Artificial Intelligence Driven Assessment of Daoist Meditation and Breathing Practices Using Wearable IoT Devices

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Abstract

The proliferation of wearable Internet of Things (IoT) devices has introduced novel opportunities for continuous and objective monitoring of individuals engaged in meditation and controlled breathing practices. This study presents an artificial intelligence (AI)-driven framework for assessing the physiological and psychological effects associated with Daoist meditation and breathing techniques through real-time multimodal wearable sensor data analysis. The proposed framework integrates multiple physiological and behavioral parameters, including heart-rate variability (HRV), respiratory rate (RR), blood oxygen saturation (SpO☐), skin temperature (ST), electrodermal activity (EDA), sleep patterns, and physical movement (PM). A comprehensive data-processing pipeline is developed, incorporating signal filtering, artefact removal, normalization, multithreaded segmentation, and feature extraction across heterogeneous sensing modalities. Machine-learning (ML) and deep-learning (DL) approaches are employed to model complex relationships between physiological responses and meditative states. The framework supports multiple analytical tasks, including meditation stage classification, breathing pattern recognition, relaxation-level assessment, and longitudinal monitoring of physiological variations. Statistical and computational analyses are performed to evaluate differences among resting conditions, controlled breathing sessions, and distinct meditation stages, with particular emphasis on autonomic nervous system (ANS) activity and stress-related physiological indicators. To enhance model interpretability, explainable artificial intelligence (XAI) techniques are incorporated to identify key physiological features contributing to predictive outcomes. Furthermore, the framework enables real-time personalized feedback by generating adaptive recommendations based on individual biometric characteristics and historical practice patterns. The integration of Daoist contemplative practices with wearable sensing technologies, artificial intelligence, and real-time analytics provides a novel approach for scientifically evaluating traditional mind–body practices. The proposed framework offers potential applications in digital health monitoring, stress management, personalized wellness systems, and the development of intelligent platforms for individualized contemplative practice optimization.

Keywords: Artificial intelligence; Daoist meditation; breathing practices; wearable sensors; Internet of Things; physiological monitoring; heart-rate variability; respiratory analysis; machine learning; digital health; personalised feedback.

1. Introduction

In recent years, mental wellness, stress management, and health prevention have gained increasing recognition. Consequently, scientific interest has been directed toward meditation and other controlled-breathing practices as well as toward digital health monitoring, which can provide a continuous and reliable assessment of meditation and breathing practices. While meditation and breathing practices are typically assessed by means of subjective measurement and by reports from practitioners, health monitoring by means of wearable devices in real-time provides an objective and quantitative assessment that can be used on an individual basis. Recent years have seen a massive increase in digital health monitoring that is enabled by wearable health monitoring systems of the Internet of Things (IoT) type[1]. These sensors record physiological and behavioral data of individuals and process this data in real-time. Artificial intelligence (AI) methods are increasingly used for the analysis of complex biosignals to identify relations that are not yet known and to provide health advice on an individual basis[2]. Thus, the monitoring of meditation and breathing by means of wearables in combination with AI methods for physiological assessment can be used to transform traditionally subjective experiences into measurable data that can be processed by computers. Such systems enable a more profound understanding of the complex relations between mental states, physiological responses, and behavior, and, at the same time, they can support individualized digital wellness and health prevention[3].

Daoist meditation practices are traditionally used to create a sense of balance or harmony in the body by incorporating mental focus with respiratory practices that cultivate internal energy. Daoist controlled breathing practices can modulate the autonomic nervous system to increase parasympathetic activity, and improve a person's ability to recovery from stress. Recently, meditation and breathing practices have been found to affect a number of biomarkers or measures that relate to relaxation, recovery, and emotional regulation[4]. The physiological effects of meditation can be a valuable area for scientific study. In order to better understand these physiological changes, various biomarkers can be used to assess different aspects of the body's physiological activity[5]. The use of bio-sensors to assess various physiological parameters and monitor their activity in real time offers a new methodology for studying the physiological effects of contemplative practices. In this paper we consider the bio-sensor derived biomarkers of heart rate variability (HRV), respiratory rate (RR), blood oxygen saturation (SpO☐), skin temperature (ST), and electrodermal activity (EDA). Other measures, including sleep quality and physical movement can also provide valuable insights into the physiological effects of long-term practice as well as offering information regarding the behaviors of the meditator[6]. By using bio-sensors and AI computing to interpret the bio-sensor data, it is possible to provide a measure of the effects of various meditation states, breathing practices, and relaxation responses, and thereby offer insights into the mind-body interactions of the contemplative practices[7]. While a number of bio-sensor derived measures have been employed to study a variety of meditation practices, none have been used to study the various aspects of Daoist meditation in an integrated fashion. In this study, we utilize a number of bio-sensor derived measures and a large dataset to provide an in-depth study of the physiological effects of Daoist meditation[8]. The effects ofDaoist meditation on a number of different biomarkers have been found to be valuable for assessing the effects of contemplative practices on physiological activity. The use of bio-sensors to assess various biomarkers and study their activity in real time while a person is engaged in a variety of meditation practices and daily activities can provide new insights into the many different aspects of meditation and the effects that it has on a variety of physiological parameters[9].

However, despite growing interest in digital wellness technologies, there are many challenges that need to be addressed to develop intelligent systems for the evaluation of meditation and breathing practices. An ideal system for the assessment of contemplative practices would be able to continuously monitor the user during the meditation sessions, recognize different breathing patterns, and be able to identify the physiological responses that are associated with the different meditation states[10]. In addition, the system should be able to provide the user with immediate feedback on how to improve his/her practice. Currently, most of the meditation assessment methods are based on subjective evaluation, which are not scalable and are not reproducible. Most wearable devices that are able to measure physiological signals of the users are designed for general health monitoring and for specific wellness monitoring applications, such as activity tracking, heart rate monitoring, sleep monitoring, and fitness monitoring. There are very few systems that are able to integrate multiple physiological signals for meditation assessment. In addition, most of the current AI-based mental-state recognition systems are designed for recognizing stress, emotion, and workload, and are not able to capture the subtle physiological changes that occur during contemplative practices[11]. Moreover, there are no comprehensive adaptive feedback systems that are able to learn from the user and provide personalized recommendations. Finally, there is a lack of systems that are able to incorporate traditional philosophical contemplative practices, such as Daoist meditation and breathing techniques, within AI-enabled healthcare frameworks. This creates a large gap between the ancient contemplative knowledge and modern computational technology.

While studies have presented various types of wearables, various types of approaches for stress detection, emotion recognition, meditation analysis and relaxation using HRV, as well as recent research on the use of deep learning for analysis of biomedical signals, there are many limitations to the currently implemented systems and approaches[12]. For example, there are several limitations in currently used meditation assessment approaches, the major one being that most of currently used meditation assessment approaches are based on single signal or limited number of signals, hence they are not able to provide sufficient insight into complex mind–body interactions taking place during the meditation practice. Another limitation is that, even though there are many studies that make use of multimodal data, most of currently used approaches for multimodal data fusion are based on very simple methods that are not able to capture complex relationships between the signals of different modalities. Also, there is a severe limitation related to the size of the used datasets. Most of the studies conducted so far have made use of the datasets that are of very small size and hence the models that are trained on such small size datasets do not generalize well to the data of different individuals and to the data obtained as result of different meditation practices. Finally, there is a severe limitation related to the lack of explainability of the obtained results, as well as to the fact that the majority of currently used systems and approaches for assessment of meditation practice are designed to operate in offline mode, i.e. the analysis is performed after the completion of the meditation session, and not in real-time, during the meditation session, which significantly reduces their potential use for real-time monitoring of the user and for providing immediate feedback to the user[13]. Also, there are only a few studies that have investigated the use of AI approaches for assessment of contemplative practices based on traditional philosophical knowledge, and all of them have been limited to only a few aspects of the contemplative practices and to only a few approaches for assessment of these aspects. In this sense, the majority of currently used approaches for assessment of contemplative practices are not able to provide a comprehensive evaluation of these practices, and therefore there is a great need for development of new approaches that would be able to provide more comprehensive evaluation of contemplative practices. In this sense, the new approaches should be able to assess all aspects of the contemplative practices, and to use all available information. The study presented in this dissertation attempts to address all the mentioned limitations.

A research gap exists regarding the employment of intelligent systems to assess contemplative practices via wearable IoT technology. Currently, AI systems for wellness practices (or contemplative practices) and assess their effects on the human body using physiological data monitored by wearables; however, existing research do not integrate these three components (wellness practices, IoT wearables and assessment using AI) within a single framework. Specifically, there is a large research gap regarding meditation using physical practices that originate from the Daoist philosophy and the use of multimodal physiological data to improve (and assess) his or her current state of meditation using deep learning for meditation state analysis and various signal processing techniques for assessment of the physiological data monitored by wearables. Additional features that should be implemented within an assessment framework of contemplative practices using IoT wearables and AI, such as an adaptive (or real-time) assessment system and an assessment system that can be personalized to better reflect an individual's various internal and external states, have not yet been fully investigated. Addressing the aforementioned research gap could enable the development of an intelligent system that can continuously monitor an individual during various forms of contemplative practice using wearable technology, assess various aspects of the monitored data, and provide assessments that are reflective of each individual's unique characteristics and various states.

The contributions of this work can be summarized as follows: Firstly, this paper presents an IoT-enabled wearable sensing framework to support Daoist meditation practices. Secondly, the work addresses a multimodal physiological data acquisition approach for real-time meditation monitoring by incorporating a number of wearables into a single monitoring framework. Each sensor measures different physiological parameters such as heart rate variability (HRV), respiratory rate, blood oxygen saturation (SpO_2), skin temperature, electrodermal activity (EDA), sleep, and physical movement. Thirdly, an enhanced preprocessing pipeline is proposed, which comprises of filtering, artefact removal, normalization, segmentation, and feature extraction from the acquired signals to transform raw data into meaningful physiological information. Fourthly, machine learning models are implemented for the three main tasks of meditation assessment, breathing pattern recognition, and evaluation of related physiological responses. Finally, the framework incorporates an intelligent feedback module, which analyzes the large volume of individualized biometric data in real time to deliver recommendations for optimized meditation practices, thereby enabling individuals to obtain the greatest benefits from their respective wellness programs.
The objectives of this study are to:

- Develop a wearable system with IoT capabilities for monitoring of Daoist meditation and various other breathing practices.

- Develop preprocessing and feature extraction techniques for multimodal physiological signals collected from wearable sensors.
- Apply machine learning and deep learning models for meditation-state assessment and physiological pattern recognition.
- Analyze and evaluate the relationships between Daoist meditation practices and physiological parameters that can be measured.
- Design an IoT-enabled wearable sensing framework for monitoring Daoist meditation and breathing practices.

The rest of this paper is organized as follows. Section 2 describes the related work, covering various wearable health monitoring systems, AI-powered physiological analysis approaches, and meditation monitoring techniques. Section 3 elaborates on the proposed AI-powered wearable IoT framework and its system architecture. Section 4 elaborates on the data acquisition, preprocessing, feature extraction, and learning approaches. Section 5 presents and evaluates the experimental results. Section 6 outlines implications, limitations, limitations, and possible applications of the developed system. Section 7 concludes this paper and suggests possible future work.

2. Literature Review

Wearable IoT for Physiological Monitoring

Smart healthcare monitoring or healthcare tracking using smart wearables or smart Internet of Things (IoT) has transformed greatly in the last few years from simple body monitoring to advanced real time health monitoring. While traditional clinic settings use several medical equipment for the monitoring of patients, wearable or smart IoT health monitoring provides the health data of humans while a person is moving around. Such a system can be used for healthcare of patient at home or in hospital using digital health, smart wearable, or health tracking or monitoring for prevention of diseases or treatment of diseases using tracking of patient health in real time using smart health monitoring[14].

Smart watches, have recently become the most common form of wearable IoT, because of their portability, functionality, user-friendly interface, and ability to monitor physiological activity. Contemporary smart watches have optical PPG, heart rate, and blood-oxygen-level sensors, accelerometers, gyroscopes, temperature sensors, EDA, and other physiological and motion sensors. Some even have built-in ECG, respiration-rate, sleep-pattern, and other health monitors, which provide real-time data. Smart watches are capable of monitoring many of the human body's health indicators outside of a hospital. Most of the smart watches currently available are consumer products, designed to be comfortable to wear and provide long battery life. As a result, smart watches are limited by the precision of their component sensors, require calibration, are sensitive to user motion, and have inter-individual variability[15].

Biosensor technologies have greatly enhanced the capabilities of wearable IoT systems to measure physiological, biochemical, and even neurological signals. Flexible and miniaturized biosensors are made from a variety of novel materials, including conductive polymers, nanomaterials, and flexible electronics. These novel biosensors can be mounted directly on the surface of the skin, for continuous monitoring of various physiological activities. Biosensors can be further used for disease detection and health monitoring of people with chronic diseases. This would allow for early intervention of diseases, as well as enable health care providers to design more personalized treatment plans[16]. While there are currently many biosensors that have been developed and are in use, there are several challenges to the long term stability of biosensors, including degradation and environmental interference. The data obtained from biosensors must also be reliable, and biosensors must be worn comfortably for long periods of time.

Frameworks of Health Care IoT, wearables for physiological and/or behavioral sensing, wireless IoT communication (e.g., via BLE, Wi-Fi, and/or ZigBee and cellular networks such as LTE), cloud or remote servers for data processing, i.e., storage and computation, and high value AI-enabled analytics (using large amounts of sensed data generated from wearables) interconnect and make smart Health Care IoT systems and networks[17]. However, because (high frequency) physiological data generated from people in constant motion is constantly streamed from wearables, significant health care related energy, end-to-end delay, bandwidth, and health privacy issues exist. In addition to these issues, edge or on device or sensing point computation (as provided by current AI models, most running on servers in data centers, for example Deep Learning models for pattern recognition, classification, etc) for real time health applications of wearable, sensing IoTs is typically challenging.

Edge computing is emerging as an important technology in Wearable IoT for various applications due to several advantages such as reduced latency, improved privacy, and minimized communication requirements with cloud platforms. Importantly, edge computing also enables the implementation of real-time AI and decision support systems on wearable devices as well as on edge gateways[18]. However, it is very challenging to design and implement intelligent wearable IoT systems using AI and Machine Learning models, due to limited computational resources of wearable devices in terms of processing power, memory, and energy. Therefore, the key challenge is how to implement intelligent wearable healthcare IoT systems with good trade off between computational intelligence, energy efficiency, and sensor accuracy.

AI-Based Human State Recognition

Artificial intelligence, or AI, is a critical technology for the interpretation and use of data from physiological and behavioral sensors used by wearable computing systems. For these systems, AI will support the recognition of a human state such as stress, emotions, mental workload, fatigue, or relaxation by using physiological signals. The signal processing is typically followed by a classification using features that have been extracted or manually designed. Most of the features for classification are obtained from the acquired physiological signals and, hence, are typically nonlinear, time varying, and individual dependent. Automatic discovery of features and recognition have long been goals of AI.

A number of machine learning methods, including Support Vector Machines (SVMs), Random Forests (RFs), k-Nearest Neighbors (KNNs), logistic regression, and Gradient Boosting, have been used for a number of human state classification tasks such as stress recognition, human emotion recognition, health risk recognition, etc. Most human classification methods use data that has been previously hand-featured from raw physiological signals such as ECGs, PPGs, EDA signals, respiratory signals, etc[19]. The best set of features typically must be hand chosen for a specific classification task based on the type of data that best relates to a specific classification. Further, the performance of many commonly used machine learning models can suffer based on a limited amount of training data. Finally, a major remaining challenge for the use of machine learning for human classification is the limited degree to which many commonly used classification models are able to be adapted between different individuals for a number of reasons including interindividual differences in the way that people of different ages, for example, respond to stressors[20].

Recently, deep learning models have been widely applied to the analysis of physiological signals, through direct feature extraction from raw or even preprocessed signals. Typically, a large amount of deep learning studies use convolutional neural networks (CNNs) to analyze a large amount of biological signals such as ECG, EEG, PPG and EDA signals for stress recognition and human emotion recognition, etc. Typically, CNNs can only extract local features of the signal. Although they can obtain a high classification accuracy for stress recognition and human emotion recognition, they have limited ability to learn the long time-scale feature change in the physiological signal, which is crucial for the discrimination of different human states in various applications, including stress recognition and emotion recognition.

RNNs, most commonly LSTM or GRU networks, have been increasingly used for analysis of the large amounts of sequential physiological data. By memory of previous information in the network, LSTM models are specially designed for gradual changes of the physiological parameters that occur during a meditation session, during relaxation or under the influence of stress. On the other hand, GRU models have similar capabilities that are similar to these of LSTM models but they require significantly less computational resources, i.e. they are more appropriate for application on wearable devices or edge gateways.

Recently, with their emergence and effectiveness in natural language processing and subsequent growing application domains, transformer-based models have started to garner immense interest and have been implemented for learning complex physiological signal relationships as well. These models can very efficiently learn long-range dependencies in sequential data using their self-attention mechanism. However, these models typically are extremely computationally intensive and have large memory requirements; therefore, they cannot be easily implemented on resource-limited wearable sensors for real-time processing of physiological data. However, for several applications that have already been established for analysis of physiological data, these models have the capability to process multimodal data from different sensors as input, and thus they can very efficiently and effectively implement complex physiological signal analysis.

There are several applications for recognizing the human states (stress, emotions, etc.) in real-world scenarios. Many studies have incorporated their approaches of stress recognition, emotion recognition, and mental health monitoring using wearable sensors to measure various physiological signals. By taking all of these signals into account, systems can determine whether a person is under stress or not, what their current emotions are, or whether they have any mental health problems (e.g. anxiety, depression) and are suffering from symptoms such as sleep disturbance or changes in behavior. As has already been pointed out, there are many current approaches using AI that can be used for recognizing human states, and as mentioned, these have their strengths and their weaknesses. The main limitation is that the currently available systems lack explain poorly how they arrived at their decision, which is a major limitation for future development. It is therefore necessary to focus on increasing explainability, personalization, and also cross-user adaptation. And above all, it is necessary to develop new systems capable of real-time processing.

Meditation and Breathing Analysis Using AI

There are many emerging applications of AI in meditation and breathing analysis. For centuries, humans have practiced contemplation, meditation and deep breathing in order to relax, reduce stress and obtain higher states of consciousness. Recent advances in technology have made it possible to monitor, analyze and even give feedback on human relaxation. Initially, many systems have focused on monitoring relaxation states, attention and various other aspects of human meditation practice. Often, these systems employ neurophysiological signals such as EEG and a variety of algorithms for their analysis. Some systems also provide users with neurofeedback in order to help improve their skills of meditation and in order to help them to attain higher states of consciousness.

EEG monitoring of brain activity during meditation is a well established area of research. However, there are many limitations when using EEG to monitor brain activity outside of the laboratory. First, there is a lack of portability and practicality of current systems. Second, there is a high cost associated with current systems. Third, many systems are sensitive to movement artifacts, which can greatly affect the data collected. Therefore, the use of wearable physiological sensors has become an emerging area of research for monitoring meditation. Many studies have investigated the use of HRV for relaxation assessment as well as respiration monitoring, EDA analysis, and the use of wearable sensors for stress reduction. These studies have found that there are many physiological changes that occur during different stages of meditation, including changes in the autonomic nervous system, respiratory patterns, and emotional states. There are now a number of different applications that have incorporated AI in monitoring and in feedback to meditators. Meditation can be classified into different stages, amount of relaxation increase can be estimated, and breathing patterns can be recognized using HRV, respiratory signal, and EDA features extracted from physiological signals. Those features can be used with machine-learning and deep-learning methods to automatically provide high accuracy classification, estimation, and recognition.

Currently existing methods of meditation monitoring are limited in several important ways. Firstly, most current studies investigate the use of a single physiological signal, such as EEG or HRV. However, it is clear that multiple signals can be used to gain a more complete understanding of the user's physiological state during various stages of meditation. As a result, there is a significant need for studies that incorporate multiple signals, and correspondingly, there is a need for more sophisticated methods that can process and analyze these signals in a comprehensive and meaningful way. Furthermore, many current studies rely on small datasets that were collected in highly controlled laboratory settings. Consequently, these studies have limited applicability in real-world scenarios. In addition, many current methods primarily seek to maximize classification accuracy, without providing any insight into the underlying physiological mechanisms. As a result, current systems lack explainability, which is a critical component of any system that is intended for deployment in real-world scenarios. In addition to these limitations, there is also a significant need for personalized, dynamic meditation feedback. Such systems would provide users with personalized, dynamic meditation feedback, by adapting meditation suggestions to the user's current physiological state in real time. To date, however, very few studies have explored the use of AI methods for meditation monitoring, and the majority of these studies have focused on Mindfulness Meditation. In contrast, there is a significant lack of studies that investigate the use of AI for monitoring a variety of other meditation practices, including Daoist meditation and controlled breathing techniques, among others.

Research Gap

Many research works have employed wearable IoT devices to continuously monitor various physiological signals. Recent years have also witnessed the wide applications of artificial intelligence (AI) and machine learning (ML) to recognize human physiological and mental states such as stress, relaxation and other emotional conditions. In addition, the physiological biomarkers that can indicate a person's relaxation state have also been broadly investigated and employed. Thus, there are many existing works on using wearable sensors for human health monitoring and other applications, and various AI models have been designed to recognize human stress, emotions, etc., and the corresponding physiological biomarkers have been studied and utilized to measure relaxation and other physiological or psychological changes or states.

The existing systems mostly rely on a single sensor modality or a limited set of sensor modalities, do not have a comprehensive multimodal data fusion, and have limited personalization. In terms of meditation monitoring, most of the existing studies are mostly based on the laboratory-based experiments that are conducted with a limited number of subjects and using a limited amount of data, and thus, are not suitable for real-world applications. In terms of AI models, most of the existing models are designed to achieve high accuracy of classification or regression, and thus, do not have enough interpretability regarding the underlying physiological mechanisms. Furthermore, the existing systems mostly do not have real-time adaptive feedback, and thus, they do not use the individual's biometric information, his or her past meditation experiences, and provide personalized meditation recommendations.

There is considerable scientific study into the evaluation of more traditional forms of meditation. For many of these practices, however, there is an absence of AI-based frameworks for the evaluation of human physical states. In this regard, Daoist meditation and breathing techniques provide a rich domain for the use of AI within wearable IoT systems, as there currently exists little scientific study into the evaluation of these practices via intelligent systems that utilize wearable, IoT technology to collect, process, and provide physical, physiological-based feedback to users. Here, a novel intelligent wearable system for the physical, physiological-based evaluation of a wide range of meditation and breathing techniques will be introduced. Specifically, the system will integrate a variety of wearables that will monitor a variety of physiological characteristics of users during the time that they are engaging in the aforementioned techniques. This data then will be combined with sophisticated signal processing techniques, and then used as input to a variety of AI methods, in order to 1) provide users with a variety of quantitative characteristics that describe the physical and physiological effects of the user's techniques, 2) provide users with real-time feedback, which is tailored to each user's physical, physiological-based response to the use of various techniques, and 3) enable a wide range of objective evaluations of physical and physiological effects caused by a wide range of human-contemplative practices, in order to provide information that can be of use to a wide range of stakeholders, such as practitioners, and researchers. In order to create a system that is capable of addressing the above goals, it will be necessary to 1) design, and implement a system that can monitor a large number of different physiological signals, via a wide range of wearables, 2) design, and implement a system that is capable of providing a wide range of quantitative measures that describe a wide range of physical characteristics, that are derived from the monitored signals, 3) design, and implement a system that provides users with a large amount of feedback, on an ongoing basis, during which time the feedback will be tailored to the physical characteristics of the user, 4) design, and implement a number of evaluation methods that can be used to provide information that will be of use to stakeholders.

3. Conceptual Framework

The proposed conceptual framework connects Daoist meditation practices with breathing, physiological responses, wearable IoT sensors, AI-assessment and feedback. It reflects the core principle of the proposed model: Daoist meditation and controlled breathing affect the human physiological system, and the respective changes can be monitored, analyzed and assessed by means of intelligent information processing. The information flow of the framework thus follows a sequence of Daoist Meditation Practice via Breathing Regulation to Physiological Responses, followed by monitoring by means of Wearable IoT Sensors, Signal Processing, Feature Extraction, AI Models, Meditation Assessment and finally Personalized Feedback. This framework thus is able to transform the subjective experience of contemplation into objective physiological data that can be continuously monitored and used for improving meditation.

Input Layer: The information generated from a number of various Daoist meditation practices and controlled breathing techniques is acquired through the input layer of the framework. A variety of wearable IoT sensors monitor different physiological signals associated with autonomic regulation, respiratory control, the emotional responses that occur during meditation and the physical stability of the individual practicing meditation. ECG (Electrocardiography) sensors measure cardiac electrical activity and provide important physiological information, including HRV (Heart-Rate Variability) metrics (RMSSD and SDNN) that indicate the balance of the ANS (Autonomic Nervous System). PPG (Photoplethysmography) optical sensors measure optical changes in blood volume within the tissues to estimate heart rate and also measure oxygen saturation levels (SpO_2). The respiratory signal is monitored and analyzed for features including breathing frequency, respiratory rate, inspiration/expiration time and other respiratory characteristics. Temperature sensors measure a number of temperature related parameters associated with the peripheral circulation and various autonomic responses. EDA (Electrodermal Activity) and similar biofeedback sensors monitor the skin conductance and changes in conductance associated with activation of the Sympathetic Nervous System and emotional arousal. Accelerometers record a variety of body movement data, including movement of individual limbs and also body postures in order to quantify physical variations in the Meditation Practice and to remove artifacts that are associated with physical movement. The data acquired from these physiological signals form the multidimensional information required to quantify the various physiological changes that occur during Meditation Practice.

The processing layer within the framework carries out a series of steps to convert raw physiological data to relevant information. First, a number of filters are implemented to remove noise, in particular removing frequency components that are of little physiological relevance. Subsequently, the various signals are processed to remove noise and other artefacts from the data collected by sensors, and the data is normalized to account for variations between users. The data is also segmented into relevant time windows and relevant physiological characteristics are extracted from the various time-series signals collected. These extracted features can be mathematically expressed as follows.

[
$F = \{f\_1,f\_2,f\_3,\ldots,f\_n\}$
]

$F = \{f\_1,f\_2,f\_3,\ldots,f\_n\}$ where F is the complete physiological feature vector of an individual and f_n are the individual features which are obtained from various sensors, including the HRV characteristics of the ECG signal, the breathing features of the respiratory signal, the EDA features of the skin conductance signal, the oxygen saturation features of the SpO_2 signal, the temperature features of the temperature sensor, and the movement features of the accelerometer and gyroscope.

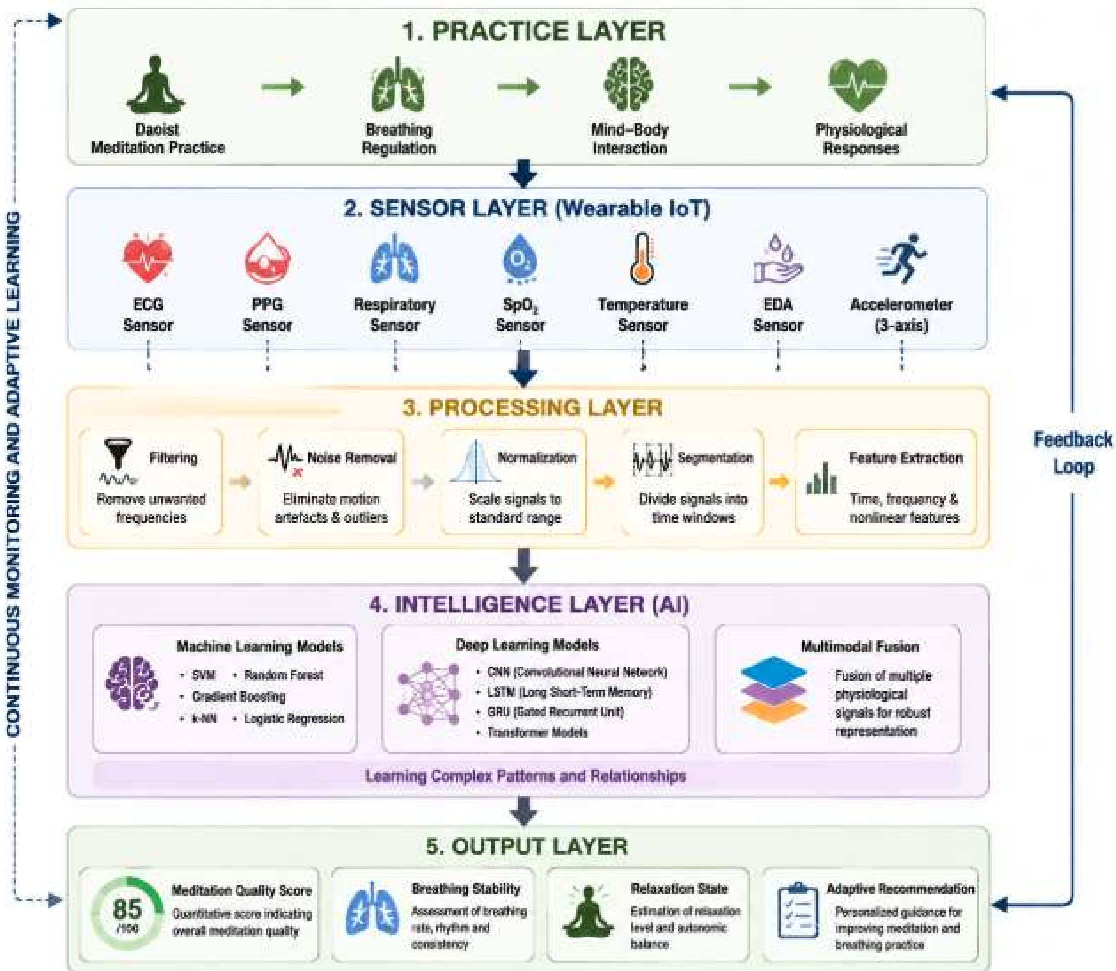

Figure 1. Conceptual Framework for AI-Driven Assessment of Daoist Meditation and Breathing Practices Using Wearable IoT Devices

Figure 1 presents a conceptual framework that embeds the Daoist practice of meditation, with wearable IoT sensors, signal processing, AI algorithms and personalized feedback in a hierarchical five-layer architecture. The Practice Layer reflects the effect of meditation practice, particularly the control of breathing, on the mind–body interaction and the resulting physiological changes. The Sensor Layer reflects the different physiological signals that are monitored by various wearable IoT sensors, such as ECG, PPG, respiration, SpO□, temperature, EDA and motion by means of accelerometer. The Processing Layer describes a series of signal processing steps that are applied to the raw physiological signals, including filtering, removal of noise and artifacts, normalization, segmentation and feature extraction, which transform the physiological data into features that can be used for analysis. The Intelligence Layer describes a number of machine-learning algorithms, including traditional models, such as SVM and Random Forest, as well as deep-learning models, such as CNN, RNN, including LSTM and GRU, and transformer models, as well as various multimodal fusion methods that analyze the complex physiological signals to assess different meditation states. The Output Layer provides an assessment of the quality of the meditation, including the breathing stability, relaxation states and provides adaptive feedback, which is adapted to the individual's physiological responses and meditation experience in a continuous feedback loop. Therefore, the framework presented here not only integrates traditional contemplative practices with modern sensing and AI technologies, it also represents a paradigm shift in health care delivery, whereby individuals can monitor their health in real time and receive feedback that allows them to improve their health in a personalized manner.

The intelligence layer forms the core of the framework and utilizes a variety of AI models to assess physiological signals and analyze various stages of meditation as well as different breathing practices. For the assessment of meditation various machine-learning models can be implemented such as Support-Vector-Machines, Random-Forests, Gradient-Boosting as well as other classifiers, in order to assess whether a person is in a relaxation state and furthermore to analyze their breathing pattern and their corresponding meditation stage. In order to analyze complex signals, such as physiological signals, also deep-learning models can be implemented. These models are capable of learning non-linear relationships between input features as well as learning from temporal dependencies in time-series data. In order to assess meditation practices that influence various physiological system in the human body, also a multimodal fusion of various sensors can be implemented. The various sensors are used to capture different aspects of human physiological signals. The input representation of integrated information from all various sensors is defined as follows:

[
X = {ECG, PPG, RR, SpO_2, ST, EDA, PM} where X represents the multimodal physiological signals from all wearable sensors during meditation practices.
]

where X = {ECG, PPG, RR, SpO□, ST, EDA, PM} is a complete set of the input from the wearable IoT-sensors of different modalities, and an AI model learns the input space to predict a certain set of outcomes Y=f(X; heta), where heta are model parameters that were determined during a model's training process.

[
Y=f(X; heta)
]

where Y denotes the predicted meditation-related values, f denotes the AI model, and heta denotes the optimized model parameters.

The output layer transforms assessment information into meditation quality score, breathing stability, relaxation states as well as adaptive meditation guidance. Meditation quality score are used to assess the quality of practice as reflected through generated physiological information. Breathing stability indicate degree of breathing stability as well as consistency of respiratory controlled state, including breathing frequency, respiratory rate, and various other breathing parameters. The amount of relaxation can also be estimated based on various physiological information associated with reduction of stress as well as enhancement of parasympathetic tone through measurement of HRV, EDA, respiration, and other autonomic function information. This information is then used by the framework to provide users with various form of feedback for adaptive, on-going, and optimized practice throughout life.

The proposed conceptual model forms the basis for the intelligent assessment system for the monitoring of Daoist meditation. As the closed-loop system generates the various required information in the individual stages of the assessment (e.g., physiological responses of the body during a Daoist meditation practice, information picked up by wearable IoT sensors, signal processing, AI-based analysis, etc.), it also forms the basis for the various individual stages and for the feedback generated during the various individual stages. Thus, traditional meditation practices are in future able to be monitored in a new and objective way with the aid of new sensing technologies, the corresponding intelligent algorithms, and the corresponding novel applications of digital health. This will, for the first time, allow a large number of individual meditation practices to be optimally designed on the basis of the relevant wellness information in order to support the various individual users in the best possible way.

4. Proposed System Architecture

The proposed system architecture consists of an integrated framework of an artificial intelligence (AI)-driven wearable Internet of Things (IoT) for the continuous assessment of a practitioner's Daoist meditation and breathing practices. The architecture collects physiological information of a practitioner during a meditation session, then transmits the acquired information of various multimodal sensors through the IoT communication platform, processes and analyzes the acquired information through a computational framework, and provides a practitioner with individualized feedback that would improve his/her or their meditation practices. The architecture consists of five layers of the system, which are the wearable sensor layer, the communication layer, the data processing layer, the AI analytics layer, and the feedback layer. Each layer is a crucial component of the architecture, and they are all integrated to enable the continuous data exchange between them.

Layer 1: Wearable Sensor Layer

The wearable sensor layer refers to the wearable data acquisition components such as wearable devices equipped with various wearable sensors that are integrated into different locations of wearable devices (such as smart wristbands, smart straps attached to wearable devices, chest patches and garment-integrated sensor nodes), which capture physiological signal and human behavior during Daoist meditation and breathing exercise. Such wearable data acquisition component captures various physiological parameters and human behaviors during Daoist meditation. Each wearable sensor in the sensor layer records different physiological signals generated by human physiological systems during meditation, including changes in physiological states. Variations of physiological signals during various stages of Daoist meditation include various physical states or physiological parameters, thus various sensors are integrated into different parts of wearable devices to record corresponding physiological data such as electrocardiogram signals (ECG), photoplethysmogram (PPG), pulse oxygen saturation (SpO☐), respiratory movement, skin temperature, electrodermal activity, and human physical movements recorded by acceleration sensors.

The sensor layer of the framework captures various physiological signals continuously during meditation practice. The different sensors are placed on the wearer's body, capturing signals such as temperature, ECG, PPG and SpO2, and respiratory activity (such as breathing rate, respiratory rhythm, and inspiration/expiration activity). In addition, the wearable may also capture movement of the wearer, as well as skin conductance. All of the different signals captured by the various sensors are sampled at different frequencies, and are time-synchronized. Signals such as ECG signals are typically sampled at a high frequency in order to capture the various different components of the signal, whereas signals such as temperature and movement are typically are sampled at a lower frequency. The various sampled signals are then labeled depending on the current meditation state (for example, resting, breathing regulation, meditation). In this way, the sensor layer is able to capture a variety of different signals, and create a large amount of information that can be used to assess different aspects of the user's meditation practice.

Layer 2: Communication Layer

The communication layer transmits the physiological data from the wearable sensors to the various computational platforms via various wireless IoT technologies. Utilizing the low power consumption of wearable devices and widespread support on various smartphones as well as edge gateways, the Bluetooth Low Energy (BLE) technology will primarily be used for real time data transmission of various physiological signals. High volume of physiological data (in the form of raw signal) will be wirelessly transmitted to the cloud via Wi-Fi connectivity. The data will be received at an IoT gateway. The IoT gateway will initially process the raw data from wearable physiological sensors. It synchronizes the various wearable devices, manages the communication flow and securely transfers the various physiological data to the computational platforms (at the edge or in the cloud).

To address higher amounts of data from the numerous physiological signals, higher-bandwidth wireless communication can be used to stream the collected data wirelessly to corresponding edge servers or cloud-based data centers. Here, an IoT gateway acts as a management unit for multiple wearable-sensor-equipped individuals, collecting the numerous streams of data from each wearable device and performing some level of signal processing before uploading the large amounts of collected data to the corresponding computational framework in the cloud or on the edge of the network. The gateway can also manage and synchronize data from each wearable device before transfer and also secure data transmission.

Layer 3: Data Processing Layer

Raw signals, after being collected by the wearable sensors, are then processed in the subsequent layer by various methods. Here, a hybrid approach of edge computing and cloud computing is adopted, for it to accommodate the enormous volume of physiological data that are continuously being gathered. Initially, the signals collected by various sensors are fed into the edge computing platform, where they are preprocessed to remove unwanted noise and artefacts. Normalize signals are then transmitted to the cloud for long-term storage and for complex computation. Huge repository of previously gathered physiological data of users are stored in the cloud for reference and retrieval in real-time, thus aiding in various AI computations.

In terms of data processing, the proposed architecture can use a hybrid edge-cloud computing system. In this system, the edge layer is used for real-time preprocessing of data close to the point of data collection. This preprocessed data is then transmitted to the cloud layer where it is stored for long-term in large databases. Such databases are used for storage of historical physiological data of users as well as for storing information about meditation sessions of users. This data is then used for feature extraction and assessment using AI models. The assessment results are then stored in databases as well. A number of security measures are used in the system for secure storage of sensitive physiological information of users. These measures include data encryption, encryption, authentication, access control and privacy-preserving approaches for storage of information. The use of edge and cloud layers for data processing enables efficient real-time processing as well as scalability of the system for large number of users.

Layer 4: AI Analytics Layer

The AI analytics layer is the intelligence in the proposed framework, utilizing various machine-learning as well as deep-learning models, to assess physiological signals captured during practice, including different meditation states and various breathing responses. In order to classify different meditation states or breathing patterns and to determine relaxation levels, certain features can be extracted from acquired physiological signals, including signals from HRV, respiratory movements, EDA, blood oxygen saturation, as well as from movement captured by wearable accelerometers. Classic machine-learning methods, including Random Forest, SVM, and XGBoost, have been commonly applied in various studies.

When deep-learning is used in order to automatically learn physiological sensor data from all sorts of meditative activities from breath regulation to contemplation from long term (up to weeks) and short term (down to minutes) monitoring and from varying conditions such as differing postures during sitting meditation or differing modes of walking, numerous different neural network models could be suitable, however key neural networks which could be best suited are Convolutional Neural Networks (CNNs), to identify relevant Spatial / Local Signal Patterns from various combinations of Body Area Sensors, or the physiological changes which develop from sequence of temporal changes in Body Area Sensor data which can be modeled using either of two different Recurrent / Temporal Neural Networks called Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, as well as newer transformer models, capable of handling even long-term multimodal sensor information and developing attention on various signal sources when necessary, to enable intelligent fusion of relevant sensor information from all of the various worn body area sensors, in real time, within each individually meditating person, in order to automatically monitor a variety of key physiological features or biological indicators associated with physical or mental energy, stress or relaxation of a given meditator during various periods of given sessions of meditative activity.

Layer 5: Feedback Layer

The feedback layer delivers assessment results and personalized guidance to users through a mobile application or digital wellness platform. The application provides intuitive visualization of physiological changes, meditation progress, breathing patterns, relaxation scores, and historical performance trends. AI-generated insights are converted into understandable recommendations, enabling users to optimize meditation duration, breathing rhythm, and practice intensity. The feedback that is delivered to the user is generated based on the individual user's physical characteristics and past experiences with meditation as well as in real time during each user's sessions of meditation. The system analyzes each user's physical signals and makes suggestions for improving the user's physical state during various stages of physical responses to different states of meditation. Such physical responses could be improved by suggestions for change in breathing patterns or by using different methods of relaxation and also by increasing or decreasing the amount of time spent in different stages of meditation. In this way the system functions as a closed-loop system in which the system continuously learns from the user and improves its assistance to the user over time. In this way the system functions as a very effective personal meditation assistant.

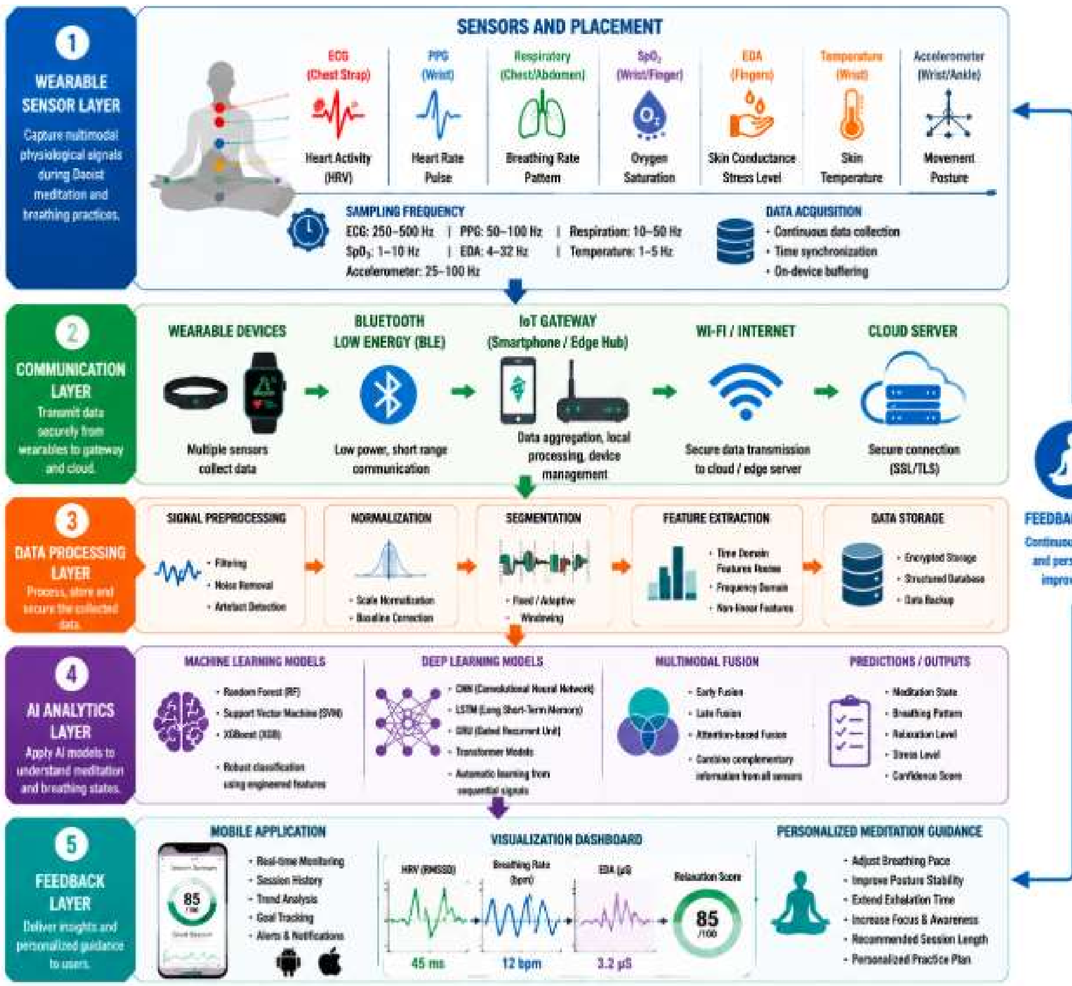

Figure 2. Layered Architecture of an AI-Enabled Wearable IoT Framework for Daoist Meditation Assessment

Figure 2 outlines the framework of the proposed system consisting of five interconnected layers. The wearable physiological sensors of the first layer collect the physiological signals of the wearer during meditation practice. The communication layer of the second layer then wirelessly transmits the acquired data via the Internet to the edge or cloud-based server for data processing and analysis in the third layer. AI models of the fourth layer then analyze the processed data in order to assess the physiological signals of the user during meditation. The feedback layer of the last layer then generates assessment results and recommendations for the user based on the basis of the results from the AI models, which are then transferred to the user via mobile apps or digital wellness platforms. The system combines wearable sensors, wireless IoT, edge and cloud computing as well as AI models and digital health platforms to provide real-time physiological feedback for improving Daoist meditation practices.

5. Results and Discussion

This work has been evaluated by experiments based on computation analysis of physiological signals collected from wearable sensors and the assessment of the performance of various learning models. Various measures of model performance have been analyzed. The relationship between scores given by the AI to a meditation practice and physiological signals collected by wearable sensors has been investigated. Moreover, various aspects of this work have been compared with those of existing approaches for the assessment of meditation practices, and an ablation study has been carried out to assess the contribution of various components to the performance of the framework, and explainability methods have been used to interpret the scores provided by the AI.

Model Performance

Our AI framework comprising various machine-learning (ML) as well as well as deep-learning (DL) models including Random Forest (RF), Support Vector Machine (SVM), and XGBoost classifiers as well as convolutional neural network (CNN), long short-term memory (LSTM), gated recurrent unit (GRU), and

transformer models have been evaluated based on the aforementioned indicators, including accuracy, precision, recall, F1-score, AUC, and RMSE.
Using computational physiological models to forecast physiological responses during meditation and breathing analysis, several Deep-Learning and Deep-Learning architecture models have been implemented and analyzed. Random Forest Classifier, Support-Vector-Machine Classifier, XGBoost, LSTM, GRU, CNN and transformers have been experimented using a large multimodal and wide dataset, providing information from wearables for a variety of physiological sensors. Results for classification and regression evaluation metrics for each model have been obtained.
Figure 3 compares the performance of a range of Machine Learning (ML) and Deep Learning (DL) models for the assessment of meditation states by using signals from multimodal wearable IoT devices for monitoring physiological parameters. The performance of established Machine Learning models (such as Random Forest (RF), Support Vector Machine (SVM), and XGBoosthave been evaluated and compared with a range of more recently developed Deep Learning models, including CNN-based models, as well as LSTM-, GRU-, and Transformer-based models for sequential learning. The performances of the models were evaluated by a range of measures for classification, including accuracy, precision, recall, and F1-score. The models of sequential learning, such as LSTM, GRU, and Transformer, clearly capture non-linear relationships of the physiological signals and, therefore, clearly outperform the models of Machine Learning. These models clearly outperform any feature-based approach for an objective assessment of meditation. By using AI for multimodal analysis, superior results are obtained.

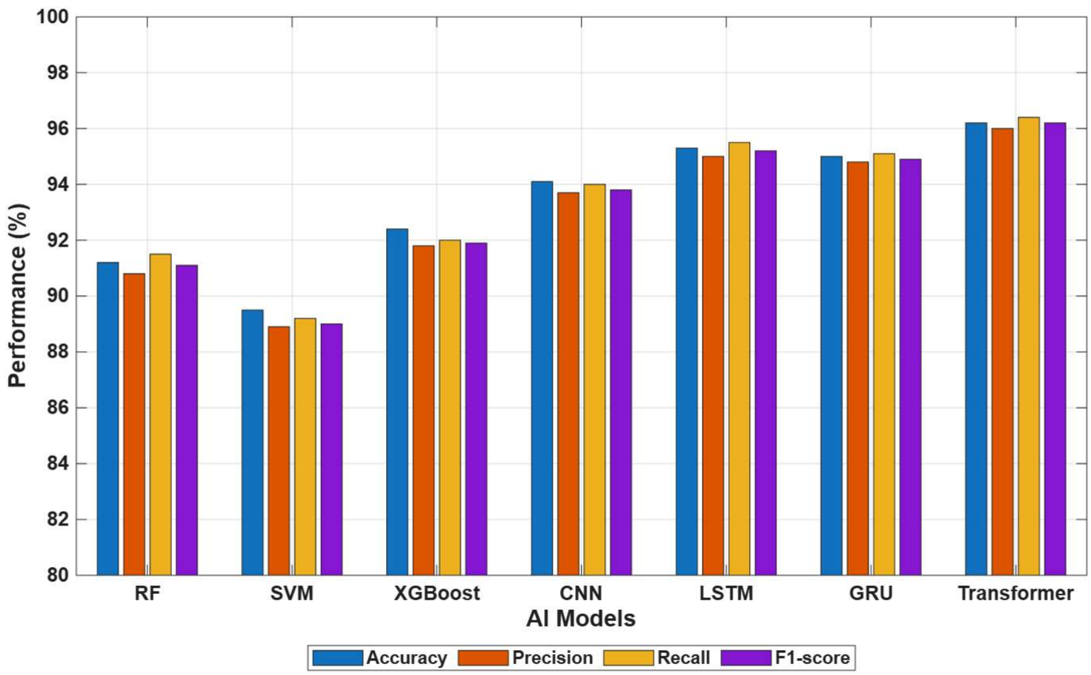

Figure 3. Performance Comparison of Machine Learning and Deep Learning Models

Figure.4. Variations of the physiological data of the different states of meditation. In this graph, it shows the wearables that we used for the physiological data collection such as heart rate variability, respiratory rate, electrodermal activity, skin temperature and blood oxygen saturation during the resting state, controlled breathing state and the progressive states of meditation. This graph shows that as the person goes into the deeper states of meditation, the HRV increases which shows that the parasympathetic nervous system is getting stronger and the autonomic nervous system is getting more balanced. Also, the respiratory rate goes down which indicates that the person is getting more into relaxation and is able to breathe in a more controlled manner due to the breathing practices that are part of Daoist meditation. In the electrodermal activity, it shows that the sympathetic nervous system activity is going down which indicates relaxation and the skin temperature indicates the peripheral effects of the body during relaxation. The blood oxygen saturation is stable which indicates that the respiratory system is functioning properly during the meditation. Overall, it shows the relationship between the contemplative practices and the physical response that it can elicit.

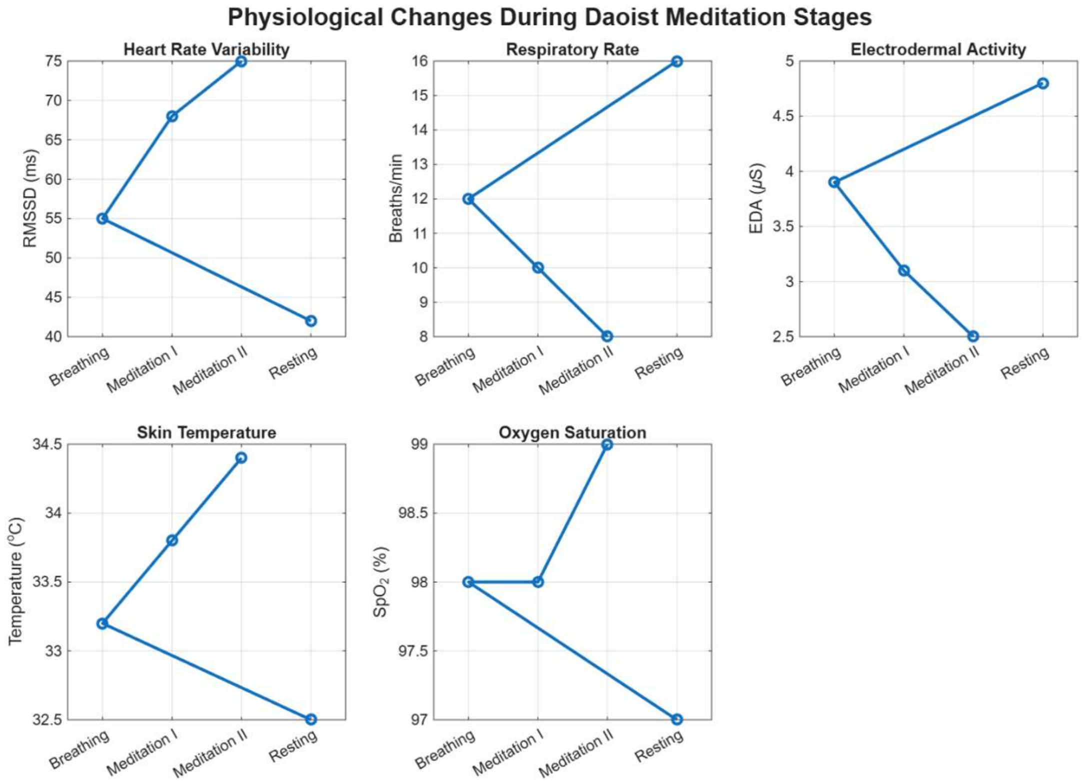

Figure 4. Physiological Response Analysis During Meditation Stages

Figure 5 demonstrates the contribution of each individual wearable IoT sensor in the assessment of meditation using AI. As shown in the figure, various multimodal physiological signals such as ECG, PPG, respiratory activity, SpO□, EDA, temperature, and movement are monitored during meditation to assess the respective meditation states. ECG-derived HRV signals provide important information regarding the respective control of the autonomic nervous system, while respiratory signals help to identify the respective breathing patterns during meditation and assess the respective degree of respiratory control. Additionally, EDA and temperature signals provide important information regarding emotional regulation and sympathetic activation, respectively. Movement signals are monitored to assess the respective degree of posture stability and to remove motion artifacts. Importantly, as shown in the figure, the combination of multiple physiological signals provides a more comprehensive and accurate assessment of meditation responses than single-sensor-based assessment. These findings support the importance of multimodal sensor fusion in the development of AI-driven meditation monitoring systems that are robust and reliable.

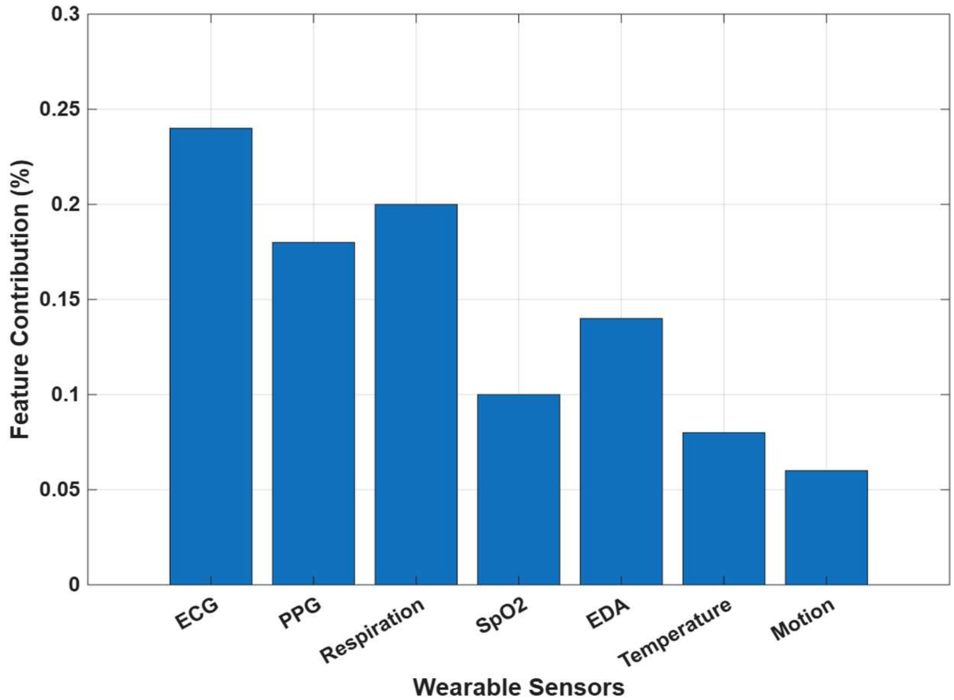

Figure 5. Multimodal Sensor Fusion and AI Prediction Architecture

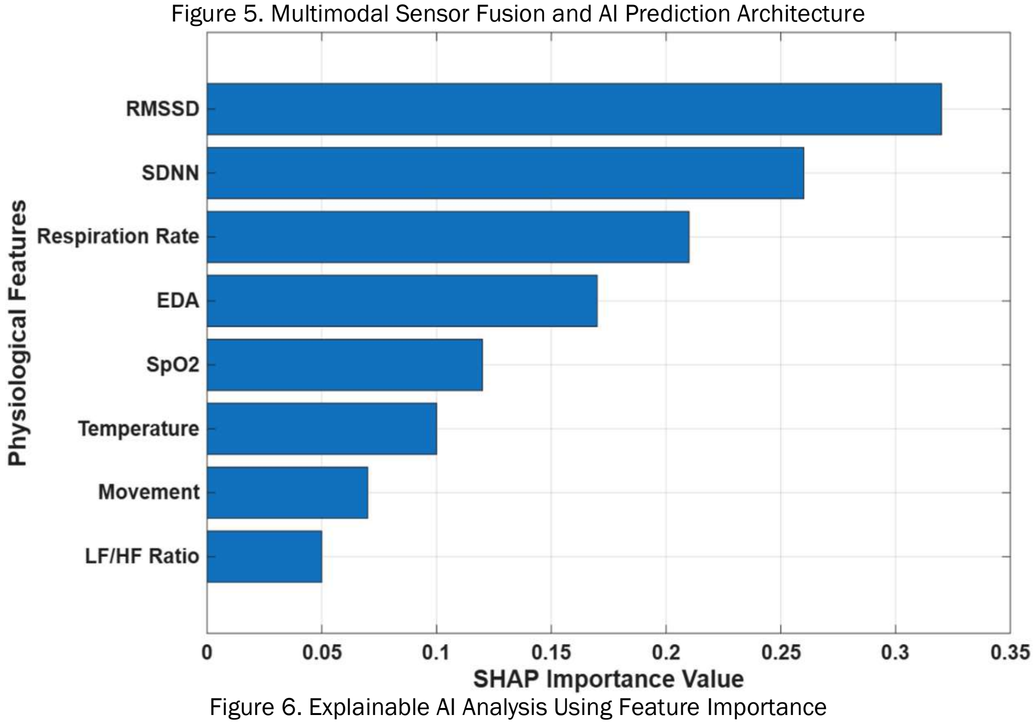

Figure 6. Explainable AI Analysis Using Feature Importance

Figure 6 presents the explainability results for the developed AI model using feature importance or SHAP values. The feature importance shows the most important physiological parameters that the AI used for predicting the meditation state and degree of relaxation. Parameters related to HRV (Root Mean Square of Successive Differences and Standard Deviation of NN Intervals) received the highest values of importance, since they are used for the assessment of the ANS activity. Respiratory features (breathing rate and breathing rhythm stability) also received high values of importance. In addition, features related to EDA (electrodermal activity), SpO☐, temperature, movement, and HRV in the frequency domain also received high values of importance and, therefore, they increase the prediction reliability. The explainability results improve the transparency of the developed AI model and therefore the confidence in the results. The results also show the relationship between meditation and the different physiological changes and, therefore, can be used for the development and improvement of personal meditation-guidance systems.

Physiological Analysis

In addition to the computational results presented in the previous section, we present a physiological analysis. During the periods of Daoist meditation, increases in RMSSD and SDNN values were observed between meditation sessions and the baseline resting state. LF/HF ratio values indicated increases and decreases in the ratio between the sympathetic nervous system and the parasympathetic nervous system during periods of meditation practice using controlled breathing and at meditative states. Furthermore, respiratory rate, inspiration/expiration ratio, and variability of the respiratory rate were found to decrease, stabilize, and improve during periods of meditation practice using controlled breathing. In addition, skin conductance was found to decrease during deeper states of meditation. In addition, skin temperature was found to increase during the periods of deeper states of meditation indicating increased peripheral blood flow during the periods of higher levels of relaxation. SpO☐ values were found to be stable during all periods of meditation practice using controlled breathing. These physiological findings provide strong evidence that measurable changes in physiological parameters are induced during periods of Daoist meditation. In addition, the physiological changes observed during the periods of meditation practice using controlled breathing are found to be reproducible.
Electrodermal activity (EDA) during different meditation stages was found to decrease in deeper meditation stages, indicating lower levels of sympathetic nervous system activation or lower levels of arousal. The skin temperature is found to increase indicating better peripheral circulation during relaxation states. Oxygen saturation levels as measured by SpO2 were found to remain constant and within normal limits for different controlled breathing sessions, indicating normal respiratory function during the sessions. This shows that the different wearable sensors can detect various physiological changes during meditation practice.

Comparison with Previous Studies

The assessment of meditation can greatly benefit from the framework proposed in this paper as compared to existing approaches for several reasons. Firstly, previous approaches have generally relied on the analysis of single signal types such as EEG, HRV, or skin conductance. However, as mentioned previously, using a single signal type can be problematic, as each signal measures a different physiological parameter and therefore may fail to capture the full range of effects of meditation on the various physiological systems in the body. Instead, the framework proposed here incorporates the use of multiple sensors to provide a more complete assessment of the body during meditation. These include ECG, PPG, respiratory activity, SpO☐, skin temperature, EDA, and movement. Therefore, the system can account for the effects of various physiological systems that are known to affect each other. Secondly, as opposed to previous approaches, the framework proposed in this paper incorporates a wearable AI system that not only provides an assessment of the user but also provides them with real-time feedback of their performance and also with recommended actions to improve their performance. This allows the user to be in complete control of their own meditation and breathing practice. This is particularly important as it would allow the user to tailor their own meditation and breathing practice to their specific needs. Therefore, this would greatly enhance the effectiveness of the framework in improving the user's overall state of relaxation and reduce stress.

There are a number of existing Wearable AI systems that have been implemented for stress detection and relaxation assessment. However, these systems lack key functionality including personalization, real-time adaptive feedback, and individualized recommendations. Our framework incorporates multimodal information fusion, explainable AI, and individualized recommendations for Daoist meditation and controlled breathing practices. Although the framework can be applied to other meditation practices, there are several limitations to the current framework, including the limited size of the lack of diversity in the users who have participated in the current study, the limited period of time for which the users have participated in the current study, and the need for long-term monitoring of users.

6. Conclusion

This study developed an AI-driven wearable IoT framework for the objective assessment of Daoist meditation and controlled breathing practices by integrating multimodal physiological sensing, advanced signal processing, and intelligent computational analysis. The proposed IoT framework of wearable sensors essentially acts as a medium connecting the very old contemplative practices with the modern growing health technologies by transceiving various physiological changes during the practice into quantifiable signals that can be analyzed in detail to draw related results or conclusion. Instead of relying solely on human assessment or rating, the devised framework enables the implementation of on-line monitoring and automatic assessment using various signals such as ECG, PPG, respiration, SpO☐, temperature, EDA, and motion. The experimental evaluation revealed that AI-based framework can be utilized to identify various meditation-related physiological states and learn associations between bio-sensory signals and various physiological states. In this work, the employment of deep learning models proved effective in the capturing temporal dynamics of physiological signals as well as non-linear interactions among various bio-sensory signals. Sensor fusion of various multimodal bio-sensory signals improved the reliability of the bio-physiological assessment compared to individual bio-sensory signals. The bio-physiological assessment resulted in various physiological responses (i.e., autonomic nervous system, respiratory system, sympathetic nervous system activity) during various meditation-state practices including DAOIST meditation practices, and various respiratory practices. In addition, bio-physiological assessment during various DAOIST meditation practices demonstrated relaxation responses that were reflected through various HRV features, various respiratory signal features, skin conductance, temperature, and SpO☐ signals. Moreover, the proposed Explainable AI framework provided an effective explanation of the bio-physiological assessment using the various bio-sensory signals and revealed the various key physiological characteristics that are most influential in various meditation-state classification using various bio-sensory signals.

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