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Development of Stress Detection and Management System Using Machine Learning Algorithm for Sulu State College: A Proposed Framework for Mitigating Stress Related Diseases

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ABSTRACT

Stress significantly impacts academic performance, mental well-being, and overall student success in higher education institutions. Sulu State College faces challenges in addressing stress among its students and staff due to limited technological interventions. This study aimed to develop and evaluate a comprehensive Stress Detection and Management System using machine learning algorithms, EMG sensors, and DHT11 sensors for the Sulu State College community. The system integrated intramuscular EMG sensors, DHT11 temperature and humidity sensors, Arduino Uno microcontrollers, and machine learning algorithms (Logistic Regression and K-Nearest Neighbors). Data were collected from 25 respondents (18 staff, 7 students). The system was evaluated using a five-point Likert scale by three experts assessing functionality, usability, reliability, and performance. The Perceived Stress Scale (PSS) was administered to measure perceived stress levels. The predictive model achieved 99% accuracy in stress prediction. Expert evaluations yielded general weighted means of 4.77778 (functionality), 4.66667 (usability), 4.5 (reliability), and 5.0 (performance), all categorized as "Very Acceptable." Survey results indicated that 20 out of 25 respondents (80%) experienced moderate stress levels. User satisfaction scored a mean of 4.5 out of 5. The developed Stress Detection and Management System effectively detects and manages stress among students and staff, demonstrating high functionality, usability, reliability, and performance. The system's personalized interventions based on physiological data provide a proactive approach to stress management in academic settings.

Keywords: Stress Detection, Machine Learning, EMG Sensors, DHT11 Sensors, Higher Education

INTRODUCTION

Stress, defined as a state where an individual experiences strain and discomfort, manifests through physical, psychological, and emotional reactions triggered by external stressors [1]. These stressors, ranging from work pressures and interpersonal conflicts to environmental factors and traumatic events, contribute to an overwhelming experience that negatively affects both physical and mental health. The body's response to stress involves the release of stress hormones, heightened alertness, increased heart rate, and changes in breathing, preparing the individual for potential threats [2].

The academic community faces unique stressors that significantly impact mental and physical well-being.[3][4] emphasize the intricate interplay of emotions within academic settings. Emotional stress, often overlooked in traditional stress assessments, significantly contributes to overall well-being. [5] demonstrated the efficacy of electromyography (EMG) in recognizing emotional states with high accuracy. This technology, when coupled with machine learning algorithms, has the potential to unveil emotional nuances that traditional assessments may miss.

Stress-related diseases, triggered by an individual's response to stress, have become pervasive, encompassing conditions such as depression, anxiety, and post-traumatic stress disorder (PTSD). The impact extends beyond mental health, exacerbating other conditions like cardiovascular disease [6]. The ubiquitous nature of stress makes it a common symptom in all humans, influencing lives across diverse professions, lifestyles, and age groups.

Previous work on stress recognition has focused on the extraction of handcrafted features, which requires human intervention and expertise [7]. The current Mental Healthcare (MHC) system for stress recognition is mostly designed for specific groups of

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Research Article

individuals, such as occupational stress, perinatal maternal stress, or health worker stress, and lacks a framework that is not targeted for a particular group of individuals [8].

In educational settings, there is a lack of effective systems to monitor and manage stress levels among students and staff. Approximately 60% of students and 45% of staff at Sulu State College report high levels of stress during peak academic periods, leading to a decrease in academic performance by an average of 20% [9]. Less than 10% of the academic population currently uses any form of technological aid for stress management, highlighting limited awareness and utilization. Existing stress management initiatives have not significantly improved the overall mental well-being of the college community, with over 70% of individuals reporting no substantial change in their stress levels after utilizing available resources [10].

Several solutions have been proposed to address stress in academic settings.[6] developed stress detection systems using ECG and EMG signals. [11] introduced Stress-Lysis, an IoMT-enabled device for automatic stress level detection. [12] designed a mental health system for stress management of knowledge workers. However, these solutions are often designed for specific populations and lack applicability to diverse academic communities in Sulu State College [7].

The research gaps identified in this study include: (1) insufficient empirical data on the effectiveness of combining EMG sensors and DHT11 sensors for stress detection in an academic setting; (2) lack of personalized intervention strategies based on real-time physiological data; and (3) limited studies on the impact of stress detection systems on academic performance and mental well-being within higher education institutions [13].

This study addresses these research gaps by developing a comprehensive Stress Detection and Management System for students and staff at Sulu State College. The specific objectives of this study were to: (1) design and evaluate the effectiveness of EMG sensors, DHT11 Temperature and Humidity Sensors, and machine learning algorithms in detecting physiological indicators of stress; (2) develop a machine learning model using Logistic Regression and K-Nearest Neighbors Algorithm to predict stress based on the data collected; (3) assess the usability and user acceptance of the system; (4) provide personalized interventions and recommendations for stress management; and (5) determine the impact of the system on the mental well-being and academic performance of students and staff [14].

This research contributes to the advancement of technology-driven solutions for promoting mental health and well-being in educational settings. The potential benefactors of this contribution include students, staff, educational administrators, healthcare providers, and technology developers. The study aligns with several Sustainable Development Goals (SDGs) including SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), and SDG 9 (Industry, Innovation, and Infrastructure) [15].

METHODS

Research Design

This study employed a developmental research design utilizing a mixed-methods approach. The quantitative component involved the collection and analysis of physiological data (EMG readings, temperature, humidity) and survey responses (Perceived Stress Scale). The qualitative component involved expert evaluations and user feedback to assess system usability and effectiveness. The research followed a structured Software Development Life Cycle (SDLC) using Agile methodology, covering phases from requirements gathering to system testing and deployment within Sulu State College [16].

Setting and Participants

The study was conducted at Sulu State College, Jolo, Sulu, Philippines. Participants included 25 respondents comprising 18 staff members and 7 students from the college community. Participants were selected using purposeful and convenient sampling methods. Inclusion criteria required that participants be current students or staff members of Sulu State College and willing to participate in the study.

MATERIALS

Hardware Components

The system utilized the following hardware components: (1) Intramuscular EMG Sensors to measure electrical signals generated by muscle contractions; (2) DHT11 Sensor, a low-cost digital sensor used to measure temperature and humidity levels; (3) Arduino Uno Microcontroller serving as the central processing unit; (4) Disposable Surface Electrodes applied to the skin surface

Journal of Information Systems Engineering and Management
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Research Article

to capture surface electromyography (EMG) signals; (5) Breadboards for prototyping and testing electronic circuits; and (6) 24V Battery as a portable power source for continuous operation [17].

Software Components

The following software tools were utilized: (1) Arduino IDE for writing, compiling, and uploading code to Arduino microcontroller boards; (2) Visual Studio Code as the primary code editor; (3) Python Interpreter for data preprocessing and machine learning model development using libraries such as TensorFlow and scikit-learn; (4) Kaggle platform for accessing datasets; (5) Google Colab for cloud-based development; and (6) Anaconda Navigator for managing Python environments and package installations [18].

DATA COLLECTION PROCEDURES

Phase 1: Data Collection

Data were collected from multiple sources: Physiological Data recorded using EMG sensors and DHT11 sensors; Self-Reported Data collected through the Perceived Stress Scale (PSS) questionnaire measuring perceived stress levels over the past month; and Contextual Information including environmental and contextual data such as location and time. The Perceived Stress Scale (PSS) measures an individual's perceived stress levels, with scores ranging from 0 to 40. Higher scores indicate higher perceived stress. Scores ranging from 0-13 indicate low stress, 14-26 indicate moderate stress, and 27-40 indicate high perceived stress [19].

Phase 2: Data Preprocessing

Collected data were subjected to preprocessing to address noise, missing values, and outliers. This encompassed data cleaning, normalization, and application of appropriate techniques to enhance data quality. Physiological signals from EMG sensors and measurements of temperature and humidity levels were filtered and artifacts removed [20].

Phase 3: Feature Extraction and Fusion

Features were extracted from different modalities (EMG, temperature, humidity) and fused to create a comprehensive representation of stress-related information. The fused features were transformed into a format suitable for machine learning algorithms.

Phase 4: Machine Learning Model Selection

Based on the nature of the data and stress patterns, Logistic Regression and K-Nearest Neighbors (KNN) algorithms were selected. Both algorithms are widely used for classification tasks and have demonstrated effectiveness in stress detection studies [21].

Phase 5: Model Training and Evaluation

The selected models were trained on the preprocessed data. A training-testing split of 75%-25% was used. Model performance was evaluated using Confusion Matrix to visualize classification performance, Accuracy Score for percentage of correctly classified instances, and Cross-Validation to assess model generalizability [22].

Phase 6: Integration and Deployment

The trained machine learning models were integrated into the stress detection system for real-time analysis. A user-friendly web application interface was developed for data input and stress detection result reception.

EVALUATION FRAMEWORK

System Evaluation

The proposed system was evaluated by three experts: one from the Admission Office, one psychological stress expert, and one IT expert from the department. The evaluation tool was based on the Software Quality Model and presented on a five-point Likert scale as shown in Table 1 [23].

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Research Article

Table 1. System Evaluation Scale

Scale	Range	Descriptive Evaluation
1	1.00 – 1.49	Not Acceptable
2	1.50 – 2.49	Fairly Acceptable
3	2.50 – 3.49	Moderately Acceptable
4	3.50 – 4.49	Acceptable
5	4.50 – 5.00	Very Acceptable

Evaluation Criteria

The system was evaluated based on four quality attributes: Functionality (how easy the system is to operate), Usability (how easy the system is to operate, remember, and use), Reliability (the system's ability to produce desired results without errors), and Performance (the speed and efficiency of the system's response time and processing speed) [24].

Theoretical Frameworks

The study was guided by the following theoretical frameworks: (1) Health Belief Model (HBM) to understand how individuals perceive and respond to health-related issues [25]; (2) Transactional Model of Stress and Coping to understand how individuals perceive and manage stress [26]; (3) Technology Acceptance Model (TAM) to evaluate user acceptance and adoption of the system [27]; and (4) Social Cognitive Theory to empower users through observational learning, self-efficacy, and self-regulation [28].

Ethical Considerations

The study adhered to the principles of the Data Privacy Act, ensuring transparent data collection, explicit consent, and stringent security measures to protect personal information. Informed consent was obtained from all participants, and confidentiality of data was maintained throughout the study. Ethical approval was obtained from Sulu State College's ethics committee [29].

RESULTS

Survey Results: Stress Levels Among Respondents

The survey results from 25 respondents (18 staff, 7 students) revealed the stress level distribution presented in Table 2. The majority of respondents (80%, n = 20) reported experiencing moderate stress levels, while 12% (n = 3) reported low stress and 8% (n = 2) reported high stress. Among staff, 2 out of 18 experienced low stress, 14 faced moderate stress, and 2 were highly stressed. Among students, 1 out of 7 reported low stress, while 6 experienced moderate stress, and none reported high stress [30].

Table 2. Survey Results: Stress Levels Among Respondents

Respondent Type	Low Stress	Moderate Stress	High Stress	Total
Staff	2	14	2	18
Students	1	6	0	7
Overall	**3**	**20**	**2**	**25**

Sensor Readings and Predictions

The stress detection system utilized specific sensor reading ranges to categorize stress levels as shown in Table 3. Table 4 presents the detailed stress level readings and predictions for all 25 respondents, showing the correlation between sensor readings (EMG, humidity, temperature), predicted stress levels, and actual stress levels [31].

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/

Research Article

Table 3. Sensor Reading Ranges for Different Stress Levels

Stress Level	EMG Reading	Humidity Reading	Temperature Reading
0 - Low Stress	0 - 75	27 - 65	98 - 100
1 - Normal Stress	76 - 100	66 - 91	90 - 97
2 - High Stress	101 - 200	92 - 120	80 - 89

Table 4. Stress Level Readings and Predictions for 25 Respondents

Respondent	Role	Stress Level Reported	EMG Reading	Humidity Reading	Temperature Reading	Predicted Stress Level	Stress Level (0-2)
1	Staff	Low	50	40	99	Low	0
2	Staff	Moderate	80	70	95	Normal	1
3	Staff	Moderate	90	75	93	Normal	1
4	Staff	High	120	100	85	High	2
5	Staff	Moderate	85	72	94	Normal	1
6	Staff	Moderate	88	78	92	Normal	1
7	Staff	Moderate	77	66	96	Normal	1
8	Staff	Moderate	82	74	93	Normal	1
9	Staff	Moderate	79	69	95	Normal	1
10	Staff	Moderate	83	73	92	Normal	1
11	Staff	Low	55	45	99	Low	0
12	Staff	Moderate	87	76	94	Normal	1
13	Staff	Moderate	80	70	96	Normal	1
14	Staff	Moderate	78	68	95	Normal	1
15	Staff	Moderate	81	72	93	Normal	1
16	Staff	Moderate	85	75	92	Normal	1
17	Staff	High	115	97	86	High	2
18	Staff	Moderate	80	70	95	Normal	1
19	Student	Low	65	50	98	Low	0
20	Student	Moderate	82	74	94	Normal	1
21	Student	Moderate	80	72	95	Normal	1
22	Student	Moderate	85	76	93	Normal	1
23	Student	Moderate	83	73	94	Normal	1
24	Student	Moderate	78	68	96	Normal	1
25	Student	Moderate	79	69	95	Normal	1

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/
Research Article

Machine Learning Model Performance

The Logistic Regression and K-Nearest Neighbors (KNN) models were trained and evaluated. The Logistic Regression model achieved 99.40% training accuracy and 99.40% testing accuracy. The K-Nearest Neighbors model achieved 99.80% training accuracy and 99.80% testing accuracy [32]. Both models demonstrated excellent accuracy, achieving approximately 99% accuracy in predicting stress levels based on the features (humidity, temperature, EMG readings). The high accuracy indicates the effectiveness of both models in precisely categorizing stress levels.

Model Deployment Testing

The trained model (stress_trained.h5) was tested with the following input: Humidity: 20.94%, Temperature: 84.94°F, and EMG Reading: 200%. The model predicted "High Stress" (Stress Level 2), demonstrating its capability to classify stress levels based on physiological and environmental parameters in real-time [33].

Expert Evaluation Results

Functionality

Table 5. Expert's Response on Functionality

Indicators	Expert A	Expert B	Expert C	Mean	Description
The system interface is working	5	5	4	4.66667	Very Acceptable
Feedback is immediate	5	5	4	4.66667	Very Acceptable
The program loads quickly	5	5	5	5.0	Very Acceptable
General Weighted Mean				**4.77778**	**Very Acceptable**

Usability

Table 6. Expert's Response on Usability

Indicators	Expert A	Expert B	Expert C	Mean	Description
The system interface is user-friendly	5	5	4	4.66667	Very Acceptable
The content is readable and easy to understand	5	4	5	4.66667	Very Acceptable
Color and text font style are appropriate	5	5	4	4.66667	Very Acceptable
General Weighted Mean				**4.66667**	**Very Acceptable**

Reliability

Journal of Information Systems Engineering and Management
2024, 9(4)
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https://www.jisem-journal.com/

Research Article

Table 7. Expert's Response on Reliability

Indicators	Expert A	Expert B	Expert C	Mean	Description
Data are acceptable by the system	4	4	5	4.33333	Very Acceptable
Display a high percentage of accurate results	5	4	5	4.66667	Very Acceptable
General Weighted Mean				**4.5**	**Very Acceptable**

Performance

Table 8. Expert's Response on Performance

Indicators	Expert A	Expert B	Expert C	Mean	Description
Speed efficiency of displaying predictions	5	5	5	5.0	Very Acceptable
Real-time update and auto-refresh	5	5	5	5.0	Very Acceptable
General Weighted Mean				**5.0**	**Very Acceptable**

Summary of Expert Evaluation

Table 9. Summary of Weighted Means for All Four Criteria

Criteria	Weighted Mean	Description
Functionality	4.77778	Very Acceptable
Usability	4.66667	Very Acceptable
Reliability	4.5	Very Acceptable
Performance	5.0	Very Acceptable
General Weighted Mean	**4.7361125**	**Very Acceptable**

All four criteria received ratings of "Very Acceptable," with the general weighted mean of 4.7361125 reflecting an overall high level of satisfaction and effectiveness across all evaluated dimensions [34].

User Satisfaction

User satisfaction with the stress detection system was measured through standardized surveys. Analysis of survey responses revealed a Mean Satisfaction Score of 4.5 out of 5. Variance and Standard Deviation indicated consistency in user satisfaction across the sample population. Qualitative feedback emphasized the system's user-friendly interface and personalized recommendations. Users expressed appreciation for the system's ability to provide tailored stress management suggestions based on their physiological data [35].

Data Visualization Results

Data preprocessing and visualization demonstrated no missing values in the dataset (Humidity, Temperature, EMG, Stress_Level columns all contained 0 missing values). The dataset contained 7,401 observations with features: Humidity, Temperature, EMG, and Stress_Level (0 = Low, 1 = Normal, 2 = High). Histograms and scatter plots illustrated the distribution of EMG readings, humidity, temperature, and stress levels [36].

DISCUSSION

Summary of Findings

The study successfully developed and validated a Stress Detection and Management System for Sulu State College. The system integrated EMG sensors, DHT11 temperature and humidity sensors, and machine learning algorithms (Logistic Regression and K-Nearest Neighbors) to accurately detect and classify stress levels among students and staff. The predictive model achieved an impressive 99% accuracy rate, confirming the system's reliability in stress prediction. Expert evaluations rated the system as "Very Acceptable" across all four quality criteria (functionality, usability, reliability, and performance), with a general weighted mean of 4.7361125 [37].

Interpretation of Findings

Stress Prevalence in the Academic Community

The survey findings revealed that 80% of respondents experienced moderate stress levels, with only 12% reporting low stress and 8% reporting high stress. This distribution aligns with previous studies that have documented the prevalence of stress in academic settings [38]. The predominance of moderate stress suggests that while most individuals are managing their stress at a functional level, there is significant room for improvement in stress management interventions. The staff population showed slightly higher proportions of both low stress (11.1% vs. 14.3% for students) and high stress (11.1% vs. 0% for students) compared to students. This may reflect the different stress profiles of staff versus students, with staff potentially experiencing more diverse workplace-related stressors while students may have a more uniform academic stress experience [39].

Effectiveness of Physiological Indicators

The integration of EMG sensors and DHT11 sensors proved effective in detecting physiological indicators of stress. The EMG readings, humidity measurements, and temperature readings showed clear patterns corresponding to different stress levels. Specifically, higher EMG readings (101-200) and lower temperature readings (80-90°F) were associated with high stress levels, while lower EMG readings (0-75) and higher temperature readings (98-100°F) were associated with low stress levels [40]. These findings align with previous research demonstrating the efficacy of EMG in recognizing emotional states [5] and the relationship between environmental temperature and stress responses [41]. The high accuracy (99%) of the predictive models confirms that the combination of EMG, temperature, and humidity provides a robust set of features for stress classification.

Machine Learning Model Performance

Both Logistic Regression and K-Nearest Neighbors algorithms achieved approximately 99% accuracy in predicting stress levels. This exceeds the accuracy rates reported in previous studies [6] reported 96.2% accuracy for four-level stress recognition. The high performance can be attributed to several factors: (1) Feature Selection - the combination of physiological (EMG) and environmental (temperature, humidity) features provided a comprehensive representation of stress-related information; (2) Data Quality - the dataset was complete and well-preprocessed; (3) Algorithm Selection - both Logistic Regression and KNN are well-suited for classification tasks with moderate-sized datasets; and (4) Model Training - the 75%-25% training-testing split and cross-validation ensured model generalizability [42].

System Acceptance and Usability

The expert evaluation results (general weighted mean of 4.7361125) indicate strong acceptance of the system across all quality dimensions. The performance criteria received a perfect score (5.0), highlighting the system's speed and efficiency. The functionality and usability scores (4.77778 and 4.66667, respectively) indicate that the system is both effective and user-friendly

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/

Research Article

[43]. These findings align with the Technology Acceptance Model (TAM), which suggests that perceived usefulness and perceived ease of use are key determinants of technology adoption [27]. The high usability ratings suggest that users found the system easy to navigate and use, which is crucial for encouraging sustained usage. The user satisfaction survey (mean score 4.5 out of 5) further supports the system's acceptance [44].

Integration of Theoretical Frameworks

The successful development and acceptance of the system can be understood through the theoretical frameworks guiding the study: (1) Health Belief Model - the system increases perceived susceptibility to stress-related health issues by providing real-time feedback on physiological stress indicators; (2) Transactional Model of Stress and Coping - the system supports both primary appraisal (identifying stressors) and secondary appraisal (providing coping resources) through its personalized intervention recommendations; (3) Social Cognitive Theory - the system empowers users through self-efficacy by providing actionable recommendations and goal-setting tools; and (4) Technology Acceptance Model - the high usability and functionality ratings confirm that users perceived the system as both useful and easy to use [45].

IMPLICATIONS

Practical Implications

The findings of this study have several practical implications: (1) Improved Health and Well-being - the system provides a tool for early detection and intervention, potentially preventing the escalation of stress-related illnesses; (2) Enhanced Academic Performance - by helping students and staff manage stress more effectively, the system may contribute to improved academic outcomes and productivity; (3) Innovation in Health Technology - the integration of machine learning algorithms with physiological sensors represents an innovative approach to stress management; and (4) Personalized Interventions - the system's ability to provide tailored recommendations based on individual stress profiles moves beyond one-size-fits-all approaches to stress management [46].

Alignment with Sustainable Development Goals

This study aligns with several Sustainable Development Goals [15]: SDG 3 (Good Health and Well-being) by developing a stress detection and management system; SDG 4 (Quality Education) by implementing stress management strategies in educational institutions; SDG 9 (Industry, Innovation, and Infrastructure) through the integration of machine learning algorithms into healthcare systems; SDG 10 (Reduced Inequalities) by promoting equal access to mental health support; SDG 16 (Peace, Justice, and Strong Institutions) by fostering a supportive and inclusive environment; and SDG 17 (Partnerships for the Goals) through collaborations between educational institutions, healthcare providers, and technology developers [47].

LIMITATIONS

Several limitations of this study should be acknowledged: (1) Sample Size - the study included only 25 respondents (18 staff, 7 students), limiting the generalizability of findings; (2) Single Institution - the findings are limited to Sulu State College and may not be generalizable to other educational institutions; (3) Short-term Focus - the study focused on short-term impacts rather than long-term sustainability; (4) Self-Reported Data - the stress levels reported by participants through surveys are subjective and may be influenced by recall bias or social desirability bias; (5) Limited Intervention Types - the system's personalized interventions were limited in scope; (6) Technical Constraints - the study used specific hardware components that may not be readily available or cost-effective for widespread implementation; and (7) False Positives - some users reported occasional instances of false positives, indicating areas for improvement in the system's accuracy [48].

FUTURE DIRECTIONS

Based on the findings and limitations of this study, several directions for future research and development are recommended: (1) Larger-Scale Studies - conduct studies with larger and more diverse samples across multiple educational institutions; (2) Long-term Follow-up - implement longitudinal studies to assess the long-term effectiveness and sustainability of the system; (3) Enhanced Intervention Types - program the system to offer a broader range of personalized interventions including mental health resources, counseling services, and relaxation exercises; (4) Integration with Existing Programs - integrate the system into the college's existing wellness programs and academic support services; (5) Model Optimization - regularly update and calibrate the machine learning model with new data and explore more sophisticated algorithms such as Support Vector Machines (SVM) and deep learning approaches; (6) Multi-parameter Measurement - explore additional sensors and data sources including heart rate variability, galvanic skin response, or cortisol levels; (7) Mobile Application - develop a mobile application version of the system to increase accessibility; and (8) Widespread Adoption - conduct marketing and promotion within the college to encourage widespread adoption [49].

CONCLUSION

This study successfully developed and evaluated a comprehensive Stress Detection and Management System for Sulu State College, integrating EMG sensors, DHT11 temperature and humidity sensors, and machine learning algorithms (Logistic Regression and K-Nearest Neighbors). The system demonstrated high effectiveness in detecting physiological indicators of stress, achieving 99% accuracy in predicting stress levels based on physiological and environmental data [50].

The findings revealed that 80% of respondents (20 out of 25) experienced moderate stress levels, underscoring the need for effective stress management strategies in the academic community. Expert evaluations confirmed the system's high functionality (4.77778), usability (4.66667), reliability (4.5), and performance (5.0), with a general weighted mean of 4.7361125, all categorized as "Very Acceptable." User satisfaction was high (mean 4.5 out of 5), with positive feedback on the system's user-friendly interface and personalized interventions [51].

The system's effectiveness can be attributed to the robust integration of hardware components, sophisticated data processing and machine learning techniques, and the adoption of appropriate theoretical frameworks (Health Belief Model, Transactional Model of Stress and Coping, Technology Acceptance Model, and Social Cognitive Theory). The system aligns with Sustainable Development Goals related to good health and well-being, quality education, innovation, reduced inequalities, and partnerships for sustainable development [52].

The study contributes to the advancement of technology-driven solutions for promoting mental health and well-being in educational settings. By providing real-time stress detection and personalized interventions, the system empowers students and staff with proactive tools for stress management, potentially improving academic performance, mental well-being, and overall quality of life [53].

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