'Critical') have fewer representative samples compared to 'Mild' or 'Moderate', the model may inherently bias toward majority classes. This bias reduces its sensitivity to minority class features, leading to poor performance in accurately classifying higher-stress categories. Addressing this could involve employing data balancing techniques such as oversampling, under-sampling, or synthetic augmentation methods like SMOTE for minority classes.

Furthermore, the feature extraction pipeline itself may be lacking in robustness. The preprocessing stages such as face detection, eye localization, and frame extractions to ensure consistent quality across samples. Any variation in lighting, occlusion, camera angle, or subject movement could introduce noise, adversely affecting the model's ability to focus on the relevant regions of interest. Enhancing preprocessing to standardize inputs and applying techniques such as histogram equalization, normalization, or edge detection may improve model input consistency.

The loss curve depicted in Fig. 4 also shows a significant downward trend, which reinforces the hypothesis of underfitting. This suggests that the optimization process may be impeded by an unsuitable learning rate, insufficient training time (only 10 epochs), or the lack of advanced regularization techniques such as dropout, batch normalization, or early stopping.

In summary, the training and validation trends in Fig. 4 provide valuable insights into the limitations of the current model. They highlight the need for a more sophisticated architecture capable of temporal learning, improved data preprocessing, class balancing, and perhaps an enriched dataset to ensure a wider representation of stress behaviors. Future improvements should consider experimenting with hybrid deep learning models, integrating multimodal inputs (e.g., questionnaire results with video), and extending training duration with careful hyperparameter tuning to enhance both accuracy and generalization capability.

```
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>
```

Figure 4. Initial stress detection training log.

In addition, as shown in Fig. 5, the model's prediction on a test instance is visualized through a probability distribution across the four defined stress levels. The predicted probabilities are relatively close in value, with the highest being 33.01% at Stress Level 3. This marginal lead suggests that the model does not exhibit a strong or confident preference toward any particular class, and its predictions are essentially uncertain. Such a flat or nearly uniform distribution across classes implies that the model struggles to distinguish between the underlying features associated with each stress level.

```
"predicted_class": 3,
"predicted_percentage": 33.01,
"probabilities": [
    0.13064958155155182,
    0.291516751050949l,
    0.33008429408073425,
    0.24774937331676483
]
```

Figure 5. Model output for a test sample.

This observation further reinforces the findings from Fig. 4, which showed low accuracy and minimal improvement during training. Together, these results reflect the model's limited capacity to learn discriminative features from the input data. In the context of stress level classification, where the distinctions between classes are inherently subtle and often nonlinear, it becomes essential for the model to develop a high-resolution understanding of eye movement cues or blinking frequency variations. The lack of such specificity is directly reflected in the probability distribution shown in Fig. 5.

Another important takeaway from this result is the model's low confidence margin, which highlights the ambiguity in its internal decision-making process. The small differences between class probabilities indicate that the model may not have established clear boundaries between stress classes, possibly due to overlapping features in the training dataset or insufficient granularity in the input representation. In such cases, increasing the richness of features—either by adding additional modalities like audio tone, questionnaire data, or even physiological inputs like heart rate—can help the model make more informed decisions.

Additionally, this kind of output suggests a need to reevaluate the loss function and training strategy. Using a standard categorical cross-entropy loss might not sufficiently penalize low-confidence predictions if class distributions are imbalanced or overlapping. Introducing strategies such as label smoothing, focal loss, or confidence-aware loss functions may help the model become more decisive during classification.

Moreover, the flat prediction distribution in Fig. 5 could be symptomatic of poor calibration, meaning the model's predicted probabilities do not align well with the actual likelihoods of correct classification. Calibration techniques such as temperature scaling, Platt scaling, or isotonic regression could be employed post-training to adjust the output probabilities and potentially enhance the model's reliability in a real-world application setting.

From a user perspective, this uncertainty in prediction could undermine trust in the system. For a stress detection app, offering vague or uncertain feedback may not be actionable for users seeking guidance on how to manage or understand their stress levels. Therefore, future enhancements should aim not only for higher accuracy but also for well-calibrated, confident predictions, even if that means deferring classification in uncertain cases and requesting additional user input or repeated video capture.

In conclusion, Fig. 5 illustrates a critical limitation in the current model's inference ability. The lack of dominant class probability points to both architectural and data-centric challenges that must be addressed to improve the system's real-world usability. Enhancing model confidence through architectural adjustments, better training objectives, and multimodal feature integration will be crucial in evolving this system into a reliable stress-level classifier.

The presence of low confidence values in classification outputs, along with inconsistent or suboptimal performance between training and validation phases—even in the absence of meaningful training progress—strongly indicates the need for a comprehensive reassessment of several critical components of the current machine learning pipeline. This includes a careful reevaluation of the model architecture, the selected hyperparameters, and the sufficiency and quality of the training dataset. These elements are foundational to the success of a classification model, and any shortcomings can significantly impact the model's ability to learn meaningful patterns and generalize to unseen data.

To address these concerns, one of the most effective strategies involves increasing the size and diversity of the dataset. This can be achieved through data augmentation techniques, such as applying transformations (e.g., rotation, flipping, scaling, brightness adjustments) or generating synthetic samples that simulate real-world variations in the data. This process not only helps prevent overfitting but also allows the model to become more robust to different input conditions, ultimately improving generalization.

In addition, tuning hyperparameters is essential for optimizing model performance. Parameters such as learning rate, batch size, number of epochs, and dropout rates should be systematically adjusted and validated using methods like grid search, random search, or Bayesian optimization. These tuning strategies help in identifying the optimal configuration that facilitates faster convergence and better model stability.

Moreover, the current model architecture should be scrutinized for its capability to capture the temporal characteristics inherent in video data, such as those used in eye-blink detection. Since video data involves sequential frames and time-dependent information, it is crucial to incorporate temporal modeling techniques. Enhancing the architecture with components such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Temporal Convolutional Networks (TCNs), or even attention-based mechanisms like Transformers can significantly improve the model's ability to understand and process time-series data. This is especially valuable in tasks where dynamic changes over time—such as eye movements or blink frequency—are core indicators for classification.

Additionally, employing techniques such as transfer learning from pre-trained video models or fine-tuning convolutional layers specifically for temporal context can boost performance, especially when the original dataset is limited in size or variability. It may also be beneficial to implement cross-validation to obtain more reliable estimates of the model's generalization capabilities.

Ultimately, by combining these strategies—dataset enhancement, hyperparameter optimization, and architectural improvements geared toward temporal modeling—a more accurate, confident, and generalizable classification outcome is likely to be achieved. Such an iterative optimization process is essential for improving model reliability and ensuring its applicability in real-world use cases.

3.1.2.Mobile Application Development

This document outlines the architecture and functionality of an innovative mobile application meticulously designed for the recording, detection, and subsequent management of user stress levels. The application leverages a contemporary technology stack, integrating Flutter for the development of a highly responsive and aesthetically pleasing cross-platform frontend interface, ensuring a consistent user experience across diverse mobile devices. The computational core resides in a Flask backend, a lightweight yet powerful Python framework serving as the central processing unit for handling complex data analysis and executing machine learning models. Complementing this is Firebase, utilized comprehensively for its robust cloud-based services, including secure user authentication protocols and a scalable NoSQL database serving as the primary data store for user profiles, assessment results, and associated metadata.

The user journey begins with a seamless onboarding process facilitated by Firebase Authentication, allowing users to securely register for a new account or log in to their existing profile. Once authenticated, users are presented with a personalized dashboard, serving as their central hub within the application. The core functionality revolves around the stress assessment process, which users can initiate at their convenience. Invoking this feature activates the device's camera through the Flutter interface, prompting the user to record a brief, 10-second video snippet of their face, specifically focusing on capturing eye movements and facial cues under controlled conditions, guided by clear on-screen instructions to ensure data quality.

Upon completion of the recording, this video snippet is automatically and securely uploaded to the Flask backend server. Here, the critical analysis phase commences. A sophisticated, pre-trained deep learning model, optimized for efficiency and accuracy, meticulously analyzes the individual frames of the uploaded video. This model is specifically trained to identify and quantify subtle physiological indicators of stress often manifested in eye behavior, such as changes in blink rate, pupil dilation fluctuations, saccadic eye movement patterns, and potentially other relevant micro-expressions. This objective, data-driven analysis provides a physiological baseline for the stress assessment.

Recognizing that stress is a multifaceted phenomenon influenced by subjective perception, the application enhances the accuracy and holistic nature of its assessment by incorporating a self-report measure. Immediately following the video upload confirmation, the user is guided through a brief, standardized questionnaire presented within the Flutter app. This questionnaire, likely based on validated psychological instruments like the Perceived Stress Scale (PSS), prompts the user to reflect on their feelings and experiences related to stress over a recent period (e.g., the last month), adding crucial subjective context to the physiological data.

Once both the video processing by the deep learning model and the user's questionnaire submission are completed, the Flask backend intelligently integrates these two distinct data streams – the objective physiological indicators from the eye-tracking analysis and the subjective responses from the questionnaire. This fusion of data allows for a more nuanced and reliable determination of the user's current stress level. The final assessed stress level (e.g., Low, Moderate, High) is then promptly relayed back to the user's device and displayed clearly on the screen via the Flutter interface, providing immediate feedback.

Beyond mere detection, the application aims to empower users in managing their stress. Based on the calculated level of tension, the system presents a pre-curated list of personalized activities known to promote relaxation and reduce stress. These recommendations are thoughtfully categorized and tailored to the detected stress intensity. Examples include suggesting specific types of calming music (e.g., ambient soundscapes, classical pieces, alpha wave binaural beats) or engaging in mandala art activities, potentially offering varying complexity levels suited to the user's current state. This provides users with actionable steps they can take immediately to improve their well-being.

The entire system is architected to guarantee smooth and intuitive user experience, facilitated by Flutter's rich UI capabilities and efficient state management. Data security and user privacy are paramount, addressed through Firebase's secure authentication and database rules, coupled with secure communication protocols between the frontend and backend. The real-time interaction between the mobile frontend (Flutter), the backend processing pipeline (Flask), and the data infrastructure (Firebase) ensures that users receive timely results and recommendations, making the application a dynamic and responsive tool for personal stress awareness and management.

This document details a comprehensive mobile application developed for the detection and management of user stress levels, employing an innovative methodology that synergizes physiological data capture via eye-tracking with subjective self-reported assessments. The application's robust architecture is built upon a Flutter-based frontend, ensuring a smooth and responsive cross-platform user interface, coupled with a powerful Flask backend dedicated to complex data processing and sophisticated analysis, while Firebase underpins the system by providing secure, scalable cloud-based data storage and reliable user authentication mechanisms.

The user journey within the application commences on a welcoming main interface that succinctly highlights the core Key Features, including its foundation in advanced eye-tracking technology, the provision of comprehensive analysis, the delivery of real-time results, and the user-friendly non-invasive nature of the assessment process partially depicted in Fig. 6. Before embarking on the primary stress detection workflow, users are meticulously guided through clear Guidelines designed to optimize the quality of data captured during the crucial eye analysis phase; these instructions emphasize maintaining a centered facial position with visible eyes towards the camera, staying perfectly still for the brief 10-second analysis duration, ensuring operation within a well-lit environment free from disruptive shadows, relaxing and blinking naturally without forcing eye movements, and selecting a quiet space to minimize external distractions that could affect the readings.

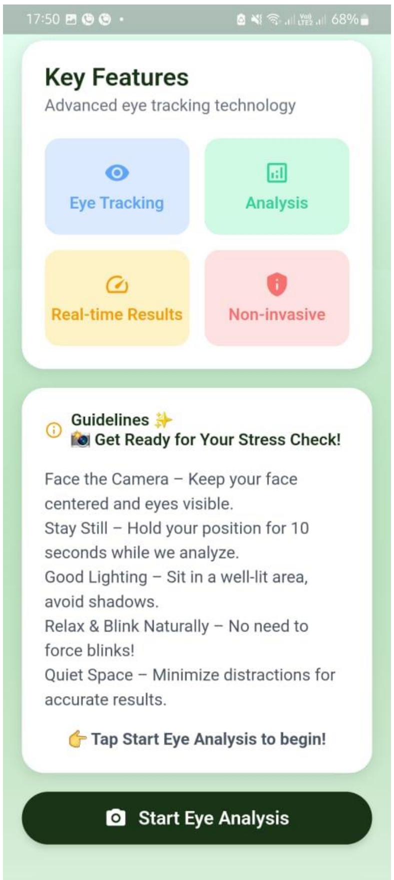

Figure 6. guidelines UI

Acknowledging these prerequisites, the user initiates the process by tapping the prominent "Start Eye Analysis" button , which prompts the application to access the device's camera and record a concise 10-second video snippet capturing their eye movements. Although Fig. 7 presents a "Video Preview" screen showing a black display (which might represent the recording phase itself, a momentary loading state, or a potential preview rendering glitch in this specific capture), its functional role is to smoothly manage the transition from the video capture stage to the subsequent assessment steps; upon successful recording, the video file is automatically queued for secure upload to the Flask backend infrastructure. The user is then guided forward by selecting the "Go to quiz" button.

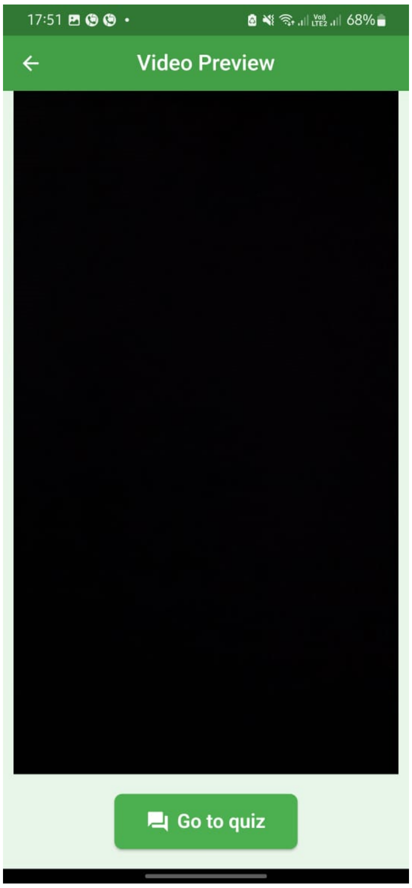

Figure 7. Video preview screen

To enrich the physiological data gathered from the eye-tracking analysis and provide a more holistic stress profile, the user is prompted to complete a standardized stress assessment questionnaire, most likely the widely recognized Perceived Stress Scale (PSS), presented intuitively within the app interface. Fig. 8 illustrates the beginning of this assessment, showcasing the first question which probes the frequency of experiencing upset due to unexpected happenings within the past month, with users selecting responses from a predefined scale (e.g., ranging from 0-Never to 4-Very Often). The user systematically progresses through the entire questionnaire, displays

10 Questions concerning the frequency of feeling overwhelmed by insurmountable difficulties; convenient navigation options, including a "Previous" button for review and a definitive "Finish" button to submit the responses, are clearly provided

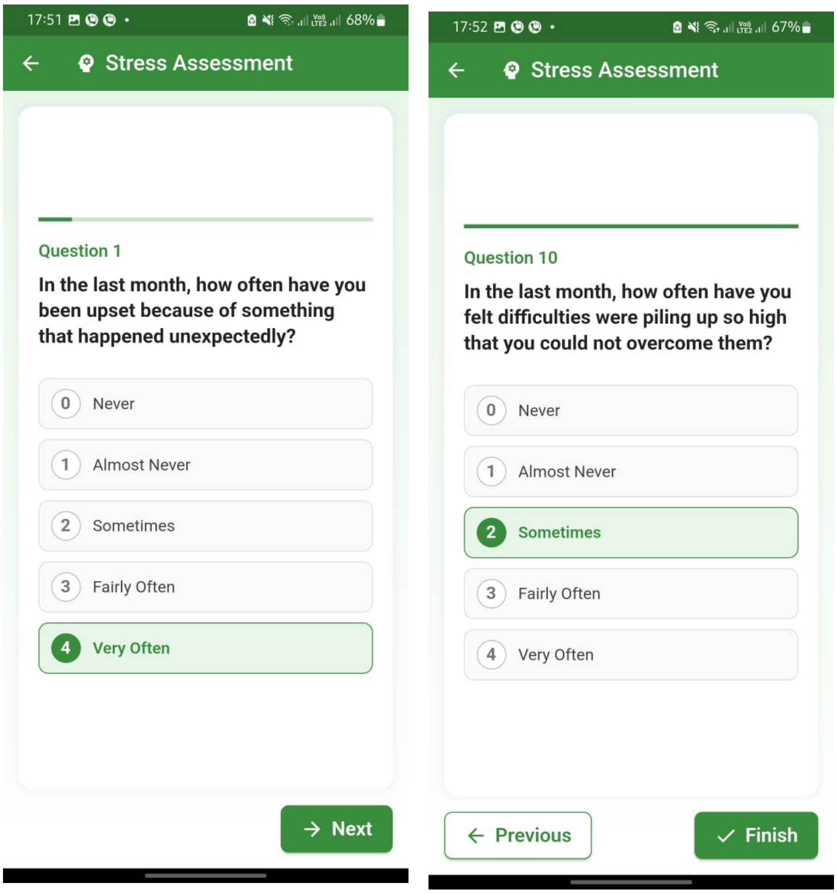

Figure 8. Perceived Stress Scale Quis

Immediately following the submission of the questionnaire via the "Finish" button the application presents an initial results screen Fig. 9 which primarily displays the user's calculated PSS Score (demonstrated here as 22 out of a possible 40), offering a preliminary insight based purely on the self-assessment. This screen also strategically outlines the anticipated "Next Steps," explicitly mentioning the pending Eye Movement Analysis, the ultimate objective of achieving a Comprehensive Assessment that integrates both the PSS score and the eye movement data, and the subsequent delivery of Personalized Insights tailored to the user's specific profile. Critically, the progression to the final, integrated analysis is user-initiated by tapping the "Analyze Stress Level" button which signals the backend to commence processing.

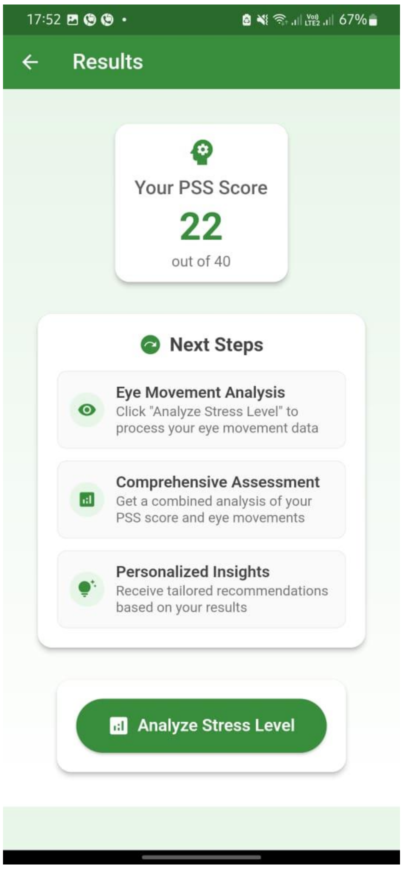

Figure 9. Results screen

Activating the "Analyze Stress Level" button triggers the Flask backend to retrieve and process the previously uploaded 10-second video file. Within this backend environment, a sophisticated, pre-trained deep learning model meticulously analyzes the video frames, concentrating on extracting and quantifying subtle eye movement patterns—such as variations in blink rate, fluctuations in pupil dilation, the frequency and nature of saccadic movements, and potentially other micro-expressions—which are scientifically correlated with varying levels of physiological stress. The output derived from this intricate eye-tracking analysis is then intelligently combined with the user's PSS score obtained from the questionnaire, creating a fused dataset for a more accurate and nuanced stress evaluation.

This integrated analysis culminates in a final stress level classification, which is relayed back from the backend to the Flutter application and prominently displayed to the user, as exemplified in Fig. 10, where the assessed condition is identified as "Moderate Stress." Based directly on this determined stress level, the application furnishes personalized Recommendations specifically curated to aid in stress reduction; these actionable suggestions may encompass activities like engaging with Mandala coloring patterns of appropriate difficulty (e.g., suggesting "Medium" complexity mandalas for moderate stress levels) and listening to specific types of audio known for their relaxation properties (such as "Alpha Waves & Soft Instrumental" music categories), as detailed in Fig. 10. A "Return to Main Page" button facilitates easy navigation back to the application's start, while a standard disclaimer thoughtfully reminds the user that the application serves as a self-assessment tool for enhancing well-being awareness and should not be considered a substitute for professional medical diagnosis or treatment advice.

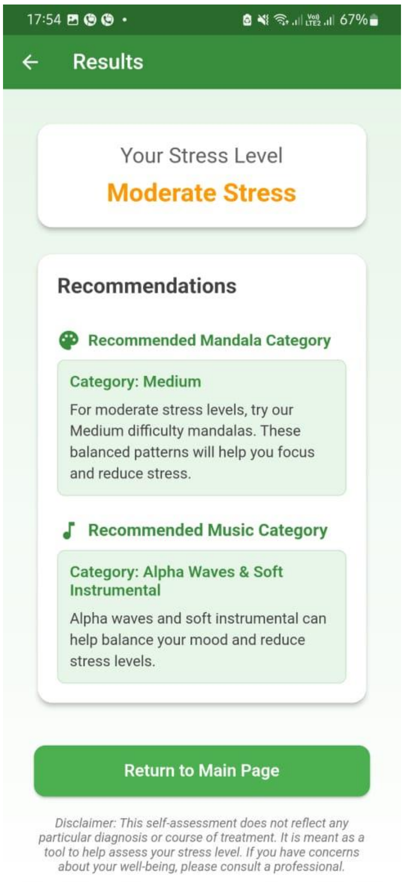

Figure 10. Display stress level UI

The seamless operation and efficacy of this system hinge on the synergistic Technological Integration of Flutter, which provides the accessible and engaging cross-platform mobile frontend visible across all figures, handling UI rendering and camera interactions; Flask, which functions as the robust backend API managing the reception of data (video, scores), orchestrating the computationally intensive deep learning model execution for eye-tracking analysis, performing the crucial result integration, and transmitting the final stress level classification and tailored recommendations back to the mobile client; Firebase, which reliably handles secure user authentication (including registration and login processes, mentioned contextually though not visually depicted) and serves as the resilient datastore for user profiles, questionnaire responses, video metadata, and the resultant stress scores and historical data; and finally, the core Deep Learning Model, deployed within the Flask environment, which embodies the specialized intelligence required to analyze complex eye movements from video frames and infer meaningful indicators of stress.

In essence, this integrated system pioneers a novel and potentially more accurate approach to stress assessment by thoughtfully combining objective physiological indicators gleaned from eye movements with subjective insights from the established PSS questionnaire, thereby offering users valuable, immediate feedback and practical, personalized recommendations within an intuitive and seamless mobile application experience, empowering them to better understand and manage their stress levels.

4.Summary of Each Student's contribution

Member Name	Contribution
Wickramasinghe B.G.W.M.C.R. IT21279652	• 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.

5.Conclusion

This research project presents the successful design, development, and partial validation of a comprehensive mobile-based system for real-time stress level detection, uniquely combining both physiological signals and behavioral indicators. The primary novelty of this study lies in its dual-modality approach, which integrates eye-blinking patterns derived from short selfie videos with subjective self-reported data collected through an Ayurvedic-based stress questionnaire. This multifaceted method aims to bridge the gap between modern machine learning-driven healthcare tools and traditional wellness frameworks rooted in Ayurvedic principles, thus fostering a more holistic and culturally sensitive method of stress assessment.

One of the notable contributions of this research is the introduction of a structured classification framework that defines four discrete stress levels—Mild, Moderate, Severe, and Critical—based on quantitative blink frequency metrics. These classifications were not arbitrarily assigned but were instead established in consultation with an Ayurvedic medical expert, who provided professional validation to ensure that the system aligns with recognized patterns of physiological stress responses as understood within Ayurvedic medicine. This collaboration added scientific depth to the classification logic and helped strengthen the overall credibility of the system, especially within contexts where traditional medical practices are commonly integrated with modern healthcare approaches.

The dataset used in this study was derived from a diverse participant pool consisting of 300 individuals, ensuring an inclusive mix in terms of age, gender, lifestyle, and stress backgrounds. This broad demographic distribution aimed to ensure the generalizability and robustness of the system across different user profiles. During data collection, each participant was asked to record a 10-second video of their eyes using the front-facing (selfie) camera of a smartphone while maintaining a fixed and focused gaze. Concurrently, participants were asked to complete a structured stress-assessment questionnaire derived from Ayurvedic diagnostic principles, aimed at identifying underlying stress symptoms.

These two data modalities—video footage and questionnaire responses—underwent comprehensive preprocessing. For the video data, individual frames were extracted at regular intervals, resized to meet the input requirements of deep learning models, normalized, and converted into arrays suitable for feeding into convolutional neural networks (CNNs). For the questionnaire responses, numerical encoding and normalization techniques were used to ensure that inputs were machine-readable and compatible with the overall stress classification pipeline.

From a machine learning standpoint, the project adopted the VGG16 architecture, a widely used pre-trained CNN known for its performance in static image classification tasks. The VGG16 model was fine-tuned and retrained on the custom dataset to serve as the core stress classification engine, using the extracted video frames as input. The choice of VGG16 was based on its architectural simplicity and ability to generalize well on a limited dataset when pre-trained on a larger dataset such as ImageNet. The final classifier outputted one of the four defined stress categories for each test input.

To support the application in a practical setting, a cross-platform mobile application was developed using Flutter for the user interface, Flask for backend API development, and Firebase for cloud-based data storage and user management. The application enables users to complete the full stress evaluation workflow independently: recording a video, completing the questionnaire, and receiving instant feedback on their predicted stress level. Furthermore, the app suggests personalized recovery activities and wellness practices tailored to the user's current stress condition, including meditation and lifestyle adjustments rooted in Ayurvedic guidelines.

Despite the system's conceptual and developmental success, the evaluation phase revealed significant challenges with the deep learning model's predictive performance. The VGG16-based classifier achieved a validation accuracy of only 32.23%, indicating poor model generalization. A deeper analysis showed a pronounced gap between training and validation accuracies, strongly suggesting overfitting and insufficient robustness in handling unseen data. Moreover, the model exhibited low confidence scores for individual test predictions, which raises concerns about its reliability in real-world deployment scenarios. These performance issues point to a fundamental limitation in the chosen modeling approach: the inability of frame-based CNN models to capture subtle blink dynamics and temporal dependencies that reflect varying stress conditions.

Given these insights, the study recognizes that while the system provides a solid proof of concept, substantial work remains to optimize the core classification model. Future improvements should focus on refining CNN-based techniques by incorporating sequential frame analysis and leveraging series-based frame representations to mimic temporal behavior. Additionally, the adoption of advanced preprocessing techniques, such as facial landmark detection to localize eye regions more precisely, and the application of optical flow analysis to enhance blink detection, may significantly improve the feature extraction process. Implementing data augmentation, class balancing, and hyperparameter optimization can also enhance model robustness and reduce overfitting.

Other avenues for enhancement include expanding the dataset further to improve model diversity, exploring ensemble CNN models that combine multiple viewpoints for decision-making, and integrating complementary sensor data, such as heart rate or skin conductance, to build a more holistic view of the user's stress profile. Such multi-modal fusion could improve the overall accuracy and reliability of the system.

In summary, this research demonstrates the feasibility and promise of a mobile-based stress detection system that synergizes modern deep learning techniques with traditional Ayurvedic insights. Although the current CNN-based implementation underperforms in predictive accuracy, the foundational architecture and application infrastructure are firmly established. With further refinement, this system holds the potential to evolve into a highly accurate, culturally adaptive, and user-friendly tool for personal stress management, contributing to the growing field of mobile health (mHealth) and digital wellness technologies.

6.References

[1] Aravind M S, Sri Bhavan Prakath, Tarunika R, M.Srividya, M.Marimuthu, "Heart-Mind Harmony: Predicting Stress from Heart Rate," *GRENZE International Journal of Engineering and Technology*, vol. 10, no. 2, pp. 4181-4187, 2024.

[2] Chan-Woo Park, Sung Wook Seo, Noeul Kang, BeomSeok Ko, Byung Wook Choi,Chang Min Park, Dong Kyung Chang, Hwiuoung Kim, Hyunchul Kim, Hyunna Lee, Jinhee Jang,Jong Chul Ye,Jong Hong Jeon, Joon Beom Seo, Kwang Joon Kim,Kyu-Hwan Jun, , "Artificial Intelligence in Health Care: Current Applications and Issues," *J Korean Med Sci*, vol. 35(42), 2020 Nov 2.

[3] R. Gupta, "Integrating Ayurveda with ModernMedicine for Enhanced Patient Care:An Analysis of Realties," *The Physician*, vol. 9, no. 1, pp. 1-6, 2024.

[4] Chandrasekharan, Jyotsna and Joseph, Amudha, "Eye Gaze as an Indicator for Stress Level Analysis in Students," pp. 1588-1593, 2018.

[5] Yousefi, Mansoureh Seyed and Reisi, Farnoush and Daliri, Mohammad Reza and Shalchyan, Vahid,, "Stress Detection Using Eye Tracking Data: An Evaluation of Full Parameters," *IEEE Access*, vol. 10, pp. 118941-118952, 2022..

[6] Ashutosh Chauhan, Deepak Kumar Semwal, Satyendra Prasad Mishra, and Ruchi Badoni Semwal,, "Ayurvedic research and methodology: Present status and future strategies," *Ayu*, vol. 36, no. 4, p. 364–369, 2015 Oct-Dec..

[7] Ramaraju, M. and Prakash, J and A, Soumya and Reddy, Nikhil and Amulya, Sai, "Stress Detection in it Professionals by Image Processing and Machine Learning," *International Journal of Advanced Research in Science, Communication and Technology,*, pp. 14-17, 2019.

[8] Thejaswini M,Harsha Vardhan K M,, E Vigneshwar,Harsha B,Darshan S, "Stress Detection in IT Professionals by Image Processing and Artificial Intelligence," *International Journal of Research Publication and Reviews*, vol. 4, no. 6, pp. 2134-2137, June 2023.

[9] M. Nilanjana,V. Poojashri,R. Umapriya,D. Vedha Vikashini,N. Krishnapriya, "Machine Learning based Image Processing for Stress Detection," *IJRESM Journal,* vol. 4, no. 6, p. 222–226, 2021.

[10] Schneiderman N, Ironson G, Siegel SD., "Stress and health: psychological, behavioral, and biological determinants.," *Annu Rev Clin Psychol,* no. doi: 10.1146/annurev.clinpsy.1.102803.144141. PMID: 17716101; PMCID: PMC2568977., pp. 607-28, 2005.

[11] M. BS., "Protective and damaging effects of stress mediators: central role of the brain.," *Dialogues Clin Neurosci,* no. doi: 10.31887/DCNS.2006.8.4/bmcewen. PMID: 17290796; PMCID: PMC3181832., pp. 367-81, 2006.

[12] Lupien, S., McEwen, B., Gunnar, M., "Effects of stress throughout the lifespan on the brain, behaviour and cognition," *Nat Rev Neurosci,* vol. 10, no. https://doi.org/10.1038/nrn2639, p. 434–445, 2009.

[13] Schwabe, L., & Wolf, O. T., "Emotional modulation of the attentional blink: Is there an effect of stress?," *Emotion,* vol. 10(2), p. 283–288, 2010.

[14] Alvaro Marcos-Ramiro, Daniel Pizarro-Perez, Marta Marron-Romera, Daniel Pizarro-Perez, and Daniel Gatica-Perez, "Automatic Blinking Detection towards Stress Discovery," *In Proceedings of the 16th International Conference on Multimodal Interaction (ICMI '14),Association for Computing Machinery,* no. https://doi.org/10.1145/2663204.2663239, p. 307–310, 2014.

[15] Kan, Y., Wang, X., Chen, X. , "Acute stress reduces the emotional attentional blink: Evidence from human electrophysiology," *Cogn Affect Behav Neurosci,* no. https://doi.org/10.3758/s13415-020-00847-9, p. 58–73, 2021.

[16] Ren, Peng and Barreto, Armando and Ma, Xiaole and Liu, Shengnan and Zhang, Min and Wang, Ying and Dong, Yeyun and Yao, Dezhong, "Dynamics of Blink and Non-Blink Cyclicity for Affective Assessment: A Case Study for Stress Identification," *IEEE Transactions on Affective Computing,* vol. 13, no. 2, pp. 689-699, 2022.

[17] Korda, A.I.; Giannakakis, G.; Ventouras, E.; Asvestas, P.A.; Smyrnis, N.; Marias, K.; Matsopoulos, G.K., "Recognition of Blinks Activity Patterns during

Stress Conditions Using CNN and Markovian Analysis," *Signals*, vol. 2(1), no. https://doi.org/10.3390/signals2010006, pp. 55-71, 2021.

[18] Mott, R and Hawthorne, S and McBride, S, "Spontaneous blink rate as a measure of equine stress," *Proceedings of the 14th Conference of the International Society for Equitation Science, Rome, Italy,* pp. 21--24, 2018.

[19] Das, N., Moharana, L., Nayak, S., "Emotional Blink Patterns: A Possible Biomarker for Anxiety Detection in a HCI Framework," *SN COMPUT. SCI*, vol. 6, no. https://doi.org/10.1007/s42979-025-03810-y, p. 277 , 2025.

[20] Hirokawa, Kumi; Yamada, Fumio; Dohi, Itsuko; Miyata, Yo, "EFFECT OF GENDER-TYPES ON INTERPERSONAL STRESS MEASURED BY BLINK RATE AND QUESTIONNAIRES: FOCUSING ON STEREOTYPICALLY SEX-TYPED AND ANDROGYNOUS TYPES," *Social Behavior and Personality: an international journal*, vol. 29, no. https://doi.org/10.2224/sbp.2001.29.4.375, pp. 375-384, 01 January 2001.

[21] Jyotsna, C. and Amudha, J., "Eye Gaze as an Indicator for Stress Level Analysis in Students," *2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI),* no. 10.1109/ICACCI.2018.8554715, pp. 1588-1593, 2018.

7. Appendices

Appendix - A

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 - B

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 - C

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.