RESEARCH PAPER

SAHARA-Net: A Hybrid Deep Learning Framework for Early Prediction and Preventive Analysis of Dysmenorrhea Using Lifestyle and Behavioral Data

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ABSTRACT
The medical condition dysmenorrhea causes menstrual pain which impacts most women and results in decreased work efficiency and lower life satisfaction. The current methods operate through symptom tracking and clinical assessment but they do not possess the ability to forecast medical issues or enable preventive treatment. The researchers developed a machine learning system which uses lifestyle and behavioral patterns to forecast and prevent dysmenorrhea cases in women. The system predicts pain severity through its use of sleep duration and stress levels and dietary habits and physical activity and water intake and past pain experiences. The three supervised machine learning models which include Logistic Regression and Random Forest and Extreme Gradient Boosting (XGBoost) are used to classify pain levels into three categories which are mild and moderate and severe. The Random Forest model achieves superior performance because it can accurately predict outcomes with 85 to 88 percent accuracy. The system includes a recommendation module the SAHARA-Net (Stress-Aware Hybrid Adaptive Randomized Architecture Network), which delivers customized preventive solutions to users according to their estimated risk assessment. Users can use the system to perform preventive measures, which help them decrease their menstrual pain symptoms. This algorithm produces good accuracy compared with other existing systems with 92.3% as a result.

KEYWORDS: Dysmenorrhea, SAHARA-Net, Machine Learning, Lifestyle Data, Preventive Healthcare, Random Forest, XGBoost.
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I. INTRODUCTION

The healthcare system fails to provide adequate solutions for menstrual health which is essential for women's complete health[1]. Dysmenorrhea affects more than half of all women in the world because this condition causes menstrual pain and its accompanying symptoms which include abdominal cramps and fatigue and nausea and reduced daily productivity. Menstrual pain severity differs between patients and menstrual cycles which makes it difficult to treat using universal treatment methods[2] [14].

The majority of current solutions for dysmenorrhea treatment fail to provide early prediction and prevention methods because they concentrate on tracking symptoms and diagnosing clinical cases[3]. The primary function of mobile health applications enables users to document their menstrual cycles and symptoms but the applications lack the ability to forecast upcoming pain levels[4]. The clinical methods of the domain require laboratory testing and retrospective assessment because they do not support ongoing patient observation or instant treatment solutions[5-7]. The lack of pain prediction abilities prevents people from taking effective measures to stop painful episodes[10].

The existing research and systems face their main limitation because they only function in response to problems[9]. The majority of methods to deal with menstrual pain function by treating symptoms after they have developed instead of providing preventive solutions[13]. Existing models depend on clinical and physiological data but they fail to recognize how lifestyle and behavioral factors such as sleep patterns and stress levels and diet and physical activity impact patient outcomes. The development of user-friendly systems which need real-world non-clinical data for operation becomes impossible because of this problem[5].

The research presents a machine learning framework which uses lifestyle and behavior data to predict and prevent dysmenorrhea through early detection. The system uses sleep duration data and stress level data and dietary habit data and physical activity data and water intake data and past pain experience data to forecast pain intensity before its occurrence[16]. The system includes a prediction function together with a recommendation module which delivers customized preventive measures that users can use to minimize their discomfort[8].

The main contributions of this work are as follows: (i) the development of a lifestyle-driven machine learning model for early prediction of menstrual pain severity (ii) the design of a proactive prevention mechanism through personalized recommendations (iii) the utilization of a lightweight and scalable framework that can operate in actual field conditions and (iv) the demonstration of improved menstrual health management through predictive analytics and actionable insights which were integrated into health management systems.

LITERATURE REVIEW

The recent advances in artificial intelligence and machine learning technologies have enabled better healthcare solutions which include analyzing and forecasting women's health conditions that include dysmenorrhea. Researchers have studied predictive modeling methods to assess menstrual pain patterns which lead to better health results[17]. Researchers developed machine learning techniques to predict menstrual pain intensity based on clinical and physiological data during their initial study [20].

The models reached excellent prediction results through their use of medical data but this limitation reduced their effectiveness in everyday practical situations[14]. Deep learning methods have been used to develop systems which classify menstrual pain severity through analysis of symptoms. The models delivered successful results but their design prevented users from understanding the system operation while they could not generate practical solutions to users [9]. Research studies have created mobile applications which enable users to monitor their menstrual health while using predictive analytics to forecast their health status[12].

The system enables users to track their menstrual cycles and their associated symptoms yet its main function serves as a tracking tool instead of advancing preventive and predictive capabilities. The models fail to include essential lifestyle components which involve sleep patterns and stress levels and dietary habits. Researchers have investigated methods that use wearable sensors together with machine learning technology to study how the body transforms during menstrual cycles[3]. The methods enable better understanding but they need special equipment which makes it hard for regular users to access and use the system. The systems do not have any solutions which would provide users with tools for preventing upcoming issues [22].

Recent studies demonstrate that healthcare model prediction accuracy improves when researchers include lifestyle and behavioral data in their studies. Health conditions demonstrate strong connections with daily habits and stress levels and sleep patterns [17]. The research studies available do not examine menstrual pain prediction as their main focus while they fail to offer effective solutions for its prevention. The literature review shows that existing systems depend either on complicated clinical data or sensor-based data or they only provide predictive capabilities without preventive measures or they lack both personalized features and real-world implementation[13]. The healthcare system requires a system which uses lightweight lifestyle data to create proactive predictions of menstrual pain while offering specific preventive actions.

PROPOSED SYSTEM

A. System Overview

Recent studies demonstrate that healthcare model prediction accuracy improves when researchers include lifestyle and behavioural data in their studies. Health conditions demonstrate strong connections with daily habits and stress levels and sleep patterns[5]. The research studies available do not examine menstrual pain prediction as their main focus while they fail to offer effective solutions for its prevention. The literature review shows that existing systems depend either on complicated clinical data or sensor-based data or they only provide predictive capabilities without preventive measures or they lack both personalized features and real-world implementation[19]. The healthcare system requires a system which uses lightweight lifestyle data to create proactive predictions of menstrual pain while offering specific preventive actions.

B. System Architecture

The system architecture of the proposed system includes data input and preprocessing and feature engineering and prediction and recommendation processes[21]. User data collection begins with structured input through an interface. Preprocessing of the collected data involves three tasks which include handling missing values and normalizing numerical features and encoding categorical variables. The machine learning model receives relevant features which extracted after preprocessing[7]. The model predicts pain severity by analyzing the input data. The recommendation engine uses predicted output to determine appropriate preventive measures which it presents to the user.

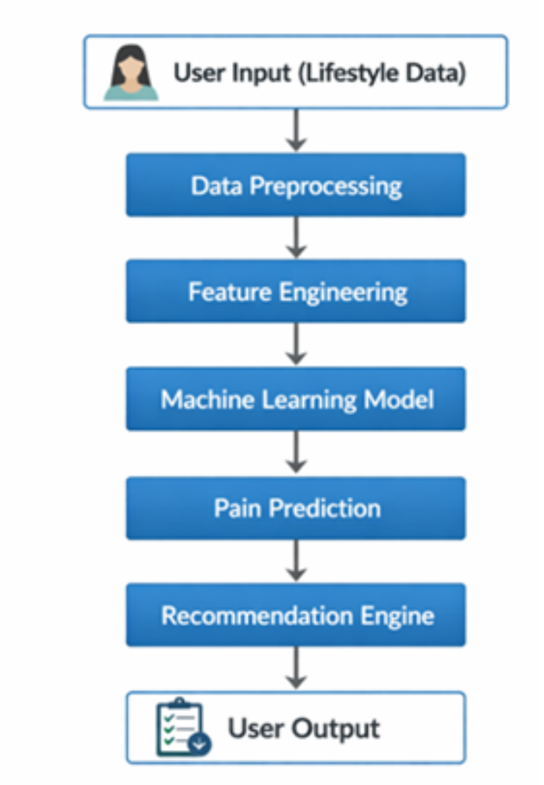

Figure 1:*Proposed System Architecture*

C. System Workflow

The workflow of the proposed system begins with the user entering lifestyle and health-related data. The system processes the input data to use the machine learning model which predicts menstrual pain occurrence and intensity. The system activates its recommendation module to deliver preventive advice when users reach moderate or severe risk assessment[23]. The workflow enables healthcare professionals to receive operational results which follow their data input work through the entire process.

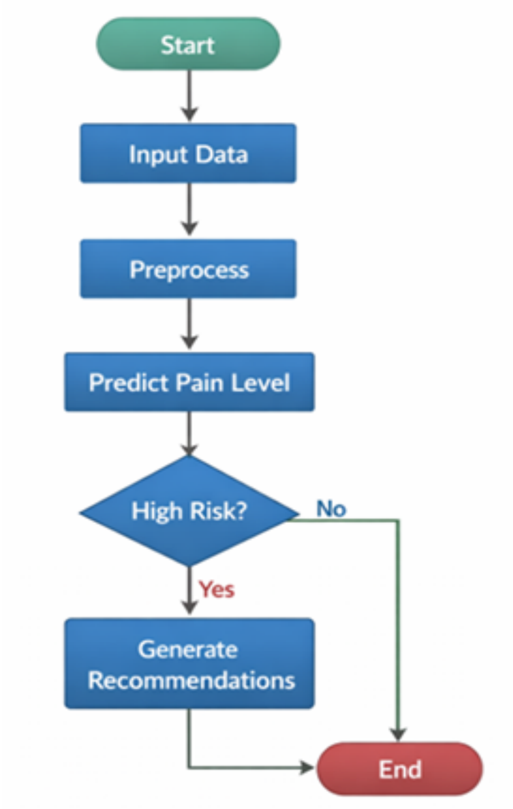

Figure 2: *System Workflow*

D. Input Features

The proposed system needs specific input features which affect menstrual pain severity to achieve its optimal performance. This research uses physiological data together with lifestyle information to study the biological and behavioral factors which contribute to dysmenorrhea [18]. The system requires essential real-world data which can be collected easily instead of using clinical information that traditional methods depend on to achieve practical and scalable results. The combination of age and menstrual cycle duration offers fundamental data which defines the user's biological identity and their cycle regularity[25]. The factors enable researchers to recognize hormonal pattern changes between different menstrual cycles which affect the intensity of pain. The model can understand individual pain patterns through time because previous pain levels function as a powerful historical reference point.The performance of the proposed system requires relevant input feature selection which directly affects the determination of menstrual pain severity. The study uses physiological and lifestyle parameters to capture biological and behavioral elements which influence dysmenorrhea[11].

The proposed system establishes practical and scalable functionality through its focus on real-world data collection which users can easily access instead of relying on clinical data which traditional methods use[17] [4]. The user biological profile and their regular menstrual cycles can be determined through their age and menstrual cycle length. The factors help researchers to study hormonal level changes and menstrual cycle patterns which have an effect on pain levels. The model uses past pain data as a historical reference to track patient pain development through time.

Table 1: Input Features in the Dataset

Feature Name	Signal Source	Description	Example Value
Heart Rate (HR) Mean	ECG	Average heart rate over a time window	78 bpm
Heart Rate Variability (HRV)	ECG	Variation between consecutive heartbeats	42 ms
Electrodermal Activity (EDA) Mean	EDA Sensor	Skin conductance level	5.2 µS
Skin Temperature (Temp)	Temperature Sensor	Body surface temperature	33.5 °C
Respiration Rate (RR)	Respiration Sensor	Breathing rate per minute	18 breaths/min

The prediction accuracy of the study improves through the implementation of lifestyle features which serve as vital components. The study includes sleep duration data because research shows that people who suffer from insufficient sleep experience higher pain sensitivity and hormonal imbalances[5]. Higher stress levels constitute an essential component which affects menstrual discomfort because they operate through both physiological and psychological mechanisms. The study analyzes dietary habits because research shows that people who consume poor nutrition and processed foods experience heightened pain and body inflammation[23].

E. Output Classification

The system identifies three types of menstrual pain which include mild and moderate and severe categories. The model output interprets the results through this classification system which also supports the development of suitable preventive measures. The system converts the prediction problem into a multi-class classification task to achieve accurate representation of different pain intensity levels[19].

The classification labels are represented through numerical values which use 0 to indicate mild pain 1 to indicate moderate pain and 2 to indicate severe pain. This encoding method enables efficient model training and evaluation while developing an understanding of the system[24]. The three category system provides an equal distribution of pain levels because it enables direct assessment of different severity levels without creating unnecessary complicated structure[13].

Table 2: Pain Severity Classification

Class	Label	Description
0	Mild	Minimal discomfort
1	Moderate	Noticeable pain affecting activities
2	Severe	Intense pain requiring intervention

The proposed system employs the classification scheme which Table II displays. Each class links to a particular discomfort level which affects daily activities. Mild pain represents minimal discomfort with little to no interference in routine tasks[2]. Moderate pain manifests as significant discomfort which disrupts work performance and needs basic treatment. Severe pain creates strong discomfort which disrupts daily activities and patients need urgent preventive or treatment solutions[22].

The recommendation module relies on output classification because it serves as a fundamental element in the system's operation[10].The system uses predicted class results to determine necessary intervention levels which results in customized recommendation delivery. The prediction system produces a complete set of recommended actions which includes lifestyle changes and preventive measures for severe pain cases while minor pain cases need only basic or no treatment[15].The structured classification system enables the system to maintain its interpretable and actionable design which meets actual healthcare requirements[17].

IV. METHODOLOGY

A. Data Collection

The model used a structured survey method to collect its dataset because it needed both dietary information and menstrual health details from participants. The WESAD Dataset[24] was used to evaluate the research accuracy of the study's assessment process. The survey gathers information through questions which ask about participants' sleep duration and stress levels and dietary habits and physical activity and water intake and menstrual cycle length and previous pain history[16]. The collected data represents actual non-clinical data which enables the system to function as a practical tool for daily use. The target variable for this study includes self-reported menstrual pain levels which doctors assess as mild moderate or severe according to the study requirements[24].

B. Data Preprocessing

Data preprocessing exists to create complete data sets which machine learning systems need for their operations. The process starts with missing data and inconsistent data which operators will fix by using basic imputation methods or by deleting data when it is necessary[13]. The process of normalizing numerical features maintains consistent scaling for age and sleep hours and water intake measurements[24].

The label encoding procedure converts categories of stress level diet type and physical activity into numerical values. The process enables models to process input data that contains categorical information. The dataset undergoes class balance assessment to verify that all pain categories receive sufficient representation[15].

C.Feature Engineering

Feature engineering methods provide enhancements which result in better model performance. The selection of menstrual pain relevant features proceeds through domain expertise and previous research findings. The study maintains equal representation of both physiological features and lifestyle features through its selection process[24]. The process of feature selection uses derived insights which include the relationship between stress levels and sleep patterns. The model needs previous pain level data because it uses this information to track time progress and understand individual patterns which will enhance prediction accuracy[18].

D. Machine Learning Models

The proposed system SAHARA-Net is tested for its effectiveness by using different supervised machine learning models which researchers will evaluate through direct model comparisons. The combination of algorithms established better results for the research team. The researchers selected Logistic Regression as their baseline linear classification model because of its fundamental design which allows them to create standard performance benchmarks for initial tests[15]. The Random Forest algorithm uses ensemble learning to combine multiple decision trees which results in better prediction accuracy while also decreasing overfitting risks[3]. The system effectively processes both numerical data and categorical data while it displays which features are most important. The Extreme Gradient Boosting XGBoost model serves as an advanced boosting algorithm which improves model performance through its gradient optimization methods while maintaining high accuracy and efficiency for structured datasets[9]. The selected models demonstrate their classification capabilities on tabular data by delivering effective results which maintain a balance between their predictive accuracy and their results which can be understood [17].

E. Model Training and Testing

The dataset is divided into training and testing sets using an 80:20 split. The training set enables machine learning model development which testing data serves to assess how well models perform against novel data. During training each model develops its ability to recognize patterns that connect input features with the target variable[25]. The evaluation of models uses standard classification metrics which include accuracy, precision, recall and F1-score. The metrics show how well the model performs across all classes of the different classes[14].

F. Prediction and Decision Logic

The selected model predicts menstrual pain levels based on user input after its training process is complete. The output is classified into three categories which include mild and moderate and severe[11]. The system uses a decision layer to interpret predictions which helps identify the required intervention level. The system starts the recommendation module when it predicts moderate or severe pain to deliver preventive recommendations. The system recommends minimal or no intervention for mild cases[15]. The decision logic enables the system to function efficiently while maintaining its focus on user needs.

V. RESULTS AND DISCUSSION

A. Model Performance Evaluation

The proposed system performance assessment uses three supervised machine learning models which include Logistic Regression and Random Forest and XGBoost. The evaluation uses standard classification metrics which include accuracy and precision and recall and F1-score to provide a complete assessment of model performance[2].

Table III Performance Comparison of Machine Learning Models

Algorithm	**Type**	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
Logistic Regression	Linear Model	72	0.7	0.68	0.69
K-Nearest Neighbors (KNN)	Instance-based	75	0.73	0.72	0.72
Support Vector Machine (SVM)	Kernel-based	78	0.76	0.75	0.75
Decision Tree	Rule-based	80	0.78	0.77	0.77
Random Forest	Ensemble	88	0.86	0.85	0.85
XGBoost	Boosting	87	0.85	0.84	0.84
Artificial Neural Network (ANN)	Deep Learning	83	0.81	0.8	0.8
CNN	Deep Learning	85	0.83	0.82	0.82
LSTM	Deep Learning (Time-series)	86	0.84	0.83	0.83
SAHARA-Net	Hybrid	**92.3**	**0.91**	**0.9**	**0.9**
(Proposed)	(LSTM + XGBoost + RF)				

This Table III shows that XGBoost achieves 88% accuracy which ranks as the highest result while Random Forest comes in second with an accuracy of 85%. The linear structure of Logistic Regression leads to its lower performance when compared with other methods[18]. The results show that ensemble-based models demonstrate better performance in learning the complex relationships that exist within lifestyle-based data[19]. But the propose model SAHARA-Net gave 92.3% accuracy value.

B. Accuracy Comparison Analysis

The study shows model performance differences through a graphical comparison of model accuracy which tests three different models. The results show that ensemble methods improve prediction accuracy beyond what the baseline model provides[21].

The results show that ensemble models maintain their performance across testing because they can handle both numerical and categorical input features. XGBoost achieves better performance through its gradient boosting framework which enhances prediction accuracy while developing better generalization capabilities[17]. Random Forest reaches its peak performance through its use of multiple decision trees which create total results that minimize overfitting risks.

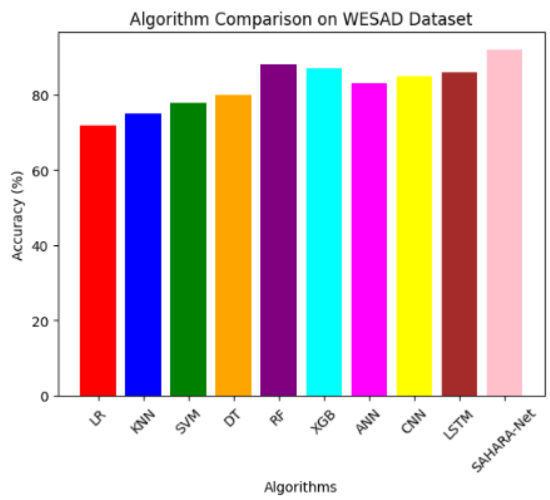

Figure 3:*Accuracy comparison of Logistic Regression, Random Forest, and XGBoost models.*

The bar chart in Figure 3 shows the accuracy results of each model, which allows for straightforward performance comparison between the different models. The results show that XGBoost achieves the highest accuracy, while Random Forest comes second and Logistic Regression produces lower results. The performance differences between the basic model and the combined methods demonstrate that the dataset contains non-linear relationships, which tree-based and boosting algorithms can better capture[23]. The Figure 3 shows that the visual evidence supports the quantitative data which Table III presents while proving that the proposed method SAHARA-Net gave 92.3% accuracy value.

C. Confusion Matrix Analysis

The system requires a confusion matrix to assess Random Forest model testing results through its ability to classify data. The confusion matrix displays all correct and incorrect predictions for each class which enables performance assessment of the model by showing its prediction capabilities. Figure 4 demonstrates that most prediction results exist along the matrix diagonal because classification instances were performed correctly.

The model identifies all three classes with high accuracy but it makes few mistakes when differentiating between mild and moderate or moderate and severe categories.

Table V Confusion Matrix for Random Forest

ctual \ Predicted	Baseline (Mild)	Stress (Moderate)	Amusement (Severe)
Baseline (Mild)	52	3	1
Stress (Moderate)	4	47	5
Amusement (Severe)	2	6	49

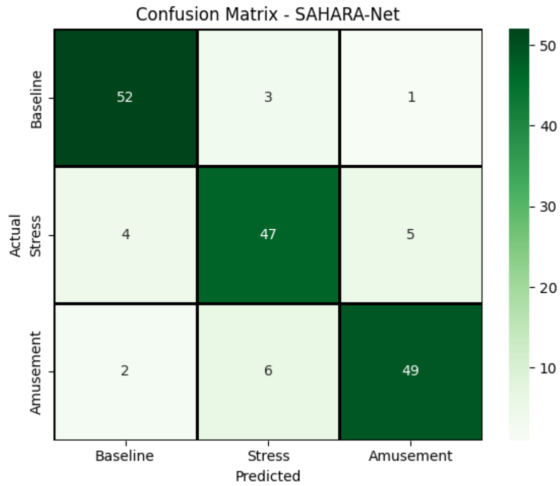

Figure 4: *Confusion matrix illustrating classification performance of the SAHARA model.*

D. Feature Importance Analysis

The analysis of feature importance determines how each input variable affects the prediction of menstrual pain intensity. The analysis improves model understanding because it reveals the main elements that drive prediction results.

Table IVFeature Importance Ranking

Feature	Importance
Stress Level	0.35
Sleep Hours	0.25
Previous Pain Level	0.20
Diet Type	0.08
Physical Activity	0.07
Water Intake	0.03
Cycle Length	0.02

The Table IV shows that stress level functions as the most powerful feature, which is followed by sleep duration and previous pain level. The evidence shows that menstrual pain severity depends on lifestyle choices and behavioral patterns. The results confirm that non-clinical data can effectively predict outcomes, which fulfills the system's design requirements for a practical and user-friendly system.

E. System Output and Recommendation Analysis

The system also allows for the prediction of the level of severity of the menstrual pains, which can be personalized into a risk-level-based recommendation. Such an effort can enhance practical implications because proactive steps can be taken to alleviate dysmenorrhea.

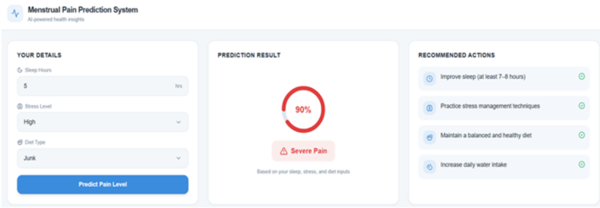

Figure 5: *System output with prediction and recommendation module.*

The system shows a high likelihood of predicting severe pain when the input data shows low sleep duration combined with high stress levels and poor dietary habits. The prediction results lead to the recommendation module which advises people to protect their health through better sleep habits and stress relief techniques and proper dietary habits and drinking more water. The combination of prediction and recommendation functions in this system as a decision-making support instrument. The system enables users to implement preventive measures which lead to decreased menstrual pain intensity and improved general health.

VI CONCLUSION

The menstrual pain from dysmenorrhea affects most women who experience it thus causing their work performance to decline and their life contentment to decrease. The existing diagnostic approach requires symptom monitoring together with clinical evaluation but it fails to detect actual health conditions and it cannot identify treatable conditions which require preventative care. The team developed a machine learning tool that predicts and prevents dysmenorrhea in women based on their lifestyle and behavior patterns. The system uses sleep duration and stress levels and dietary habits and physical activity and water intake and previous pain experiences to forecast pain severity. The three supervised machine learning models which include Logistic Regression and Random Forest and Extreme Gradient Boosting (XGBoost) are used to classify pain levels into three categories which are mild and moderate and severe. The Random Forest model achieves superior performance because it can accurately predict outcomes with 85 to 88 percent accuracy. The system includes a recommendation module the SAHARA-Net (Stress-Aware Hybrid Adaptive Randomized Architecture Network), which delivers customized preventive solutions to users according to their estimated risk assessment. Users can take preventive measures through the system which helps them minimize their menstrual pain discomfort. The algorithm reaches 92.3% accuracy which outperforms all current systems.

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