|  |  |
| --- | --- |
|  |  |

Enhanced Menstrual Cycle Prediction and Stress Monitoring Using EEG and Hidden Semi-Markov Models (HSMM)

Riya Jawarkar1, Kasturi Baviskar2, Shriya Mechineni3, Vaishnavi Koche4, Priyanka Patil5, AnuradhaIngole6

1 Prof Ram Meghe College of Engineering & Management Badnera, Amravati, India

Email: riyanaitik1@gmail.com

2-3-4-5-6 Prof Ram Meghe College of Engineering & Management Badnera, Amravati, India

Email: {kasturi.r.baviskar.es@gmail.com, shriyamechineni@gmail.com, vaishnavikoche05@gmail.com, priyanka.amuc@gmail.com, anuradha.ingole@prmceam.ac.in}

**Abstract**—Accurate prediction of menstrual cycles and effective stress monitoring are crucial for women's health and well-being. Traditional methods often rely on subjective data and lack precision, making it challenging to offer personalized healthcare solutions. This paper proposes an advanced approach leveraging Electroencephalogram (EEG) signals and Hidden Semi-Markov Models (HSMM) for precise menstrual cycle prediction and stress monitoring. EEG signals, known for capturing neurophysiological changes associated with hormonal fluctuations and stress responses, provide a rich source of information. HSMM, with its ability to model duration-dependent states, enhances the detection of subtle patterns in EEG data related to menstrual phases and stress levels. The proposed method integrates feature extraction techniques with HSMM to classify different menstrual phases and assess stress variations accurately. Experimental results demonstrate improved prediction accuracy compared to traditional models, highlighting the potential of EEG and HSMM in developing personalized and proactive healthcare solutions for women.

Index Terms***—*Menstrual tracking, Personal health care, Stress detection, Hidden Semi-Markov Model (HSMM), Galvanic Skin Response (GSR), Support Vector Machine (SVM), Personal health care, Stress management*.***

**I. Introduction**

In recent years, digital health management has merged with advanced computing techniques. New opportunities have opened for the management of women’s health and stress management provided in [1]. Moreover, by surveying [12], the study exemplifies this trend: menstrual health management through self-monitoring and reflection research using EEG and biofeedback-animal theory, these things confirm that the potential of machine learning models and its hybrid approaches to deliver personalized healthcare Research is conducted in [11]. The first area of focus is menstrual health care through self-monitoring data provided in [10], [15]. Millions of Women around the world use health apps [14] to record data about menstruation, making it more widely available. Multivariate time-series datasets are almost always affected by missing information. Such datasets contain the great benefits of a greater understanding of reproductive factors and health trends, but their usage is often inconsistent among the user. To address this, recent research a Hidden semi-Markov model in [1] (HSMM) algorithm provided in [4] for classification and prediction of menstrual phases ovulation in [2] and other reproductive issues, despite the lack of complete data.

HSMM’s is a unique ability to Capture detailed measurements and dealing with missing data makes them particularly suitable for event detection. There was incredible accuracy in the birth cycle, achieving 93% of real-world app data provided in [13] shows significant changes in frequency reported by users effectively translating the cyclical into the organic the nature of the menstrual cycle provides individuals with a promising tool, within the right range menstrual health care. Furthermore, cycle characteristics are examined according to length and phase duration, tailored to each user’s individual viewing characteristics. Parallel studies have addressed the stress detection using EEG in [11] and Galvanic Skin Response (GSR) in [12] by providing biofeedback. Stress is a common health issue with significant psychological and physical effects. The investigation found that by the way like K-means clustering and SVM classification, provided in [9], [11], [12], EEG can achieve an accuracy of up to 98% in differentiation of stress levels, therefore allowing accurate detection of stress. As a nutritional supplement, GSR which has used in biofeedback-assisted mindfulness meditation in [12] to manage stress period. Users receive feedback on their body issues and are guided through meditation exercises stress response, which has been shown to be effective in promoting relaxation and reducing stress symptoms. This the GSR-based biofeedback approach provides a user-friendly, accessible method for collective stress intervention usefulness in daily life as shown in [11], [12]. Although it may yield lower accuracy than EEG, real time benefits similarly, its ease of use makes EEG a valuable adjunct to its profound diagnostic potential. Both approaches rely heavily on machine learning, techniques in [3], [4], [7] reflecting the growing role of AI in healthcare. Unsupervised and semi-supervised studies for menstrual health enable HSMM to address data gaps and encourage application-specific modelling, personalized cycle forecasting and tracking. Meditation introductions, SVM and clustering algorithms in [9] enable EEG-based methods track stress-related activity, while biofeedback provides real-time, scalable stress reduction strategies in [11], [12]. This study emphasizes that each method plays a unique, complementary role: HSMM models in provides accurate, subjective insights into menstrual health over time, while EEG and GSR biofeedback provided in makes it easier to accurately identify stress and manage stress with ease, on the go. Taken together, these findings highlight the importance of hybrid computational models for development Personal health assessment. By combining physiological data with sophisticated modelling techniques, this study highlights innovative approaches to track and engage critical aspects of women health and stress management. As these tools evolves, they promise to help active users health care, allows, and empowers individuals to manage their health accurately. A valuable insight into their physical and mental well-being in [10].

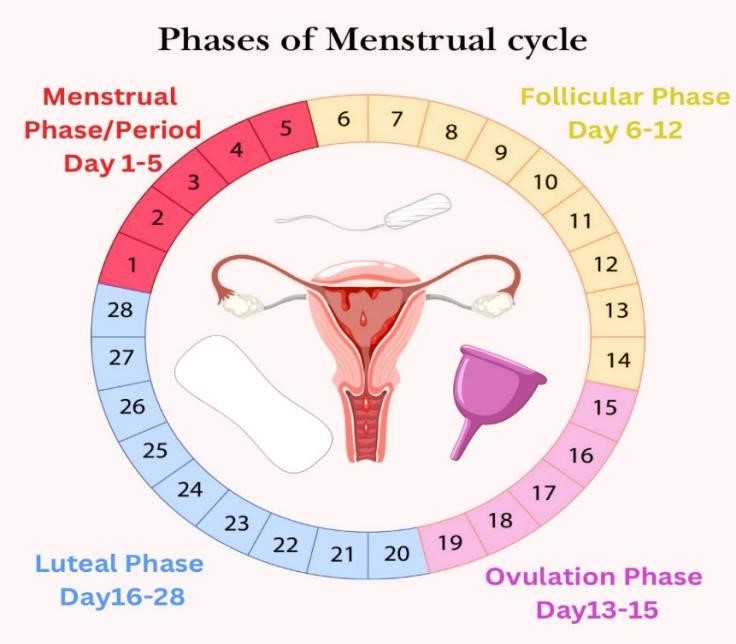


Fig. 1. Phases of menstrual cycle

As shown in the shown fig. 1 we can achieve the accuracy in phases of menstrual cycle, which can give a systematic and clear prediction up to 98% by using.

**II. Literature Review**

The combination of Hidden Semi-Markov Models (HSMM) and EEG-based stress detection with biofeedback systems emphasizes the important developments in the management of menstrual health and stress monitoring [15]. This HSMM approach [1] as addressed in the "Labelling Self-Tracked Menstrual Health Records" study the addresses and concerns regarding self-monitored menstrual data with missing or abnormal data, therefore giving an indication on ovulation and other reproductive functions. This model uses hierarchical structures in HSMMs to include variability in user engagement and data quality, maintaining 93% accuracy even with missing data. This approach work provides the strong solution for labelling menstrual phases and predicting cycle lengths and critical in improving the knowledge on reproductive health from self-reported data. On the other side, the literature on stress detection using EEG traces shows complementarity to focus on mental health monitoring, especially of biofeedback-assisted meditations explained in [11], [12], [18]. In this approach, EEG classifiers are combined with SVMs used in, for high accuracy stress the categorization are targeted to regions of the brain sensitive to stress and achieve high accuracy rates of 98% prefrontal cortex. Galvanic skin response used in these models has several advantages, including giving real-time feedback facilitating immediate stress reduction during meditation [12], [18]. This dual system validates the impact of mindfulness interventions and using both EEG and GSR consistently to measure stress and Personalized feedback shown in [11], [12]. It is evidenced and in mobile health such methods are adopted feedback on both physiological and mental wellness [13], [17]. These studies reflect the health monitoring systems' hybrid, adaptive nature in bridging the distance between the medical and psychological treatment [17], [19]. Using machine learning to read complex and multivariate data enables the full evaluation for several statuses of health from menstrual health to acute stress levels [3], [17].

This hybrid approach promises more inclusive and accessible health management tools and reducing barriers to personal health insights through non-invasive endoscopy data-driven solutions [1], [10], [13]. More and more such technologies become available like HSMM for menstrual cycle. Tracking and EEG-GSR Biofeedback against stress also opens the pathway for customized health applications, which then can improve both diagnostic precision and user engagement [1], [11], [12], [14]. These advancements position the hybrid models that are all important inputs in the broader sphere of health, increasing user self-governance over health management challenges in different contexts [10], [17]. The collection of studies reviewed illustrates how data-driven models and machine learning techniques are transforming the landscape of health and clinical data analysis by providing targeted solutions across multiple domains.

In [1] where Hidden Semi-Markov Models are an advanced statistical approach and evaluated with metrics like accuracy, FID, IS, and LPIPS on menstrual health data from the Kindara app. By adopting the multi-metric assessment, this model not only aims to improve accuracy but also robustness and reliability across different types of health data. This approach highlights the importance of flexibility in model evaluation and especially in areas where individual variability plays a crucial role such as reproductive health.

Linear Regression models focusing on menstrual cycle predictions use hormonal data from a select group of women of accuracy in predicting cycle phases [2]. This model sheds light on how specific biomarkers can be used to understand physiological processes better, leading to more accurate predictions of individual health trends. By analysing fluctuations in hormone levels and Linear Regression models contribute significantly to fertility tracking and cycle monitoring and potentially to understanding hormonal patterns linked with health conditions.

In another study of [3], machine learning algorithms notably the Random Forest Classifier are leveraged to sift through extensive datasets. After narrowing down 23 features to the 8 most relevant model achieves an impressive 89% accuracy rate. This study underscores the value of feature selection in enhancing model efficiency and accuracy, especially when dealing with high-dimensional data in health informatics.

A related approach, machine learning techniques are evaluated for their predictive power using a broad spectrum of metrics, including recall, F1-score, ROC curves, and K fold Cross Validation on clinical and metabolic factors [4]. This multi-metric validation is critical as it demonstrates the ability of these models to maintain consistency and reliability even when tested against diverse health-related factors.

Data Dependent Systems (DDS) target error reduction in object recognition tasks with an ambitious error goal of 8%, facilitated by high SNR levels [5]. Analysing shape and profile data from object boundaries and DDS offers insights relevant for applications in medical imaging and biometric verification, where precise object recognition is critical. This model's emphasis on reducing error rates is particularly valuable in fields that depend on high-fidelity data interpretation and such as diagnostic imaging and pattern recognition in medical devices.

DEXA assessments utilize both correlation coefficients and linear regression to investigate body composition’s relationship with bone mineral density (BMD) in pre- and post-menopausal women [6]. By examining these

relationships, the study contributes to understanding the hormonal impacts on bone health, supporting preventative care and targeted treatments for osteoporosis. This approach is significant as it provides a foundation for the personalized health assessments and interventions aimed at maintaining bone health across different life stages.

A novel approach in [7] involving Conditional Random Fields (CRF) enhances menstrual cycle prediction accuracy with the CRF Ovulation Detector achieving minimal deviations from actual data across a large dataset. The model’s success in aligning closely with labelled data illustrates the potential of CRF-based models in cycle tracking and ovulation prediction offering accurate insights for reproductive health applications. The ability to consistently align predictions with actual observations makes this model a strong candidate for mobile health applications in ovulation and fertility tracking.

Biometric and situational data are processed in a risk maximization model and that integrates biosensor inputs with environmental and locational factors to dynamically assess the health risks. This approach represents a step forward in personalized health risk assessment and enabling the model to factor in situational influences that may impact health outcomes. By maximizing risk ratios based on multimodal inputs and the model provides a comprehensive and adaptable tool for monitoring health in real-time contexts, such as occupational health or travel-related health monitoring.

The combined use of KNN, Random Forest, SVM, and Naive Bayes algorithms in analysing a PCOS dataset allows for a thorough examination of diagnostic accuracy. Each algorithm’s performance is assessed using accuracy and precision, recall, and F1 score, enabling a comparative analysis that identifies the most effective models for accurately classifying PCOS cases. This evaluation contributes to the development of robust diagnostic tools in reproductive health as it identifies the most reliable machine learning techniques for this complex syndrome.

A hybrid approach is shown in [10] utilizing Hadoop MapReduce and a Dingo Coyote Optimization algorithm is implemented to analyse the mental health and physical activity data with the high accuracy and precision. This integration of distributed computing and optimization strategies proves advantageous for handling the large datasets in health data analytics and illustrating the potential for scalable health insights in areas like behavioural health and physical rehabilitation, where vast amounts of sensor or activity data are common.

The K-Means-SVM hybrid model, EEG signals from VR horror videos and IQ tests are used to gauge mental and cognitive responses under simulated conditions. This hybrid approach provides a deeper understanding of emotional and cognitive reactions, as metrics such as accuracy, sensitivity, specificity, precision, F1 score, and AUROC are applied to evaluate performance. This research is particularly relevant for applications in neurofeedback and cognitive health monitoring, where real-time assessment of mental states can support therapeutic interventions.

Biofeedback meditation using Galvanic Skin Response (GSR) shows promising results in [12] classifying stress levels and using EEG signals recorded in VR environments. By measuring skin conductance changes in response to stress and GSR offers a non-invasive way to monitor emotional health and supporting applications in stress management and mental health care. This approach highlights the effectiveness of biofeedback for managing stress and demonstrates its potential for integration into mental health interventions, such as therapy programs or self-care applications.

In a Support Vector Classifier (SVC) enhanced with NLP techniques shows high accuracy, recall, and F1 scores on a health-related dataset shown in [13]. This model’s capacity to effectively process and classify textual health data showcases NLP’s role in automating analysis in healthcare, where patient records, clinical notes, and reports often require categorization. By facilitating faster and more accurate text analysis, this approach can streamline workflows in clinical settings, improving diagnostic and record-keeping processes.

The GDPR compliance of mobile health apps are analysed in [14] through a dual-method approach that uses both static and dynamic monitoring. By evaluating the long-term adherence of these apps to GDPR standards and the study underscores the critical importance of user data protection in digital health applications, especially given the sensitive nature of health data. This analysis serves as a benchmark for ensuring compliance and safeguarding the privacy in the rapidly growing digital health sector and fostering trust among users.

Data mining algorithms, specifically J48 and Random Tree, are tested on a PCOS dataset, revealing J48 as the more accurate of the two. This insight aids in identifying the most effective data mining techniques for reproductive health applications, where accurate data classification is essential for early detection and management of conditions like PCOS. The findings support the selection of algorithms that provide both accuracy and computational efficiency in health diagnostics.

A mobile monitoring system designed for pregnant women incorporates adaptive and real-time health tracking and risk assessment storing the vast amounts of data in the cloud for detailed analysis. This architecture is critical for prenatal care, where continuous monitoring and proactive risk evaluation can contribute to safer pregnancies. By leveraging big data analytics this model offers an advanced and scalable approach to managing the health of expectant mothers and enabling more personalized care through adaptive monitoring.

Deep learning models applied in [17] to multimodal datasets as it shows the enhanced prediction capabilities and especially in feature recognition across the complex datasets. While specific performance metrics are not always detailed, the models demonstrate potential for handling diverse data inputs, making it particularly suitable for all the applications in comprehensive health tracking where various data types are integrated to capture a holistic view of patient health.

Heart Rate Variability (HRV)-driven and VR therapy effectively reduces the pain and anxiety in patients undergoing surgery, and they are highlighting VR’s potential as a therapeutic tool in [18] medical settings. By leveraging HRV biofeedback in a virtual reality context and this model provides a unique pain management approach that it could be beneficial in reducing reliance on pharmacological interventions and during recovery and they are offering a complementary tool for managing pain and stress.

Lastly, in [19] a systematic literature review provides a thorough on analysis of quality, safety, and management practices in Biological Sample Management for Assisted Reproductive Treatment (ART). By exploring these standards, it is necessary for safely handling and preserving biological samples this review emphasizes the importance of quality management in reproductive health and it highlights best practices essential to ART success. This study contributes a foundational framework for managing sensitive biological samples and supporting ART’s broader goals of advancing fertility treatments and reproductive health technologies.

Table 1. Literature Review Table

|  |  |  |  |
| --- | --- | --- | --- |
| Authors | Methods | Performance Evaluation Parameter | Dataset |
| Laura Symul and Susan Holmes | Hidden Semi-Markov Models | Measures model performance using accuracy, FID, IS, or LPIPS | Kindara app dataset |
| ÖzlemKarabiber, Yalçın İşlerBiyomedikal ,MühendisliğiBölümü, KatipÇelebi Üniversitesi,İzmir, Türkiye | Linear Regression | |  | | --- | | Gives prediction accuracy of  menstrual cycle days using  hormonal values and linear  regression model . |  |  | | --- | |  | | |  | | --- | | Dataset of 20 women’s hormone levels analyzed via linear regression. |  |  | | --- | |  | |
| |  | | --- | | Amsy Denny et al. |  |  | | --- | |  | | |  | | --- | | Machine learning |  |  | | --- | |  | | |  | | --- | | Random Forest Classifier achieved the best, with 89% accuracy after optimizing the data. |  |  | | --- | |  | | |  | | --- | | Dataset included results from 541 women, with 23 features identified and 8 selected for analysis. |  |  | | --- | |  | |
| |  | | --- | | Samia Ahmed et al. |  |  | | --- | |  | | |  | | --- | | Machine learning techniques |  |  | | --- | |  | | |  | | --- | | Algorithms tested with accuracy, precision, recall, F1-score, ROC curve, Area Under Curve Score, and K-fold Validation |  |  | | --- | |  | | |  | | --- | | Sources like Kaggle and included different clinical and metabolic factors. |  |  | | --- | |  | |
| |  | | --- | | S. M. Pandit, R. M. Guo |  |  | | --- | |  | | |  | | --- | | Data Dependent Systems (DDS) |  |  | | --- | |  | | |  | | --- | | Recognition errors, 8% error goal, SNR levels at 30 dB. |  |  | | --- | |  | | |  | | --- | | Dataset comprises shape/profile data sampled from object boundaries. |  |  | | --- | |  | |
| |  | | --- | | Mallikarjun S. Holi and S. Radhakrishnan |  |  | | --- | |  | | |  | | --- | | DEXA assessment |  |  | | --- | |  | | |  | | --- | | Correlation coefficients and linear regression analysis were used to evaluate the relationship between body composition and BMD. |  |  | | --- | |  | | |  | | --- | | Data from 24 pre-menopausal women (ages 23–50) and 31 post-menopausal women (ages 42–79). |  |  | | --- | |  | |
| |  | | --- | | Amos Azaria, Seagal Azaria |  |  | | --- | |  | | |  | | --- | | Machine learning (CRF Ovulation Detector - CRF-OD) |  |  | | --- | |  | | |  | | --- | | Average Absolute Deviation (AAD) was 1 day off from actual labeled data on average. |  |  | | --- | |  | | |  | | --- | | Dataset included 2,286 profiles (women) with 8,466 cycles encompassing measurements over 183,266 days. |  |  | | --- | |  | |
| |  | | --- | | Yuchae Jung, Yong Ik Yoon |  |  | | --- | |  | | |  | | --- | | Biometric data and risk maximization |  |  | | --- | |  | | |  | | --- | | Evaluated by maximizing risk ratios from biosensor and situational data. |  |  | | --- | |  | | |  | | --- | | Includes biometric data from multimodal biosensors and situational information like location and environmental factors. |  |  | | --- | |  | |
| |  | | --- | | Aroni Saha Prapty, Tanzim Tamanna Shitu |  |  | | --- | |  | | |  | | --- | | KNN, Random Forest, SVM, Naive Bayes |  |  | | --- | |  | | |  | | --- | | Accuracy, precision, recall, and F1 score. |  |  | | --- | |  | | |  | | --- | | 542 records from ten hospitals, with 177 diagnosed with PCOS and the remaining being normal. |  |  | | --- | |  | |
| |  | | --- | | Mustafa Haider Abidi et al. |  |  | | --- | |  | | |  | | --- | | Hadoop MapReduce and a Hybrid Dingo Coyote Optimization Algorithm |  |  | | --- | |  | | |  | | --- | | Accuracy, precision. |  |  | | --- | |  | | |  | | --- | | mHealth dataset and UCI-HAR dataset. |  |  | | --- | |  | |

##### III. Methodology

The first aspect of the observer makes use of Hidden Semi-Markov Models (HSMM) to research menstrual fitness statistics, specially centred on reproductive activities like ovulation [1]. The model's design considers the variable and often has incomplete nature of self-suggested menstrual data. This methodological approach includes the following key steps:

* Data Collection: Data is acquired from users of menstrual monitoring apps, which has log signs such as bleeding, cervical mucus consistency, basal body [1]. These capabilities are accrued as timeseries records however it showcases the substantial missingness because of various monitoring behaviours.
* HSMM Design and Parameterization: The HSMM is particularly adapted for this have a look at to accommodate non-geometric distributions for kingdom length, addressing the range in menstrual section lengths and reproductive states [1]. To manage the records irregularity and lacking values and state particular censoring chances are also included, adjusting for variable-unique and kingdom-structured missingness. For example, in states the customers are much less probably to log sure signs and the version factors are within the extended chance of facts absence.
* Hierarchical State Adaptation: To ensure accurate labelling regardless of modifications in person monitoring conduct and in a hierarchical method categorizes statistics primarily based on the logged variables as shown in [1]. For example, the versions distinguish between an excessive likelihood of ovulation and a high probability of non-ovulation the way of adjusting country transition probabilities based on available statistics (e.g., temperature, cervical mucus, bleeding patterns). This method includes assigning probabilities to the observations of each nation the usage of the Viterbi set of rules are expecting the series of menstrual phases and reproductive events.
* Synthetic Data Testing and Model Validation: To evaluate the versions of robustness, synthetic datasets with the controlled tiers of missing facts are used [1]. The version's accuracy is assessed by the way of evaluating its nation predictions to simulated ground fact. Additionally, the actual-international datasets from menstrual monitoring apps are employed and attaining 93% accuracy in figuring out reproductive levels in spite of high ranges of missingness and Stress Detection through EEG and GSR Biofeedback. The second issue of the examiner integrates EEG-based totally stress detection with biofeedback from Galvanic Skin Response (GSR) sensors, employing gadget learning techniques to enhance class accuracy and validate biofeedback-assisted meditation as a strain discount intervention as mentioned in [11],[12].
* Participant Selection and Task Design: The strain detection observe includes 50 members subjected to the tasks designed to set off various strain levels, consisting of mental arithmetic and public speak which is mentioned in [12]. GSR sensors file skin reaction statistics to seize physiological adjustments related to pressure and whilst the EEG video display units are targeted at the brain's prefrontal cortex to seize relevant brainwave hobby in Alpha, Beta, and Theta bands.
* Data Preprocessing and Feature Extraction: EEG records undergoes Fast Fourier Transform (FFT) and Power Spectral Density (PSD) analysis to isolate features corresponding to strain ranges [11]. Key bands, especially the Beta band, show the maximum tremendous correlation with stress, supplying primary indicators for category. GSR information is processed to take away noise and with the rest pressure states recognized through variations in skin conductance.
* Machine Learning Models and Biofeedback Integration: A hybrid method combining the K-way clustering and Support Vector Machine (SVM) algorithms is implemented to classify stress degrees based on EEG and GSR records [12]. SVM is chosen for its effectiveness in handling high-dimensional EEG statistics and attaining the classification accuracy of 98% for EEG-primarily based strain detection and up to 82% with GSR based biofeedback [11].
* Biofeedback-Assisted Meditation: Participants have interaction in mindfulness meditation classes supported with the aid of real-time GSR feedback to control pressure. The effectiveness of these interventions is evaluated by using looking at shifts in GSR and EEG metrics from pre- to publish meditation and confirming the widespread reduction in stress markers and high category accuracy in differentiating among pressure and rest states [11],[12].

The third aspect is Comparative and Integrated Analysis A comparative analysis of the HSMM version for menstrual fitness and the EEG-GSR version for strain detection highlights the strengths of each in personalized fitness monitoring [1],[11],[12].

Reliability and Flexibility: HSMM’s adaptability to self-suggested records allows it to address variability and missingness efficaciously, offering consistent menstrual segment predictions [1]. Meanwhile, EEG-primarily based pressure detection, even though system-extensive it offers high precision and while GSR biofeedback is extra on hand it is suitable for actual-time programs and powerful for meditation-based totally interventions [11],[12].



Fig.3. Mobile App Overview

Also, in the shown fig. 3 we can get the proper representation of mobile app overview and its functions

The authors can conclude on the topic discussed and proposed. Future enhancement can also be briefed here.

IV. Experimental

This study done in [1], [13], [17] looks at two main areas menstrual health tracking and stress management-using machine learning techniques that analyse self-reported and physiological data. The menstrual health study uses a Hidden Semi-Markov Model (HSMM) to track reproductive events such as ovulation. The model explained in [1] is trained on self-reported data from the Kindara app, which contains bleeding patterns. It further more ensures its robustness to different tracking frequencies based on real-world and synthetic data sets, cervical mucus properties, basal body temperature, and hormone test results which are clearly explained in [2], [3], [4]. In [1], the HSMM produced accurate cycle phase prediction for 90% missing data, and the system used in real world data exhibited 93% event identifications.

Experimental validation provided in [7] covers synthetic data sets containing percentages of missing data with reported variables and different combinations towards the adaptability of accuracy under various tracking conditions.

An EEG-based method used in [11] that employed SVM classification for the detection of stress and focusing on the level of stress detected from the brainwave data from EEG through techniques such as FFT and power spectral density, was proposed. This model achieved accuracy up to 98% especially with Beta band signals on the right prefrontal cortex, which were very indicative of stress. GSR biofeedback explained in [12] was also tested for real-time stress reduction. The subjects undertook tasks in [18] that elicited stress and then practiced GSR-assisted meditation. The EEG and GSR experiments done in [11], [12] demonstrated high accuracy in the differentiation of states of stress and validated the efficacy of biofeedback-supported meditation. The GSR-based results obtained up to 82.4% accuracy in discrimination between the states of stress and relaxation.

These two methods used in [1], [8], [13] indicates the possibilities of machine learning in menstrual and mental health applications. Both methods exhibit high precision in health insights. The HSMM in [1] shows the good responses to user-specific reporting behaviour and provides relatively accurate reproductive event prediction regardless of variable data completeness. An EEG-GSR-based hybrid approach in [11], [12] applying the detailed brain wave analysis or biofeedback presents one of the available approaches for real time stress monitoring and management. Combining these approaches in [1], [10], [17] allows machine learning to be applied to personal health through applicable and accurate tools complementing women's health and aiding in related stress management through better health care interventions.

V. Result

The papers are under two categories: (1) Methodologies for Stress Detection itself and, respectively the paper includes work on EEG-based stress classification as well as GSR biofeedback-assisted meditation; the Very few past works have claimed classification accuracy better than 60%. The EEG-based classifier (employing k-means clustering supporting vector machine) got up to an accuracy in excess of 98% general mainly for Beta band (%) class which was related with stretch reactions. GSR biofeedback was skin conductance response-based and monitored stress while the participant performed relaxation, obtaining a classification accuracy of 82.4 in case of real mental state (stress/relaxed) changes opposed to randomly switched ones for all the participants. Although it is less accurate but helps to manage stress in real-time. It has been used to interpret menstrual health data for menstrual health by the Hidden Semi-Markov Model (HSMM): up-to 93% accuracy in capturing reproductive events, on real-world-data as reported within one study. The ability of the model to adapt the changes in users tracking exercises improved the accuracy compared to a traditional hidden Markov model (HMM). The HSMM also enhanced the predictive power of cycle-related factors, such as next-period it estimates and detects an ovulation. In PCOS detection, machine learning models, such as random forest and SVM, demonstrated reliable classification, with an accuracy of up to 93%, which demonstrated potential for early diagnosis and intervention.

VI. Conclusion

A comparative study of the methods provides valuable insights into the stress and health screening. Stress classification based on EEG demonstrated excellent accuracy and fine granularity assessment of stress levels, making it suitable for research and clinical settings. However, G.S.R the biofeedback method, although slightly imprecise, is highly suitable for real-time and accessible applications because of its non-intrusive nature and ease of use. Combining biofeedback-supportive meditation with GSR may be promising for achieving beneficial stress management the solution is the HSMM method appears to have significant benefits for menstruation and women’s health traditional models, especially in dealing with data with frequent missing information and characteristic of self-monitoring health information. This model captures and validates the variation in tracking practices interprets reproductive health events, improving cycle prediction. Using the machine teaching PCOS recognition and further supports the potential for predictive modelling in medicine emphasis and was placed on transmission and diagnostic accuracy in diagnosis and women’s health.

##### Acknowledgment

We would like to acknowledge the valuable contributions of earlier researchers in developing the insights and methodologies that greatly influenced this work. Comprehensive research on women’s health and nutrition during menstruation provided a strong foundation. We are particularly grateful for the open data and programs have supported our research on hybrid recommendation systems. In addition, the continuous advances in machine learning have allowed us to use state-of-the-art techniques. Finally, we thank our mentors for their unwavering guidance and support throughout this research journey.

##### References

1. Symul, L., & Holmes, S. (2021). Labelling self-tracked menstrual health records with hidden semi-Markov models. *IEEE Journal of Biomedical and Health Informatics, 26(3),* 1297-1308.
2. Karabiber, Ö., &İşler, Y. (2016, October). Determination of the day of the menstrual cycle from hormonal measurements using linear regression. In *2016 Medical Technologies National Congress (TIPTEKNO)* (pp. 1-4). IEEE.
3. Denny, A., Raj, A., Ashok, A., Ram, C. M., & George, R. (2019, October). i-hope: Detection and prediction system for polycystic ovary syndrome (pcos) using machine learning techniques. In *TENCON 2019-2019 IEEE Region 10 Conference (TENCON)* (pp. 673-678). IEEE.
4. Ahmed, S., Rahman, M. S., Jahan, I., Kaiser, M. S., Hosen, A. S., Ghimire, D., & Kim, S. H. (2023). A review on the detection techniques of polycystic ovary syndrome using machine learning. *IEEE Access*, *11*, 86522-86543.
5. Pandit, S. M., & Guo, R. (1995, October). Shape mensuration and recognition by DDS approach. In *Proceedings., International Conference on Image Processing* (Vol. 3, pp. 49-52). IEEE.
6. Holi, M. S., & Radhakrishnan, S. (2002, April). Effect of body mass index, body composition, age and menopause on total body bone mineral density in Indian women. In *Proceedings of the IEEE 28th Annual Northeast Bioengineering Conference (IEEE Cat. No. 02CH37342)* (pp. 251-252). IEEE.
7. Azaria, A., & Azaria, S. (2019, November). Semi-Supervised Ovulation Detection Based on Multiple Properties. In *2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)* (pp. 222-228). IEEE.
8. Jung, Y., & Yoon, Y. I. (2015, July). Wellness contents recommendation based on human emotional and health status using em. In *2015 Seventh international conference on Ubiquitous and Future Networks* (pp. 977-981). IEEE.
9. Prapty, A. S., &Shitu, T. T. (2020, December). An efficient decision tree establishment and performance analysis with different machine learning approaches on polycystic ovary syndrome. In *2020 23rd International conference on computer and information technology (ICCIT)* (pp. 1-5). IEEE.
10. Abidi, M. H., Umer, U., Mian, S. H., & Al-Ahmari, A. (2023). Big data-based smart health monitoring system: using deep ensemble learning. *IEEE Access*.
11. Wen, T. Y., & Aris, S. A. M. (2022). Hybrid approach of EEG stress level classification using K-means clustering and support vector machine. *IEEE Access*, *10*, 18370-18379.
12. Perera, J. A. P. H., Rathnarajah, L. M., & Ekanayake, H. B. (2016, September). Biofeedback based computational approach for working stress reduction through meditation technique. In *2016 Sixteenth International Conference on Advances in ICT for Emerging Regions (ICTer)* (pp. 132-140). IEEE.
13. Sumana, D., Goswami, P., Faujdar, N., & Singh, G. (2024). Gynaecological Disease Diagnosis Expert System (GDDES) based on Machine Learning Algorithm and Natural Language Processing. *IEEE Access*.
14. Papageorgiou, A., Strigkos, M., Politou, E., Alepis, E., Solanas, A., &Patsakis, C. (2018). Security and privacy analysis of mobile health applications: the alarming state of practice. *Ieee Access*, *6*, 9390-9403.
15. Soni, P., & Vashisht, S. (2018, October). Exploration on polycystic ovarian syndrome and data mining techniques. In 2018 3rd International Conference on Communication and Electronics Systems (ICCES) (pp. 816-820). IEEE.
16. Kumar, S., Gupta, Y., & Mago, V. (2019, January). Health-monitoring of pregnant women: Design requirements, and proposed reference architecture. In *2019 16th IEEE Annual Consumer Communications & Networking Conference (CCNC)* (pp. 1-6). IEEE.
17. Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., & Yang, G. Z. (2016). Deep learning for health informatics. *IEEE journal of biomedical and health informatics*, *21*(1), 4-21.
18. Prabhu, V. G., Stanley, L. M., Linder, C., & Morgan, R. (2020, September). Analyzing the efficacy of a restorative virtual reality environment using HRV biofeedback for pain and anxiety management. In *2020 IEEE International Conference on HumanMachine Systems (ICHMS)* (pp. 1-4). IEEE.
19. Trujillo, L. M., García, J. A., Lizcano, D., &Mejías, M. (2019). Traceability management of systems of systems: a systematic review in the assisted reproduction domain. *Journal of Web*

*Engineering*, *18*(4–6), 409-445.