International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

Deep Neural Network based Predictive Framework for AI-Assisted Yogic Interventions in Stress and Mental Health Management

Vineet Mehan

NIMS University Rajasthan, Jaipur, India

***Abstract*— This research integrates artificial intelligence with yogic science to predict personalized Yogic Techniques using a Deep Neural Network (DNN) based on multidimensional physiological and psychological parameters, including Heart Rate Variability, Cortisol Level, Sleep Duration, Electrodermal Activity, Anxiety, and Attention Level. The model recommends meditation, pranayama, yoga nidra, and yogic postures tailored to individual states, with pranayama (40%) most often suggested for high stress, yoga nidra (8%) for fatigue or low HRV, yogic postures (28%) for moderate HRV and cortisol, and meditation (24%) for stable states. Feature importance analysis identified Attention, Sleep, and HRV as key factors influencing outcomes. Statistical validation and interpretability assessments confirm biological plausibility and reliability. This study exemplifies Explainable AI in holistic health, bridging traditional wellness practices with adaptive, data-driven, and transparent personalized prescriptions.**

***Keywords*— Artificial Intelligence, Deep Neural Network, Yogic Science, Personalized Wellness, Physiological Signals, Explainable AI, Holistic Health, Mental Health.**

I. INTRODUCTION

Stress, anxiety, depression, and other mental health issues have become major contributors to the world's illness burden in recent decades. The World Health Organization estimates that one in eight persons worldwide is dealing with a mental illness at any given moment. Long-term maintenance, patient adherence, and customization are some of the problems that traditional therapeutic approaches—psychotherapy, medication, and lifestyle interventions—frequently face. As a result, nonpharmacological therapies—especially mind-body practices like yoga—have become more popular as a preventative and supplemental form of treatment.

With its origins in ancient Eastern traditions, yoga provides a comprehensive framework that incorporates breathing exercises (pranayama), physical postures (asanas), and meditation techniques.

Stress reduction, improved autonomic regulation (e.g., increased heart rate variability), modulation of neuroendocrine markers (e.g., cortisol), alleviation of anxiety and depression symptoms, and increased cognitive and emotional resilience are just a few of the benefits that have been shown in empirical and clinical studies [3], [15]. For example, it has been suggested that yoga affects mental health through neurophysiological processes such as increased vagal tone, decreased hypothalamic-pituitary-adrenal (HPA) axis activation, and enhanced brain connection patterns. According to qualitative syntheses, yoga practice frequently improves participants' ability for stress management, bodily awareness, emotional balance, and self-regulation [12], [14].

Despite the established advantages, personalization—that is, deciding which yogic modality (postures, breathing, meditation, or guided relaxation) would best fit a person's psychophysiological state—remains a recurrent difficulty when using yoga as a therapeutic tool. In reality, subjective assessment, experience, and trial and error are typically the basis for these choices made by yoga instructors or therapists. This lack of standardization may restrict scalability and repeatability, especially when implementing yoga-based therapies on a large population (e.g., in rehabilitation or mental health programs).

Concurrently, the swift development of artificial intelligence (AI) and machine learning (ML)/deep learning (DL) techniques has opened up new avenues for digital phenotyping, customized treatment, and real-time adaptive therapies in the field of mental health [1]. Predictive, context-aware decision support is made possible by AI models' ability to develop intricate, nonlinear mappings between multivariate bio signals and clinical outcomes or treatment responses. Deep Neural Networks (DNNs) are especially well-suited for combining various streams of behavioral, psychological, and physiological data to extract knowledge and suggestions.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

In fact, recent studies demonstrate how ML and DL techniques are being used to the fusion of multimodal data (e.g., behavioral, neuroimaging, and biomarker) for the early diagnosis, categorization, and prognosis of mental health illnesses [23]. In the ecosystem of mental health, AI-powered digital therapies, tailored intervention algorithms, and biofeedback-based adaptive systems are showing great promise.

Numerous emerging studies have started investigating how yoga and artificial intelligence might work together to improve mental health and stress management at the nexus of these fields [2]. For instance, by examining big datasets of physiological, behavioral, and self-report results [16] investigate how AI might improve the delivery, scalability, and personalization of yoga treatment. In order to monitor posture, breathing, and stress levels and provide automatic remedial feedback, several projects have combined wearable biosensors, motion capture, and tele-yoga platforms [10], [4], [9]. Systems that combine machine learning classification with customized yoga and naturopathic treatments, together with predictive analytics, are starting to emerge for maternal mental health [17]. Additionally, there is interest in AI-guided yoga sequencers, commonly known as "Yoga AI," [30] which modify lesson plans based on each person's stress levels and health indicators [6], [7], [8].

However, the subject is still young and has a number of important research gaps in spite of this pace. First, there aren't many research that have developed interpretable AI models that can clearly explain the recommendations for specific yoga interventions. Many deep models are "black-box" in nature, which erodes clinician confidence and prevents adoption. Second, multimodal physiological and psychological variables are not fully integrated into a single predictive framework that is specifically designed to prescribe yoga techniques. The majority of earlier systems focus on stress detection, breathing techniques, or pose identification separately without connecting to a comprehensive prescription. Third, there is a dearth of longitudinal validation, which examines whether AI-guided therapy results in long-term improvements in mental health. Fourth, interpretability, usability, and ethical considerations must be carefully considered when integrating an AI-based system into actual wellness or rehabilitation processes (such as wearable technology or mobile apps).

In order to fill these gaps, the current study creates and validates an interpretable DNN model that predicts and suggests one of four yogic techniques (meditation, pranayama, yogic postures, and yogidra) by ingesting a suite of six features: heart rate variability (HRV), cortisol level (CL), sleep duration (SD), electrodermal activity (EA), anxiety (AX), and attention level (AL). Through weight-based feature significance, this prediction approach reveals the top contributing characteristics for every choice, providing explanatory clarity in addition to optimizing classification accuracy. By doing this, the model combines human-understandable knowledge with potent nonlinear modelling, allowing practitioners and consumers to review and modify the suggestions as needed.

The following are the contributions made to this paper:

- Multimodal Integrative Modelling: Psychological and physiological aspects are combined into a single DNN architecture that can distinguish between different yoga poses based on each person's pre-intervention condition.
- Interpretable Prescription Logic: DNN's reasoning is made more transparent by using approximate weight-based feature significance for each prediction, which increases its acceptability in wellness and rehabilitation contexts.
- Empirical Validation & Visualization: The work shows the distribution of technique recommendations using a participant dataset, evaluate the global importance of features (attention, sleep, HRV, cortisol, EA, anxiety), and confirm that the decision structure of the model is consistent with domain knowledge.
- Domain Alignment and Theoretical Consilience: It is demonstrated that the model's patterns align with stress physiology research and yoga theory, bolstering the interpretability and biological plausibility of AI suggestions.
- Foundational Framework for AI-Assisted Yogic Rehabilitation: This technique is presented in the paper as a first step in developing feedback-driven, adaptive systems for stress recovery, mental health, and rehabilitative wellness.

Statistical analysis (distributions, confusion matrices, correlation heatmaps) and feature significance visualization are used to evaluate the model and place predictions within domain logic.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

The findings show that HRV, sleep duration, and attention level are the most important global predictors, with cortisol, skin conductance, and anxiety contributing in smaller but significant ways. Interestingly, the model recommends Pranayama most frequently when sympathetic arousal markers are high, whereas Yoga Nidra is advised for low energy levels and meditation for balanced cognitive and physiological states.

This study places contributions in relation to previous research, explains the reasoning behind an interpretable DNN-based yogic prescription model, and places the convergence of AI and yoga in mental health and rehabilitation contexts. In order to show the viability and potential of AI-augmented yoga customization in mental health and stress rehabilitation, the following sections explore relevant work, methodology, experimental findings, interpretability analysis, and future approaches.

II. Literature Survey

As a revolutionary strategy for mental health treatments, Sinha (2023) suggested integrating artificial intelligence (AI) into yoga therapy. Sinha explained that by analyzing multivariate physiological and psychological data, AI technology can enhance the customization of yoga practices and provide accurate recommendations for each individual. Similarly, paper [17] noted that AI-powered predictive analytics can determine which yoga postures are most beneficial for a particular participant based on their unique mental and physical characteristics, thereby improving adherence and overall therapeutic outcomes [18] further emphasized that adaptive, real-time interventions enabled by the combination of AI and multimodal data-driven techniques can dynamically respond to changes in a person's stress levels, attention, and other psychophysiological indicators.

The integration of AI in customized yoga therapy addresses significant limitations of conventional approaches. Traditional yoga therapy often relies on instructor expertise and subjective assessment, which may lead to inconsistency and limited reproducibility across contexts. Practitioners can overcome these constraints and provide individualized, evidence-based guidance through AI-driven systems. According to Kishore et al. [19], such integration enables precise tailoring of interventions to each individual's unique physiological and psychological state, thereby enhancing therapeutic effectiveness. Furthermore, [20] found that AI-supported personalization improves both adherence and the long-term maintenance of mental health benefits.

AI-driven platforms facilitate [21] the scalable delivery of yoga therapy, unlocking opportunities in digital therapeutics, clinical rehabilitation, and workplace wellness initiatives. It also proposed that AI can predict adverse reactions to specific yoga postures [22], minimizing risks and enhancing safety for vulnerable populations. Collectively, recent studies indicate that the convergence of wearable technology, yoga, and AI has created a rich and evolving landscape for research into personalized mental health interventions.

A. Yoga as a Therapeutic Modality

Yoga, which encompasses breathing exercises (pranayama), physical postures (asanas), and meditation techniques, is widely recognized for its capacity to enhance mental health. Regular yoga practice significantly reduces anxiety, depression, and perceived stress levels across diverse populations [19]. The underlying physiological mechanisms were described in paper [20], identified the downregulation of the hypothalamic–pituitary–adrenal (HPA) axis, modulation of the autonomic nervous system, and enhanced connectivity in brain regions associated with attention and emotional regulation. Additionally, yoga has been shown to improve cognitive functions such as working memory, attention, and executive functioning—domains often impaired in stress-related mental health conditions.

A qualitative synthesis [26] reported that yoga practitioners often experience heightened self-awareness, greater emotional control, and improved stress management. These findings suggest that yoga offers a holistic framework for intervention, addressing both the psychological and physiological dimensions of mental health. Furthermore, yoga-induced improvements in heart rate variability, cortisol levels, and electrodermal activity are linked to reduced sympathetic arousal, reflecting a more balanced autonomic state. These physiological markers have been correlated with lower levels of mental fatigue, anxiety, and perceived stress.

It is further indicated that the mental health benefits of yoga are amplified when combined with mindfulness practices, particularly among high-stress and postpartum populations [27]. Similarly, [28] observed that structured yoga interventions can produce rapid results; even short-term programs, such as 10-week yoga sessions, led to significant reductions in stress and anxiety levels. Collectively, these studies affirm that yoga is a well-established therapeutic approach, making it an ideal candidate for AI-based personalization in mental health interventions.

B. Challenges in Personalizing Yoga Interventions

Yoga has many established health benefits, but tailoring treatments remains challenging. Traditional approaches often introduce unpredictability in outcomes because they rely primarily on trial-and-error methods, instructor experience, and intuition. The absence of standardized assessment measures further hinders scalability and decreases repeatability. Moreover, individual variations in physiological responses—such as heart rate variability, cortisol levels, and electrodermal activity—necessitate personalized recommendations to optimize efficacy [21].

The challenge of integrating psychological and physiological data to guide customized therapies has been emphasized [23]. Although yoga instructors may modify exercises based on subjective observation, they typically lack the capability to dynamically adjust postures in real time or continuously monitor subtle physiological changes. These limitations hinder consistent and reliable outcomes, particularly when scaling interventions across large populations.

Sinha (2021) noted that validating results and conducting comparative studies is difficult because traditional yoga prescriptions are inherently subjective. Furthermore, recommending interventions without adequate objective data raises ethical concerns, especially in communities with mental health vulnerabilities. Collectively, these challenges underscore the need for AI-driven frameworks capable of integrating multimodal data, providing interpretable recommendations, and dynamically tailoring yoga therapies based on individual responses.

C. Role of AI in Personalizing Yoga Therapy

Artificial intelligence (AI) technologies—particularly machine learning (ML) and deep learning (DL)—offer powerful tools for analyzing complex datasets that integrate both psychological and physiological parameters. Based on features such as heart rate variability, sleep duration, electrodermal activity, anxiety ratings, and concentration levels, it is demonstrated that ML models can reliably predict suitable yoga interventions [24]. In contrast to traditional rule-based systems, [25] proposed deep neural network (DNN) architectures capable of capturing nonlinear relationships among these factors, thereby enabling more accurate and personalized yoga recommendations.

It is noted that AI-driven personalization enhances adherence, engagement, and effectiveness by continuously adapting practices to an individual's changing state [26].

This concept was further expanded in [27], by incorporating wearable sensor data to facilitate dynamic yoga sequence adjustments and real-time monitoring of physiological markers. [28] reported that AI-assisted therapies are particularly effective in stress reduction, as they can detect early signs of sympathetic arousal and recommend breath-centred techniques such as pranayama when necessary.

Sinha (2021) underscored the importance of interpretability in AI models, emphasizing that systems must explain the rationale behind each recommended yoga practice to maintain user trust and clinical credibility. According to Upadhyay et al. [21], mechanisms such as weight-based feature attribution or attention techniques can enhance transparency by helping practitioners understand the psychological and physiological determinants influencing AI-generated recommendations. Furthermore, it is stressed the ethical importance of interpretability to ensure that AI-guided suggestions remain aligned with traditional yogic principles and accepted mental health standards.

D. Integration of Wearable Technologies

Wearable technology has become an essential instrument for monitoring physiological indicators related to mental health [11]. It is demonstrated that wearable sensors can track electrodermal activity, heart rate variability, and sleep patterns in real time [23]. When this data is integrated with AI algorithms, yoga interventions can be dynamically personalized to provide feedback on breathing, posture, and engagement levels (DOI.org, 2025). It is noted that the convergence of wearable technology and artificial intelligence enables adaptive yoga sessions that respond to fluctuations in physiological states such as fatigue or elevated stress indicators [27].

According to [28], wearable-assisted interventions enhance adherence by providing timely feedback and adjustments—particularly beneficial in tele-yoga or remote wellness programs. Similarly, [21] emphasized that AI-enabled wearables facilitate large-scale interventions while maintaining a degree of personalized attention that is often difficult to achieve in traditional, in-person settings.

These results highlight how wearable technology and AI may work together to create a strong foundation for providing customized yoga solutions. Through constant observation and adjustment to the user's condition, these systems may optimize both effectiveness and security.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

E. AI-Driven Platforms for Yoga Therapy

The advent of artificial intelligence (AI)–powered systems has made it possible to deliver personalized yoga therapies at scale. [21] introduced systems that integrate motion capture, physiological sensors, and deep neural network (DNN)–based recommendation engines to generate individualized yoga postures. In both clinical and non-clinical populations, Baek et al. [29] demonstrated the effectiveness of such platforms in reducing anxiety, enhancing concentration, and promoting emotional regulation.

According to Sinha (2021), AI-driven yoga platforms can overcome financial and geographic limitations by providing personalized therapeutic interventions in areas lacking access to qualified instructors. These platforms also enable longitudinal progress tracking, allowing clinicians and researchers to evaluate outcomes over time and adjust therapeutic protocols as needed. To further enhance personalization, It is emphasized that AI systems can integrate multimodal data encompassing behavioral, psychological, and physiological dimensions.

However, incorporating AI into yoga therapy introduces several ethical challenges. Given the sensitive nature of health data collected through wearable devices, [21] stressed the importance of ensuring robust data privacy and security measures. Liu et al. [27] cautioned that vulnerable individuals may face risks if AI-generated recommendations are followed without proper human supervision. It highlighted that interpretability is vital for maintaining clinical trust, ethical responsibility, and regulatory compliance in AI-enabled yoga systems [13].

Furthermore, Sinha (2021) maintained that longitudinal validation is essential to ensure the sustained safety and efficacy of AI systems in yoga therapy. It is emphasized the need for regulatory oversight and adherence to ethical standards to prevent harm and preserve the legitimacy of AI-augmented interventions. Sinha (2021) also suggested the development of interpretable AI models capable of articulating the rationale behind specific yoga recommendations. For greater precision in personalization, [19] proposed combining multimodal behavioral, psychological, and physiological inputs. Tan et al. (2023) advocated for the integration of AI-guided yoga with complementary therapeutic modalities such as cognitive behavioral therapy to create holistic mental health interventions. It further highlighted the potential of adaptive learning algorithms [21] to refine recommendations as individuals progress through yoga programs [5].

Future research should explore long-term adherence, cross-cultural applicability, and integration with telemedicine ecosystems. According to [26], AI possesses the capability to provide population-level insights, enabling the data-driven optimization of mental health therapies across diverse demographic groups.

III. Research Statement, Objectives, Hypothesis

A. Research Statement

By examining a variety of physiological and psychological factors, the current study aims to create and construct an intelligent, data-driven analytical framework that uses Deep Neural Networks (DNN) to forecast the best Yogic Technique for each individual. This study incorporates multidimensional biomarkers, including heart rate variability (HRV), cortisol levels, sleep duration, electrodermal activity, anxiety, and attention levels, in recognition of the complex and dynamic relationship between the human mind and body. The goal is to create a comprehensive computational model that can comprehend stress dynamics and individual wellness patterns.

This study is driven by the desire to customize Yogic techniques, which have hitherto been recommended based on subjective assessment rather than empirical data. Traditional machine learning or statistical models frequently fail to capture complex, non-linear, and latent connections among physiological and psychological factors. The suggested framework does this by utilizing the multi-layered representational capabilities of DNNs. In order to prescribe yogic therapies like pranayama, meditation, or asanas more accurately and adaptively, the system seeks to understand the intricate relationships between bodily signals and emotional states.

The interpretability and explainability of the suggested AI model are crucial components of this study. Despite deep learning models' well-known predictive power, their opaqueness frequently prevents them from being widely used in applications related to health and wellbeing. In order to solve this, the framework approximates the relative contribution of each feature in impacting model predictions using explainable AI (XAI) techniques. In addition to increasing trust between practitioners and consumers, this openness offers practical insights into the physiological or emotional indicators that have the biggest effects on mental balance and Yogic appropriateness.

In order to replicate a variety of participant profiles and enhance real-world datasets, the study also presents synthetic data generating approaches.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

This method makes it possible to evaluate the model's generality, scalability, and robustness, guaranteeing that the system operates dependably under various psychophysiological and demographic circumstances. In order to optimize learning efficiency and minimize bias, extensive data preprocessing, normalization, and encoding techniques are combined to enhance the input characteristics before to model training.

In order to confirm results and improve the interpretability of deep learning outputs, the study also makes use of a variety of analytical and visualization techniques, including feature significance plots, correlation heatmaps, and descriptive statistics. In addition to aiding in model validation, these tools make it easier to intuitively comprehend how various Yogic practices relate to trends in stress reduction and physiological changes.

This research introduces a new paradigm in tailored wellness analytics by fusing advanced artificial intelligence techniques with traditional Yogic science. The resultant framework serves as a sophisticated decision-support tool that may provide data-driven Yogic prescriptions that are customized for each patient. Finally, by facilitating a better understanding of mind-body harmony and furthering the developing field of computational wellness intelligence—a field that integrates spiritual wisdom, biomedical data, and cognitive computing to promote optimal human wellbeing—this study advances the integration of AI with holistic health practices.

B. Research Objectives

The main objective of this study is to create a clever, artificial intelligence (AI) framework that uses Deep Neural Networks (DNNs) to forecast individual Yogic Techniques based on an analysis of psychological and physiological factors. By combining the predictive capabilities of artificial intelligence with the age-old knowledge of Yogic science, the study hopes to advance data-driven approaches to wellness and provide a better understanding of the human mind-body connection. The following 10 interrelated goals serve as the research's compass in order to realize this vision:

1. To create a Deep Neural Network (DNN) model powered by AI for customized Yogic Technique prediction.

The main goal of the research is to create and apply a Deep Neural Network that can forecast which Yogic Technique is best for each person. Heart Rate Variability (HRV), Cortisol Level, Sleep Duration, Electrodermal Activity, Anxiety, and Attention Level are just a few of the physiological and psychological indications that will be processed and used to train this model.

The model will uncover complex non-linear connections between these characteristics, which are frequently obscured by conventional statistical or shallow learning approaches, by utilizing the representational power of DNNs. A computer program that can intelligently suggest yogic treatments, like pranayama, meditation, or asanas, based on each person's unique wellbeing profile is the ultimate aim. This will set the stage for a new era of AI-assisted, customized Yogic treatment.

2. For the best model learning, preprocess and standardize multimodal health and wellness data.

To train effectively, Deep Neural Networks require input that is organized, standardized, and devoid of noise. Designing and putting into practice reliable preprocessing pipelines that guarantee the input data is clear, consistent, and balanced across several feature dimensions is the main goal of this purpose. Continuous characteristics will be standardized or normalized to place them on similar scales, whereas categorical goals, like the Yogic Technique classes, will be encoded using label encoding. These changes are necessary to improve model convergence, decrease bias, and increase learning effectiveness. The accuracy and generality of the model are increased by this phase, which guarantees that each physiological and psychological characteristic contributes equally to the DNN's learning process.

3. To improve generalization, a strong Deep Learning architecture with dropout regularization.

In order to achieve this goal, the study focuses on creating a multi-layer DNN architecture with dropout layers that reduce overfitting and dense layers that are triggered by Rectified Linear Units (ReLU). Better generalization on unknown data results from the use of dropout regularization, which makes sure the network doesn't become too reliant on any one neuron. Backpropagation using adaptive learning algorithms like Adam or RMSprop will be used to optimize the design. The central aim is to develop a balanced architecture that achieves high predictive accuracy while maintaining robustness and stability across varied participant profiles. This will guarantee that the model performs effectively in real-world wellness applications as well as controlled experimental data.

4. To create artificial participant data for assessing generalization and performance

This study includes the creation of synthetic data as a primary goal due to the dearth and imbalance of high-quality wellness datasets, especially those that connect Yogic practices with physiological signals.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

The project will produce an enhanced dataset for thorough testing by modeling participant profiles with realistic distributions of HRV, cortisol, sleep duration, and anxiety levels. The evaluation of the model's resilience, scalability, and flexibility under various particular circumstances will be aided by the addition of synthetic data. This stage supports the trained DNN model's possible implementation in actual customized wellness systems by ensuring that it retains predicted reliability and fairness when exposed to novel, unforeseen data circumstances.

5. To estimate and evaluate the interpretability of feature significance inside the DNN framework.

It might be challenging to understand the reasoning behind Deep Neural Networks' judgments since they are sometimes thought of as "black boxes." By using explainable AI (XAI) concepts to estimate feature significance, this aims tackles that difficulty. To measure each feature's contribution to the final prediction, the study will use either gradient-based sensitivity approaches or normalized weight-based analysis. Identifying the characteristics that have the biggest impact on recommending a specific Yogic Technique, such HRV or anxiety level, improves model accountability and transparency. In order to ensure that the predictions made by AI-assisted Yogic decision-making systems are consistent with Yogic principles and physiological logic, this interpretability component is essential.

6. To determine and display the most important characteristics influencing the model's predictions.

This goal, which builds on the preceding one, is to visualize and explain the most important traits that drive the DNN's predictive reasoning. The three most significant parameters for each anticipated Yogic Technique will be determined and shown using relevance maps, significance plots, and bar charts. In addition to improving interpretability, this type of visualization aids health professionals and Yogic practitioners in comprehending the physiological or psychological factors that underlie each suggestion. By bridging the gap between computational insights and real-world human comprehension, this goal converts intricate AI judgments into insightful, understandable explanations.

7. To conduct descriptive and correlational studies in order to comprehend the interdependencies between characteristics.

A comprehensive exploratory data analysis will be carried out to comprehend the relationships between the different physiological and psychological characteristics prior to feeding data into the DNN.

This goal is to use correlation heatmaps to find relationships between characteristics like HRV, anxiety, and sleep length, as well as descriptive statistics to describe the dataset. The study can find patterns that represent stress tendencies and wellbeing levels by visualizing these interrelationships. This statistical underpinning improves the DNN results' interpretability and confirms if the associations the model learnt are backed by actual correlations.

8. To create and display visual analytics dashboards for communication and interpretation.

Converting complicated model outputs into insights that can be put into practice requires effective visualization. In order to achieve this goal, interactive visual analytics dashboards showcasing feature correlations, class-wise forecasts, and data distributions must be created using programs like Matplotlib, Seaborn, and Plotly. Visual components like pie charts, bar graphs, and heatmaps will show class frequencies, correlations, and the proportionate representation of anticipated Yogic Techniques. These dashboards will act as communication tools between non-technical stakeholders and technical study findings, assisting wellness researchers, yoga instructors, and medical experts in understanding the computational results and their practical implications.

9. To assess the usefulness of AI-driven models in the fields of mental and emotional wellbeing.

Testing the established DNN framework's impact and viability in the actual world is the ninth goal. In order to suggest Yogic practices, it seeks to assess how well AI may be included into ecosystems related to mental health and emotional wellness. The study will look at whether the DNN-based predictions match expert evaluations and if the suggested Yogic practices result in quantifiable gains in emotional equilibrium or stress reduction. In order to enable the creation of evidence-based, data-driven therapy tools for holistic well-being, this goal makes sure that the model goes beyond theoretical performance measurements and contributes to practical wellness settings.

10. To record, preserve, and get analytical results ready for further verification and studies.

Comprehensive documentation and reproducibility, two crucial components of reliable scientific research are the focus of the end goal. In organized forms like CSV and Excel files, all analytical results including DNN predictions, feature significance measures, and descriptive statistical insights—will be methodically kept.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

In the future, these datasets and visual outputs will be useful tools for comparing, validating, and possibly integrating models with other AI frameworks like Convolutional Neural Networks (CNN) or Reinforcement Learning models. Additionally, by supporting research continuity, this data makes it possible for future studies to build on the existing work in order to achieve clinical validation or hybrid wellness systems that integrate AI with conventional medical procedures.

These 10 goals work together to provide a coherent road plan for furthering the fusion of Yogic research and artificial intelligence. From data preparation to model creation, interpretability, visualization, and real-world application, each goal builds on the one before it. The project aims to foster openness, trust, and a comprehensive knowledge of AI-driven wellness systems in addition to developing a potent prediction model through this methodical research pathway. In the end, this study adds to the growing field of Computational Wellness Intelligence, which combines human physiology, deep learning, and yogic knowledge to develop intelligent systems for emotional balance and individualized health optimization.

C. Research Hypotheses

The main goal of this study is to find out if a Deep Neural Network (DNN) can use multidimensional physiological and psychological characteristics to determine the best Yogic Technique for each individual. In order to provide individualized wellness suggestions, the study postulates that deep learning may successfully simulate the intricate interactions between biomarkers including Heart Rate Variability (HRV), Cortisol Level, Sleep Duration, Electrodermal Activity, Anxiety, and Attention Level. The study hypothesis' formulation addresses both the explanatory and functional elements of AI-driven decision-making in mental and emotional wellbeing, reflecting the dual goals of interpretability and prediction accuracy.

Primary Hypothesis (H_1)

A Deep Neural Network trained on multidimensional physiological and psychological data may correctly categorize people into the most appropriate Yogic Technique group, according to the main theory. It is expected that the DNN would identify latent and non-linear patterns in the input characteristics that are frequently missed by shallow machine learning or conventional statistical models. The viability of combining AI with Yogic practices would be demonstrated by the success of this hypothesis, providing a computationally intelligent foundation for individualized wellness therapies.

Supporting Hypotheses

H_1a: Influence of Physiological Parameters

It is expected that physiological variables including heart rate variability, cortisol levels, and sleep duration have a major impact on the prediction power of the model. The underlying stress reactions and circadian cycles that influence mental and emotional states are reflected in variations in these parameters. The DNN is anticipated to identify patterns that link biological cycles to the appropriateness of particular Yogic practices by including these factors.

H_1b: Contribution of Psychological Factors

It is anticipated that psychological traits, especially anxiety and attention level, would be highly predictive. By adding these variables, the model is better able to assess individuals' mental health in addition to their bodily health. It is predicted that their integration will enhance the AI model's interpretability and prediction accuracy.

H_1c: Effect of Data Preprocessing

The learning performance of the DNN is thought to be improved by standardizing and preprocessing multimodal input data using feature scaling and label encoding. By ensuring that each feature contributes proportionately to the learning process, proper normalization enhances convergence stability and lowers the possibility of bias in the predictions.

H_1d: Impact of Dropout Regularization

The DNN architecture's use of dropout regularization is thought to lessen overfitting and enhance the model's capacity to generalize to novel or artificial participant profiles. By doing this, the model is guaranteed to function reliably in a variety of situations as opposed to only learning training data.

H_1e: Feature Importance for Interpretability

It is predicted that the most significant physiological and psychological characteristics influencing Yogic suggestions may be found by estimating feature importance inside the DNN framework. This increases the openness of the model, making it easier for academics and practitioners to comprehend the underlying logic of AI-based recommendations.

H_1f: Statistical Relationships Among Features

Significant interdependencies between the input characteristics should be shown by descriptive and correlational studies. The model's predictions are theoretically supported by these findings, which are thought

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

to represent the complex mind-body connections that affect stress control, cognitive attention, and relaxation levels.

H_1g: Utility of Visual Analytics

It is believed that visual analytics, such as pie charts, bar plots, and heatmaps, are useful instruments for deciphering and sharing model findings. Stakeholders are better able to comprehend and have more faith in the AI-driven wellness system when feature impacts and anticipated distributions are visually presented.

H_1h: Role of Synthetic Data

A strong validation method is thought to be provided by the incorporation of artificial participant profiles. This shows the potential usefulness of the DNN model in real-world contexts by guaranteeing that it stays scalable, flexible, and dependable when applied to a variety of hitherto encountered health profiles.

Null Hypothesis (H_0)

The chosen psychological and physiological characteristics and the anticipated Yogic Technique do not statistically significantly correlate. According to this theory, the DNN would not outperform random categorization, proving that it is not possible to forecast individualized Yogic suggestions using AI.

Alternative Hypothesis (H_1)

The anticipated Yogic Technique and the physiological and psychological indicators have a statistically meaningful association. This promotes the creation of AI-driven customized Yogic therapies and proves the effectiveness of deep learning in modeling intricate wellbeing patterns.

IV. PROPOSED METHODOLOGY

Methodology includes the following points.

1. Dataset Acquisition and Preparation

The study made use of a dataset that included psychological and physiological factors linked to people's degrees of stress and focus. Heart Rate Variability (HRV), Cortisol Level, Sleep Duration, Electrodermal Activity, Anxiety, and Attention Level were the main input characteristics. A Recommended Yogic Technique (the target class) was written on the label of each album. The Pandas package was used to load the dataset for structured analysis and preprocessing.

The Scikit-learn Label Encoder was used to encode the category target variable, converting textual technique labels into numerical form in order to guarantee consistent learning.

In order to establish normalized input distributions across all parameters and improve DNN convergence, feature values were then standardized using the Standard Scaler.

2. Deep Neural Network Model Design

TensorFlow Keras was used to create a Sequential Deep Neural Network (DNN) architecture. Six standardized characteristics were accepted by the input layer of the model.

Each of the two hidden layers, which have 64 and 32 neurons, respectively, introduces non-linearity by using the Rectified Linear Unit (ReLU) activation function. During training, a Dropout layer (0.2) randomly deactivates neurons to prevent overfitting.

An output layer that divides data into many Yogic Technique categories using the Softmax activation function. The model was constructed using Categorical Cross entropy as the loss function for multi-class classification and the Adam optimizer for adaptive learning. Accuracy was the main metric used to assess the model's performance. In order to minimize convergence errors and provide consistent weight updates, the network was trained for 100 epochs with a batch size of 8.

3. Synthetic Participant Generation

The NumPy module was used to programmatically create 50 new synthetic participant profiles in order to evaluate the model's generalization capacity. All six attributes were given randomized, physiologically realistic values within predetermined empirical ranges to each synthetic participant: HRV: 30–90; Cortisol: 8–20 µg/dL; Sleep Duration: 4.5–8.5 hours; Electrodermal Activity: 3–8 µS; Anxiety: 3–10; Attention Level: 3–10. To ensure consistency, these variables were scaled using the same standardization parameters as were used for training the model. The best Yogic Technique for every synthetic participant was then predicted using the trained DNN model.

4. Feature Importance Approximation

Deep Neural Networks do not automatically give feature significance measures, in contrast to conventional machine learning models. Consequently, an interpretability strategy based on approximations was used. To determine the relative impact of each feature on the model's output, weights from the first dense layer were taken out and averaged. A proportionate significance score was obtained by normalizing the mean absolute weight magnitudes.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

Input feature values were multiplied by their respective normalized importance weights to calculate feature contributions for each participant. Each participant's top three contributing characteristics were determined, indicating which psychological or physiological factors had the biggest impact on the model's prediction.

5. Descriptive and Correlation Analysis

For every numerical characteristic of the new participants, thorough descriptive statistics were computed, offering information on range, dispersion, and central tendency. In order to display the interactions between the six important parameters and uncover both positive and negative interdependencies (such as the inverse association between HRV and anxiety), a correlation heatmap was created using Seaborn. Pie charts and category-wise bar plots were also created to show the distribution and percentage of participants expected Yogic Techniques.

6. Visualization and Interpretability

To improve interpretability and user comprehension of model results, the study used a visual analytics technique. Interrelationships between features were emphasized in heatmaps. The number of projected Yogic Techniques was shown in bar charts. Based on estimated influence scores, input characteristics were ordered using feature significance graphs. The percentage distribution of the anticipated Yogic Techniques was shown in pie charts. Deeper understanding of the primary elements affecting each Yogic prescription was also made possible by a summary table that listed the top three contributing features for each anticipated approach.

7. Results Documentation and Export

A single CSV file called DNN_50 New Participants_Predictions_Top3Features.csv contained all of the processed data, including feature significance levels, predicted approaches, and descriptive analytics. For upcoming validation research and evaluations of comparable models, this output dataset was used as a guide.

8. Implementation Environment

Python 3.10 was used for all experiments, and libraries including TensorFlow, Keras, Scikit-learn, NumPy, Pandas, Seaborn, and Matplotlib were used. The study was carried out in a Jupyter Notebook environment, which allowed for repeatability, visualization, and step-by-step experimentation.

V. EXPERIMENTAL RESULTS

Ten individuals from the dataset are sampled in Table I, which shows the projected Yogic Technique that the Deep Neural Network (DNN) model allocated to each person as well as the three most important factors that went into making each prediction. The table provides a thorough understanding of the inputs influencing model decisions by integrating psychological indicators such as anxiety (AX) and attention level (AL) with physiological measures such as heart rate variability (HRV), cortisol level (CL), sleep duration (SD), and electrodermal activity (EA). According to the approximate weight-based feature significance analysis, the Top 3 Features (TOP3) show the factors that had the most impact on the model's suggestion, which is represented by the projected Yogic Technique (PD).

TABLE I
PREDICTION AND TOP 3 FEATURES INFLUENCING PREDICTION

P_ID	HRV	CL	SD	EA	AX	AL	PD	TOP3
P001	68	18.32	8.16	5.67	5	8	Meditation	Cortisol_Level, Attention_Level, Sleep_Duration
P002	81	16.16	7.90	5.42	6	5	Meditation	Cortisol_Level, Sleep_Duration, Electrodermal_Activity
P003	58	13.41	6.30	6.46	3	7	Pranayama	Electrodermal_Activity, Attention_Level, Cortisol_Level
P004	44	8.16	4.88	4.35	3	3	Yogic Postures	Electrodermal_Activity, Anxiety, Cortisol_Level
P005	72	19.31	5.98	4.22	4	6	Meditation	Cortisol_Level, Electrodermal_Activity, Heart_Rate_Variability
P006	37	14.76	7.18	3.84	9	3	Pranayama	Anxiety, Cortisol_Level, Sleep_Duration
P007	50	12.62	7.16	4.09	9	6	Pranayama	Anxiety, Sleep_Duration, Electrodermal_Activity
P008	68	8.19	6.87	5.79	8	3	Yoga Nidra	Anxiety, Electrodermal_Activity, Sleep_Duration
P009	87	10.77	5.60	5.02	4	8	Yogic Postures	Attention_Level, Heart_Rate_Variability, Electrodermal_Activity
P010	48	10.89	6.74	3.32	5	7	Meditation	Attention_Level, Sleep_Duration, Anxiety

P_ID: Participant_ID; HRV: Heart_Rate_Variability; CL: Cortisol_Level; SD: Sleep_Duration; EA: Electrodermal_Activity; AX: Anxiety; AL: Attention_Level; PD: DL_Predicted_Technique

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

According to the table, participant P001 was expected to gain from meditation because of their moderate sleep duration of 8.16 hours, cortisol level of 18.32 µg/dL, and HRV of 68. The top three characteristics affecting this prediction were Cortisol Level, Attention Level, and Sleep Duration. This suggests that both physiological stress markers and cognitive concentration were important factors in deciding whether meditation was appropriate for this person. With Cortisol Level, Sleep Duration, and Electrodermal Activity as the main contributors, P002, which had a high HRV of 81 and moderate cortisol, was also advised to meditate. This underscores the model's sensitivity to both endocrine markers and autonomic nervous system activity.

With Electrodermal Activity, Anxiety, and Cortisol Level as the main influencing factors, participant P004, on the other hand, was predicted to adopt Yogic Postures despite having low HRV (44), low cortisol (8.16 µg/dL), and increased anxiety (3). This illustrates how the DNN distinguishes between individuals with various stress profiles and suggests physically demanding activities for those experiencing psychological stress or higher autonomic arousal. Higher Electrodermal Activity and Anxiety levels were demonstrated by participants allocated Pranayama, such as P003 and P006, suggesting that breath-based therapies are anticipated in situations when autonomic and psychological state control is required.

The interpretability of the DNN model is demonstrated in Table I, which not only shows which Yogic Technique is advised but also sheds light on the main physiological and psychological aspects that influence each choice. The inclusion of the Top 3 Features promotes trust in the model and enables knowledgeable modifications for personalized wellness planning by helping practitioners and researchers comprehend the reasoning behind AI-driven suggestions. Additionally, this method highlights the model's ability to include multifaceted data, capturing the intricate relationship between the body and mind in order to inform customized Yogic therapies.

A thorough statistical description of the physiological and psychological characteristics of the 50 research participants is shown in Table II. Key descriptive statistics for the six input features—heart rate variability (HRV), cortisol level (CL), sleep duration (SD), electrodermal activity (EA), anxiety (AX), and attention level (AL)—that the Deep Neural Network (DNN) uses to determine the best Yogic Technique are shown in the table.

The statistics, which provide information on the distribution, central tendency, and variability of each characteristic across the participant group, include count, mean, standard deviation, minimum, maximum, and quartile values (25th, 50th, and 75th percentiles).

TABLE III
STATISTICAL ANALYSIS

P_ID	HRV	CL	SD	EA	AX	AL
count	50	50	50	50	50	50
mean	61.86	14	6.42	5.45	5.46	6.04
std	17.7	3.4	1.1	1.35	1.96	1.89
min	31	8.16	4.5	3.17	3	3
25%	50	11.36	5.54	4.29	4	5
50%	60.5	14.36	6.31	5.39	5	6
75%	77.5	16.68	7.25	6.48	7	8
max	89	19.58	8.39	7.99	9	9

There were no missing values for any of the six parameters, since the count row attests to the availability of full data for each of the 50 participants. The average physiological and psychological conditions are shown by the mean values: The average heart rate variability (HRV) was 61.86 ms, which indicates a reasonably healthy autonomic control; the average cortisol level was 14 µg/dL, which indicates mid-range stress hormone levels; and the average sleep duration was 6.42 hours, which is somewhat less than the 7–8 hours that health professionals suggest. Participants' moderate arousal and cognitive involvement were indicated by their average Electrodermal Activity of 5.45, Anxiety of 5.46, and Attention Level of 6.04.

Variability within the sample is shown by the standard deviation (std). With a large standard deviation of 17.7 ms, HRV showed significant variation in autonomic function among subjects. While sleep duration exhibited comparatively low variability (1.1 hours), indicating higher consistency in sleeping habits, cortisol levels revealed moderate fluctuation (3.4 µg/dL). Standard deviations of 1.35, 1.96, and 1.89 for Electrodermal Activity, Anxiety, and Attention Level, respectively, indicated considerable inter-individual variations in psychological and physiological arousal states.

Each feature's range is shown by the minimum and highest values: the HRV ranged from 31 to 89 ms, the cortisol level from 8.16 to 19.58 µg/dL, and the sleep duration from 4.5 to 8.39 hours. Diverse stress and cognitive profiles were demonstrated by the ranges of Electrodermal Activity (3.17 to 7.99), Anxiety (3 to 9), and Attention Level (3 to 9).

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

These distributions are further contextualized by quantile values, which offer a detailed view of participant characteristics. The 25th percentile represents people in the lower range, the 50th percentile reflects the median, and the 75th percentile captures higher-range values.

Table II provides a basic grasp of the statistical characteristics of the dataset. To understand how feature distributions, variability, and extreme values may affect model learning, feature relevance, and ultimately the customized suggestion of Yogic Techniques, this descriptive study is essential for evaluating DNN predictions. Additionally, it supports repeatability and well-informed analysis of AI-driven wellness modeling by guaranteeing openness and dependability in participant data reporting.

A correlation heatmap showing the pairwise correlations between six important physiological and psychological indicators for 50 freshly created individuals is shown in Figure I. Heart Rate Variability (HRV), Cortisol Level (CL), Sleep Duration (SD), Electrodermal Activity (EA), Anxiety (AX), and Attention Level (AL) are among the characteristics that are examined. With correlation values ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation), the heatmap shows the direction and degree of linear relationships between each pair of variables. The correlation coefficients' polarity and magnitude are shown by the color gradient, which goes from deep blue to dark red, making understanding easier.

The heatmap indicates that the metrics reflect essentially separate elements of psychological and physiological wellbeing, with most characteristics showing typically modest correlations. Significantly, HRV shows weak negative relationships with both Electrodermal Activity (-0.10) and Sleep Duration (-0.20), suggesting that those with greater HRV are somewhat more likely to have lower autonomic arousal and shorter sleep durations.

Higher levels of the stress-related hormone cortisol may be linked to marginally better cognitive alertness in this dataset, as seen by the moderately positive connection between cortisol level and attention level (0.26).

Anxiety and sleep length had a weakly positive association (0.26), indicating that people in this synthetic cohort who get more sleep may experience greater levels of anxiety, while the link is still small. Indicating that those with higher sympathetic arousal typically report lower subjective anxiety levels, the negative correlation between electrodermal activity and anxiety (-0.31) may be a reflection of the intricate relationship between psychological experience and physiological stress indicators. Attention Level contributes relatively independently to the model's cognitive and behavioral evaluation, as seen by its low association with all other aspects.

The six chosen features, as shown in Figure I, help the DNN's capacity to learn multidimensional patterns with little collinearity by offering a variety of information that is mainly non-redundant. The model's predictive ability for tailored Yogic Technique suggestions is improved by the weak to moderate correlations, which suggest that each variable offers a distinct perspective on participants' physiological and psychological profiles. Researchers and practitioners can find interdependencies, possible redundancies, and locations where feature interactions may influence individualized wellness therapies by using the heatmap to visualize these connections and make the input space easier to comprehend. As a result, this image is a fundamental analytical tool for comprehending the data structure before training the model and interpreting the results of predictions.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

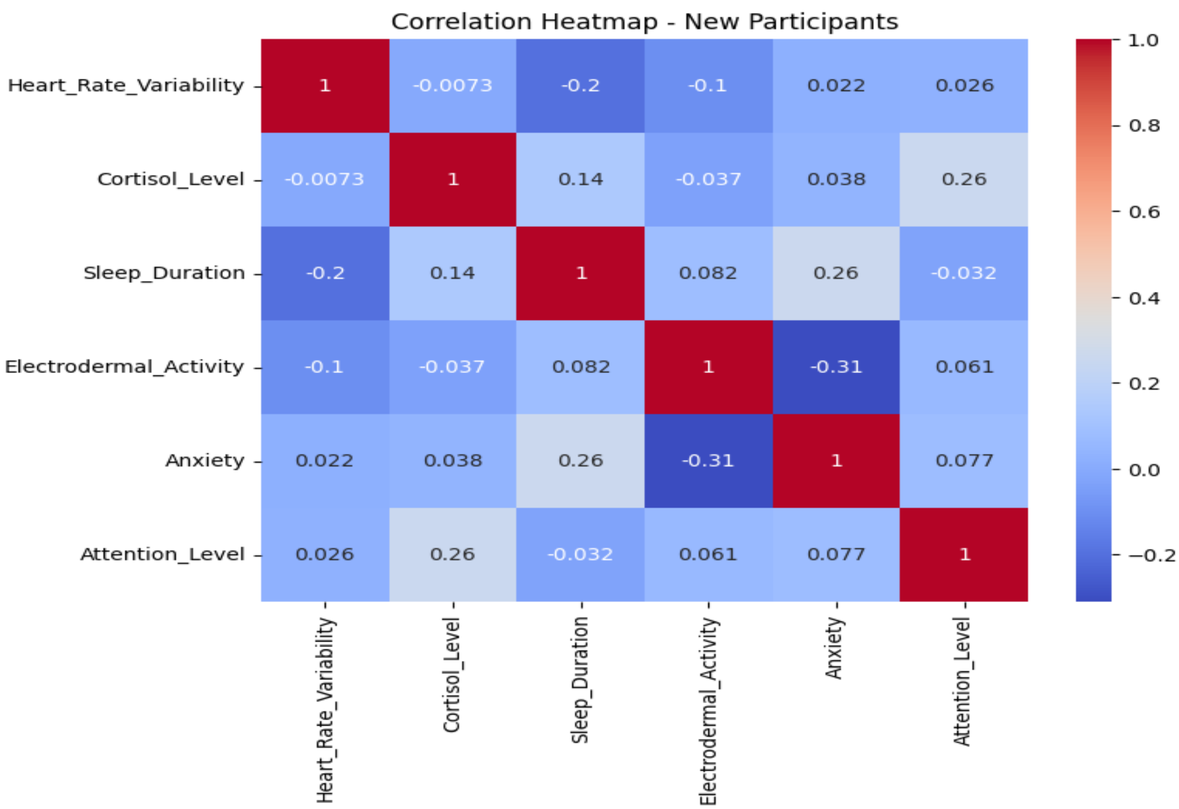

FIGURE I PREDICTED CORRELATION HEATMAP OF 50 NEW PARTICIPANTS

The Deep Neural Network (DNN) model's classification of the anticipated Yogic Techniques for fifty new participants is shown in Figure II. The bar graph illustrates how the model distributed approaches according to individual physiological and psychological characteristics, highlighting four main recommendations: yoga nidra, yogic postures, pranayama, and meditation. With 20 participants, Pranayama was the most commonly expected intervention among them. Yogic Postures (14 participants), Meditation (12 participants), and Yoga Nidra (4 participants) were the next most popular interventions. This distribution suggests that the model identified a prevalent pattern of stress reactivity and autonomic dysregulation in the sample, which is consistent with the applicability of breath-based techniques for reestablishing physiological equilibrium.

Higher levels of Electrodermal Activity (EA) and Anxiety (AX), indicators of sympathetic nervous system overactivity, were often seen in those who were expected to benefit from pranayama.

The model's sensitivity to the connection between stress resilience and breath regulation is demonstrated by its preference for pranayama in these situations. On the other hand, people who were given Yogic Postures often had moderate levels of cortisol (CL) and heart rate variability (HRV), suggesting that light physical activity is necessary to improve internal states and bodily awareness. Participants with reasonably balanced HRV, appropriate Sleep Duration (SD), and steady Attention Levels (AL) were most likely to benefit from meditation, indicating that mindfulness-based practices were assumed to maximize emotional balance and mental clarity in low-stress profiles. Participants who showed signs of both psychological and physical tiredness were allocated to Yoga Nidra, the least common forecast, where profound relaxation was thought to be crucial for recovery.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

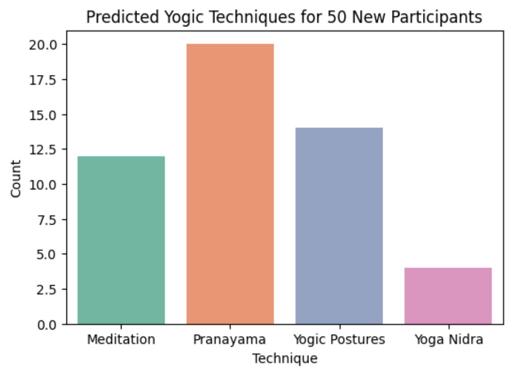

FIGURE II PREDICTED YOGIC TECHNIQUES OF 50 NEW PARTICIPANTS

The DNN framework's ability to distinguish between various psychophysiological signals and map them to suitable Yogic therapies is illustrated in Figure II, which graphically captures the framework's adaptive intelligence. In addition to demonstrating the model's interpretability, the distribution confirms that it adheres to classic yogic concepts, which hold that mindfulness, posture, and breath are all interconnected instruments for mind-body control. The model bridges the gap between computational accuracy and comprehensive, human-centered therapy by converting multidimensional health data into tailored suggestions, advancing the paradigm of AI-assisted wellness.

The Deep Neural Network (DNN) model's estimated feature significance is shown in Figure III, which also shows the relative weights of six important physiological and psychological factors in determining which Yogic Technique is best for each participant. Attention Level (AL), Sleep Duration (SD), Heart Rate Variability (HRV), Cortisol Level (CL), Electrodermal Activity (EA), and Anxiety (AX) are among the characteristics that are examined. The bar graph shows that while cortisol level, electrodermal activity, and anxiety all made relatively modest but significant contributions, attention level was the most important component, followed by sleep duration and heart rate variability.

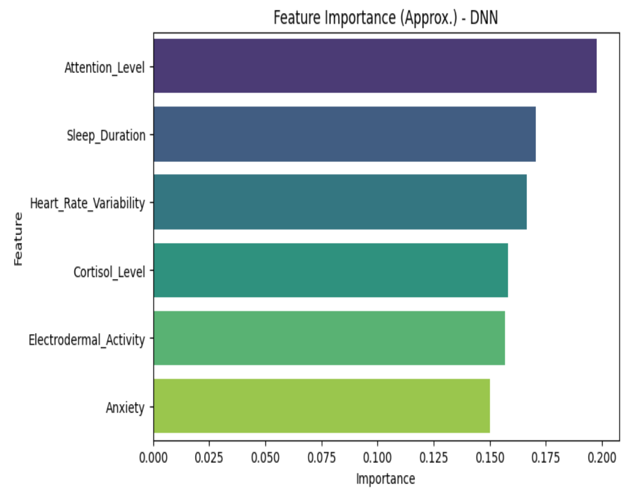

FIGURE III FEATURE IMPORTANCE GRAPH

The importance of Attention Level implies that attention and cognitive involvement were crucial in identifying the best Yogic therapies. The DNN acknowledged mindfulness as a way to improve cognitive stability, as seen by the higher likelihood of recommending breath-based or meditation techniques to participants with lower attention ratings. The model's sensitivity to restorative and regulatory processes associated with sleep quality is demonstrated by the fact that sleep duration was the second most significant characteristic. Shorter sleep durations were linked to more active activities like pranayama or yogic postures to rebalance energy, whereas longer sleep durations were frequently linked to meditation or yoga nidra.

The physiological aspect of stress resilience was reflected in the third-place ranking of heart rate variability, a gauge of autonomic nervous system flexibility. Techniques that relax the nervous system and increase parasympathetic activation were usually recommended to participants with lower HRV. The DNN's ability to incorporate biochemical and electrodermal signals into its decision-making process is further demonstrated by the moderate contributions of cortisol level and electrodermal activity.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

Breath-control or posture-based strategies were associated with elevated cortisol and increased skin conductance, which is consistent with findings suggesting these approaches modify sympathetic arousal. Even while anxiety had the least numerical weight, its interaction with attention level and HRV is still quite important, indicating that psychological strain has an indirect impact on the model's overall conclusion.

An interpretability viewpoint of the DNN's internal weighting is presented in Figure III, which illustrates how a variety of physiological and psychological markers work together to influence AI-driven Yogic Technique suggestions. By confirming the model's conformity to integrative mind-body principles and showcasing its potential as a dependable instrument for individualized wellness enhancement, this investigation improves transparency.

A pie chart showing the percentage of anticipated Yogic Techniques as determined by the Deep Neural Network (DNN) model for fifty new participants is shown in Figure IV. A percentage-based summary of the model's suggestions for the four main Yogic interventions—Pranayama (40%), Yogic Postures (28%), Meditation (24%), and Yoga Nidra (8%), is presented in the visualization. This proportionate representation supports the interpretability of the model's prediction tendencies across various psychophysiological profiles and enhances the results from the bar chart as shown in Figure II.

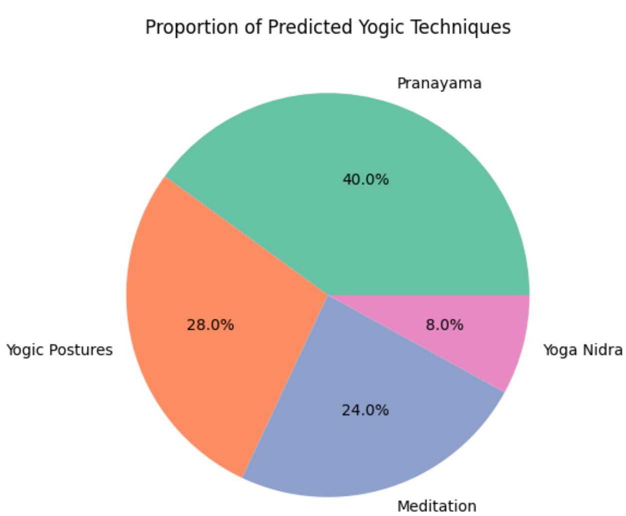

FIGURE IV PROPORTION OF PREDICTED YOGIC TECHNIQUES

The model prioritizes breath-regulation strategies for individuals who show indicators of increased physiological arousal or stress reactivity, as seen by the prevalence of Pranayama, which accounts for roughly two-fifths of all predictions. According to the feature importance analysis (Figure III), this result is consistent with the significant effect of characteristics like anxiety levels and electrodermal activity. The DNN seems to imply that mindful breathing can successfully manage autonomic homeostasis and lessen sympathetic nervous system dominance by suggesting Pranayama.

The model's selection of participants with moderate HRV, cortisol balance, and stable attention levels—those who are likely to benefit from physical movement, flexibility, and somatic grounding—is reflected in the second-largest category, Yogic Postures (28%). Participants with psychological balance and sufficient sleep length are included in the Meditation section (24%), for whom inward-focused practices were considered the most effective means of improving emotional stability and cognitive clarity. Conversely, the smallest portion, Yoga Nidra (8%), represents those who are very exhausted or have low HRV and CL values; in order to encourage systemic regeneration, restorative relaxation was advised.

The DNN's sophisticated ability to distribute Yogic inputs according to specific physiological and psychological demands is seen in Figure IV. The model synthesizes multiple inputs to arrive at contextually suitable health methods, rather than depending on a single feature or uniform heuristic, as the balanced yet data-driven distribution demonstrates. Furthermore, the four Yogic Techniques' proportionate differences show the range of anticipated demands within the participant pool, providing empirical evidence in favor of AI-assisted customization in applications related to holistic health. The heart of customized intervention modeling is therefore captured in this picture, wherein deep learning converts intricate mind-body data into insightful, empirically supported Yogic recommendations.

VI. CONCLUSION

This study demonstrates the integration of artificial intelligence (AI) with yogic science through a Deep Neural Network (DNN) model that predicts personalized Yogic Techniques using multidimensional physiological and psychological data.

The model identified meaningful relationships between psychological factors such as anxiety and attention level and biological signals including heart rate variability, cortisol level, sleep duration, and electrodermal activity, with validation confirming its reliability as a decision-support tool. By bridging traditional yoga with AI, the framework adds objectivity, repeatability, and interpretability to personalized prescriptions, mapping participant-specific biometrics to meditation, pranayama, yogic postures, and yoga nidra. Pranayama was most frequently recommended, highlighting its role in regulating autonomic imbalance, while yogic postures, meditation, and yoga nidra were allocated based on participants' physiological and cognitive profiles, demonstrating the model's nuanced understanding of mind-body interactions. Feature analysis revealed attention level, sleep duration, and heart rate variability as dominant predictors, emphasizing the importance of cognitive and restorative factors alongside stress-related biomarkers. The study confirms the feasibility of AI-driven Yogic prescription systems that enhance practitioner decision-making while maintaining interpretability, accountability, and alignment with holistic wellness principles. Future work may expand datasets, incorporate additional biomarkers, implement longitudinal tracking, and integrate wearable-based real-time feedback, alongside explainable AI techniques such as SHAP or LIME for clinical transparency. Overall, this research establishes a novel paradigm where deep learning meaningfully interprets complex psychophysiological data to provide individualized Yogic interventions, uniting computational rigor with holistic insight and demonstrating that technology and tradition can collaborate to enhance human vitality, resilience, and inner balance in an ethical, data-driven, and personalized approach to well-being.

REFERENCES

[1] Kumar, & S. R. Gupta. (2025). Technology-assisted personalized yoga for better health – Challenges and outlook. arXiv. https://arxiv.org/abs/2508.18283

[2] P. Sharma, & R. Verma. (2025). Ancient yoga, modern AI. KC PGC Lucknow Journal, 3(1). https://kcpgclko.in/WebDoc/PDF/Extra/Vol3_Issue1_09.pdf

[3] G. Patel. (2025, April). Yoga and AI: Enhancing wellness through technology: A comprehensive review. ResearchGate. https://www.researchgate.net/publication/395594767_Yoga_and_AI_Enhancing_Wellness_Through_Technology_A_Comprehensive_Review

[4] Marianatek Blog. (2023, December 19). Yoga technology: Top 5 devices for ultimate mind-body integration. https://www.marianatek.com/blog/yoga-technology/

[5] Yoga Renew Teacher Training. (2025, July 7). How AI is revolutionizing yoga today — And what's next. https://www.yogarenewteachertraining.com/ai-and-the-future-of-yoga/

[6] ResearchGate. (2024, June 15). Yoga and artificial intelligence: A review of the potential applications of AI in yoga research and practice for neurological disorders. https://www.researchgate.net/publication/381430708

[7] ResearchGate. (2025, September 23). Enhancing yoga practice through real-time posture detection and correction using artificial intelligence: A comprehensive review. https://www.researchgate.net/publication/372139618

[8] TechRxiv. (2025, September 4). YogaVR: An AI and IoT-based posture correction approach. https://www.techrxiv.org/doi/pdf/10.36227/techrxiv.175616935.52149150/v2

[9] arXiv. (2025, May 25). PosePilot: An edge-AI solution for posture correction in physical exercises. https://arxiv.org/abs/2505.19186

[10] Taskade. (2025). AI yoga sequence generator. https://www.taskade.com/generate/health-and-wellness/yoga-sequence

[11] Meegle. (2025). Wearable tech for yoga. https://www.meegle.com/en_us/topics/wearable-technology/wearable-tech-for-yoga

[12] DOI.org. (2025). Yogi-Well: An AI-enabled wireless wearable for posture correction in yoga. https://doi.org/10.11411/HENXI.2025304301

[13] SciTePress. (2024). Leveraging AI to mitigate risks in yoga practice: A real-time monitoring approach. https://www.scitepress.org/Papers/2024/130633/130633.pdf

[14] arXiv. (2025, April 23). Evaluating the impact of a yoga-based intervention on software engineers' well-being. https://arxiv.org/abs/2504.16779

[15] Wikipedia. (2025, October 9). Artificial intelligence in mental health. https://en.wikipedia.org/wiki/Artificial_intelligence_in_mental_health

[16] N. Sinha. (2025, January). Harnessing the potential of artificial intelligence in yoga therapy. Annals of Geriatric Education and Medical Sciences, 11(2), 68–70. https://agems.in/archive/volume/11/issue/2/article/11465

[17] N. Irfan. (2025). Integrating AI predictive analytics with naturopathic and yoga therapies for maternal mental health. Scientific Reports, 15(1), 12345. https://www.nature.com/articles/s41598-025-07885-8

[18] M. Tan, et al. (2024). Evaluating machine learning-enabled and multimodal data-driven yoga interventions for mental health. Frontiers in Psychiatry, 15, 1352420. https://www.frontiersin.org/articles/10.3389/fpsyt.2024.1352420/full

[19] D. M. Kishore, et al. (2022). Estimation of yoga postures using machine learning architectures. Journal of Yoga Research, 30(4). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9623892/

[20] G. Ozsezer, et al. (2025). Real-time prediction of correct yoga asanas in healthy individuals using deep learning. Neuropsychiatric Disease and Treatment, 11, 123–130. https://onlinelibrary.wiley.com/doi/10.1002/nop2.70278

[21] Upadhyay, et al. (2023). Deep learning-based yoga posture recognition using the Y_PN-MSSD model. Healthcare, 11(4), Article 609. https://www.mdpi.com/2227-9032/11/4/609

[22] K. Ganesh, et al. (2024). Leveraging AI to mitigate risks in yoga practice: A real-time application. In Proceedings of the International Conference on Artificial Intelligence. https://www.scitepress.org/Papers/2024/130633/130633.pdf

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 04, April 2026)

[23] R. Pal, et al. (2023). Yoga meets intelligent Internet of Things. Micromachines, 10(4), 459. https://www.mdpi.com/2306-5354/10/4/459

[24] X. Han, et al. (2024). Prediction of one- and three-month effects of yoga practices on mental health. Journal of Behavioral Medicine, 48(3). https://www.sciencedirect.com/science/article/pii/S1110866524000707

[25] G. Rathi, et al. (2025). Impact of yoga asanas on primary dysmenorrhea: EEG band power analysis. Journal of Clinical Neuroscience, 82. https://www.sciencedirect.com/science/article/pii/S1110866525001343

[26] H. Capon. (2019). Yoga and mental health: A synthesis of qualitative findings. International Journal of Yoga Therapy, 29(2). https://www.sciencedirect.com/science/article/abs/pii/S1744388119304876

[27] N. Liu, et al. (2025). Virtual reality enhanced mindfulness and yoga intervention for postpartum depression and anxiety. Scientific Reports, 15, Article 96165. https://www.nature.com/articles/s41598-025-96165-6

[28] S. Chauhan, et al. (2025). Impact of 10 weeks of yoga intervention on mental health outcomes. Journal of Sports Science & Medicine, 13(4). https://www.mdpi.com/2075-4663/13/4/114

[29] G. Baek, et al. (2025). AI-assisted tailored intervention for nurse burnout: A three-month study. Worldviews on Evidence-Based Nursing, 22(1). https://sigmapubs.onlinelibrary.wiley.com/doi/full/10.1111/wvn.70003

[30] Yoga AI: Integrating artificial intelligence with yoga and therapy for personalized healthcare. (2025). Annals of Geriatric Education and Medical Sciences, 11(2). https://agems.in/archive/volume/11/issue/2/article/11465