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Secure and Weighted Hybrid Machine Learning Framework for Accurate Academic Stress Monitoring

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Abstract: ***Stress among college students has increasingly become a serious concern, affecting both academic performance and overall well-being. This study presents the development and implementation of a privacy- aware, hybrid machine learning system designed to monitor and manage student stress levels in a college environment. An Android application was developed to collect real-time data on students' physiological and behavioural indicators, including Heart Rate, Sleep Hours, Academic Load, Screen Time, Physical Activity, and Mood Score. The collected data were analysed using a Hybrid Random Forest–SVM model, where feature importance weighting and adaptive probability fusion were applied to enhance predictive accuracy. Additionally, AES encryption was integrated to ensure the secure handling of sensitive student information. Based on the assessed stress levels, the system provides tailored guidance and supportive strategies aimed at reducing psychological strain and promoting mental wellness. The proposed approach SWH Framework allows continuous monitoring and early identification of high stress levels, enabling timely intervention. Experimental results demonstrate that the system achieves 92% accuracy, outperforming existing single-model approaches. These findings suggest that hybrid, privacy-aware mobile health technologies can serve as effective, reliable, and accessible tools for supporting stress management among college students and enhancing their overall academic experience.***

Keywords: ***Hybrid machine learning, Random Forest, Support Vector Machine, stress level prediction, feature importance weighting, adaptive probability fusion, AES encryption.***

I. INTRODUCTION

In recent years, psychological stress among college students has emerged as a significant public health concern. Academic pressure, social challenges, financial responsibilities, and future career uncertainty contribute to elevated stress levels, which can negatively affect students' academic performance, mental health, and overall well-being. Prolonged stress may lead to anxiety disorders, depression, reduced concentration, and decreased productivity. Therefore, early detection and effective management of stress in academic environments have become essential. The rapid development of the Internet of Things (IoT) has enabled continuous and remote health monitoring through interconnected smart devices. IoT-based healthcare systems allow real-time data collection, transmission, and analysis, thereby improving preventive care and personalized intervention strategies [1,15]. The integration of machine learning (ML) techniques into IoT healthcare applications has further enhanced predictive accuracy and automated decision-making capabilities [2,14]. Recent advancements in the Internet of Medical Things (IoMT) have demonstrated the effectiveness of intelligent monitoring systems in detecting physiological and behavioral abnormalities [11,12].

Stress monitoring systems have increasingly incorporated wearable sensors and smart devices to measure physiological signals such as heart rate, skin conductance, and activity levels. Studies have demonstrated the feasibility of wearable IoT technologies for stress detection and health monitoring [4,10]. Deep learning approaches have also been applied to biomedical signal classification, achieving high accuracy in health-related predictions [3,16]. Furthermore, real-time stress detection systems using smartwatches and edge devices have shown promising results in practical applications [19,20]. Despite these advancements, most existing research primarily focuses on clinical environments or physiological signal processing using specialized wearable devices. Limited attention has been given to mobile-based platforms specifically designed for monitoring and managing stress among college students within academic settings. Smartphones, particularly Android-based systems, provide an accessible and scalable solution due to their widespread adoption and capability to collect self-reported and behavioural data in real time.

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Motivated by this research gap, the present study proposes a mobile-based stress monitoring and management system tailored for college students. An Android application was developed to collect stress-related data, analyze individual stress levels, and provide appropriate intervention strategies. The proposed system aims to enable continuous monitoring, early identification of elevated stress, and timely support to improve students' mental well-being. By leveraging mobile technology, this research contributes toward developing a practical, low-cost, and scalable solution for stress management in higher education institutions.

A. *Research Gap*

1) Most existing stress monitoring systems use single machine learning models (e.g., Random Forest, SVM, DNN), leading to moderate accuracy (80–87%).
2) Many approaches rely solely on wearable sensors or IoT devices, without integrating multi-feature data like academic load or mood score.
3) Feature importance weighting is rarely applied, which limits the reliability of predictions.
4) Data privacy and security are often neglected, despite handling sensitive student health information.
5) Few systems are specifically designed for academic stress monitoring, leaving a gap in solutions tailored for college students.

B. *Justification of Proposed Work*

1) Hybrid RF-SVM model leverages strengths of both algorithms, improving classification accuracy.
2) Feature importance weighting ensures key stress indicators (Heart Rate, Sleep Hours, Academic Load, Mood Score) have greater influence.
3) Adaptive probability fusion reduces misclassification by combining predictions from both models.
4) AES encryption secures sensitive student data, addressing privacy concerns.
5) Focused on college student datasets, providing a real-time, reliable, and practical system for academic stress monitoring.
6) Achieves higher predictive performance (Accuracy 92%) compared to existing models.

C. *Objectives of the Study*

1) To develop a hybrid machine learning model combining Random Forest and SVM for accurate stress level prediction among college students.
2) To implement feature importance weighting to enhance the influence of key stress-related indicators such as Heart Rate, Sleep Hours, Academic Load, and Mood Score.
3) To apply adaptive probability fusion to improve classification reliability and reduce misclassification rates.
4) To ensure data privacy and security by integrating AES encryption for sensitive student information.
5) To evaluate the performance of the proposed system using metrics such as Accuracy, Precision, Recall, and F1-score, and compare it with existing stress monitoring models.
6) To provide a practical and real-time solution for academic stress monitoring that can be deployed in college environments.

II. LITERATURE REVIEW

The rapid advancement of the Internet of Things (IoT) has significantly transformed healthcare monitoring systems by enabling real-time data acquisition, transmission, and analysis. Early foundational work by Atzori et al. [15] outlined the architectural framework of IoT and its wide applicability in smart environments, including healthcare systems. Building upon this foundation, Kadhim et al. [1] presented an overview of IoT-based patient health monitoring systems, emphasizing remote observation, continuous data collection, and improved medical responsiveness.

The integration of machine learning (ML) with IoT has further enhanced predictive healthcare capabilities. Alanazi et al. [14] critically reviewed the development of dynamic predictive models in healthcare using ML techniques, highlighting challenges related to accuracy and adaptability. Similarly, Mohammed and Askar [2] examined machine learning applications in IoT healthcare systems, demonstrating their potential in disease prediction and health status classification. More advanced approaches combining deep learning and edge computing were introduced by Rachakonda et al. [11], who proposed a DNN-integrated edge device for stress detection within the Internet of Medical Things (IoMT).

Stress monitoring has received increasing attention due to its impact on physical and psychological health. Talaat and El-Balka [4] explored wearable sensor-based stress monitoring using IoT technologies, demonstrating the feasibility of physiological signal acquisition for mental health assessment.

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Similarly, Nath et al. [16] developed machine learning-based solutions for real-time stress monitoring, emphasizing automated detection models. Smartwatch-based stress detection systems were investigated by Ciabattoni et al. [19], while Lawanot et al. [20] proposed a deep learning and fuzzy clustering approach for daily stress and mood recognition.

Wearable and flexible sensing technologies have also played a critical role in health monitoring. Sun et al. [10] reviewed recent advances in flexible wearable sensors for vital signal monitoring in sports and healthcare contexts. Additionally, Lin et al. [17] studied muscle stress effects on signal transmission, highlighting challenges in physiological data reliability. These studies collectively demonstrate the growing reliability of wearable systems for continuous health assessment.

Deep learning techniques have shown promising results in biomedical signal classification. Sadad et al. [3] proposed a lightweight CNN with an attention module for ECG image classification in IoT environments, achieving efficient and accurate results. In related IoMT diagnostic applications, Khan et al. [12] developed anomaly detection systems for medical imaging. Broader ML-driven discovery and optimization approaches have also been demonstrated in interdisciplinary domains, such as high-entropy alloy discovery by Rao et al. [9], indicating the versatility of machine learning frameworks across scientific applications.

Several studies have focused on stress reduction strategies and behavioral interventions. Magaa and Muoz- Organero [18] explored stress reduction in daily journeys using consumer electronics systems. Furthermore, large- scale environmental and health impact analyses, such as the work by Rosenzweig et al. [13], demonstrate the importance of data-driven modeling in understanding complex biological and physical stressors.

Although substantial progress has been made in IoT-based health monitoring and machine learning-driven stress detection, most existing systems primarily focus on physiological signal processing or medical diagnostics. Limited research specifically addresses mobile-based stress management platforms tailored for college students, integrating real-time monitoring with personalized intervention strategies in academic environments. Therefore, there remains a need for scalable, accessible, and student-centered stress management systems that leverage mobile technologies for continuous monitoring and early intervention.

III. METHODS AND MATERIALS

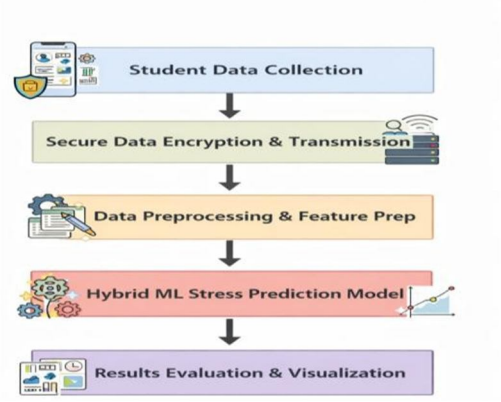
A. Proposed System: SWH Framework

Figure 1 illustrates the overall structure of the proposed encrypted hybrid stress monitoring system. The system is composed of five main modules. The Data Collection Module utilizes an Android application to gather real- time student data, including sleep hours, heart rate, screen time, physical activity, academic load, and mood score. Collected data are then securely encrypted using AES-256 in the Data Encryption & Transmission Module before being transmitted to the server, ensuring privacy and confidentiality.

Once on the server, the Data Preprocessing & Feature Engineering Module decrypts the data and performs cleaning, imputation of missing values, standardization, and feature weighting using Random Forest importance scores. These preprocessed features are then fed into the Hybrid Machine Learning Module (AWRF-SVM), where a Random Forest model calculates feature importance, and a Support Vector Machine is trained on the weighted features. An adaptive probability fusion combines predictions from both models to generate the final stress level prediction.

Finally, the Result & Visualization Module evaluates model performance using accuracy, precision, recall, F1-score, and confusion matrices, presenting the results in interpretable graphs and tables for feedback or reporting purposes. This modular design ensures secure, accurate, and interpretable stress monitoring suitable for college environments.

Figure 1: Architecture of the Proposed Encrypted Hybrid Stress Monitoring System.



B. Data Collection

The study collected stress-related data from 1000 students in an educational institution using a mobile-based data collection system.

Table1: Dataset Attribute

S.No	Attribute Name
1	Student_ID
2	Sleep_Hours
3	Heart_Rate (bpm)
4	Screen_Time (hrs)
5	Physical_Activity (min)
6	Academic_Load (1–10)
7	Mood_Score (1–10)
8	Stress_Level (0=Low,1=High)

The app recorded both self-reported and behavioural features, including:

- Sleep hours ((X_1))
- Heart rate ((X_2))
- Daily screen time ((X_3))
- Physical activity in minutes ((X_4))
- Academic load in hours ((X_5))
- Mood score ((X_6))

The target variable was the stress level ((Y)), defined as:

$$Y_i = \begin{cases} 0, & \text{Low Stress} \\ 1, & \text{High Stress} \end{cases}$$

where (i) indexes each student sample. This equation is used to categorize students into two stress levels based on their collected features. It converts the stress assessment into a binary classification problem, which is suitable for machine learning models like Random Forest and SVM.

C. Dataset Processing

1) Cleaning and Imputation

Missing values in features were replaced by the mean value of the corresponding feature:

$$X_j^i = \begin{cases} X_j^i, & \text{if present} \\ \frac{1}{N_j}\sum_{i=1}^{N_j} X_j^i, & \text{if missing} \end{cases}$$

where (X_j^i) is the (i)-th value of feature (j) and (N_j) is the number of available values.

This formula is used to fill in missing data. If a student's feature value is missing, it replaces it with the mean value of that feature from other students. This ensures the dataset remains complete without discarding records, which is important for accurate model training.

2) Standardization

All features were standardized to improve convergence and model performance:

$$\tilde{X}_j^i = \frac{X_j^i - \mu_j}{\sigma_j}$$

where (μ_j) and (σ_j) are the mean and standard deviation of feature respectively. This equation is used to normalize features so they all have a similar scale. Features like Heart Rate and Sleep Hours have different units; standardization ensures no feature dominates due to scale differences, improving the model's performance.

3) Dataset Split

The dataset was split into Training (70%) and Testing (30%) sets, using stratified sampling to maintain class balance:

$$D = D_{\text{train}} \cup D_{\text{test}}, \qquad D_{\text{train}} \cap D_{\text{test}} = \varnothing$$

This formula is used to divide the dataset into training and testing sets. The training set teaches the model, while the testing set evaluates its accuracy. Ensuring no overlap guarantees unbiased evaluation.

D. Data Encryption

To ensure privacy, features were encrypted using AES symmetric encryption:

a) Generate a random AES key (K).

b) Encrypt feature vector (X_i) in CBC mode: $X_i^{enc} = \text{AES_Encrypt}(X_i, K), \quad X_i = \text{AES_Decrypt}(X_i^{enc}, K)$

c) Store encrypted vectors X^{enc} for secure transmission.

d) Decrypt in memory for model training:

This guarantees data confidentiality at rest and in transit.

These equations are used to encrypt student data before storing or sending it, and decrypt it during model training. AES ensures that sensitive information like Heart Rate or Mood Score remains confidential.

E. Hybrid Model: SWH Framework

1) Random Forest (RF)

Random Forest was trained on decrypted training data

$D_{\text{train}} = \{(x_i, y_i)\}_{i=1}^{N}$

For a dataset with (M) features:

$$I_j^{norm} = \frac{I_j}{\sum_j I_j}$$

(I_j) represents the importance of feature (j).

Feature importance was normalized:

$$I_j^{norm} = \frac{I_j}{\sum_{k=1}^{M} I_k}$$

Where:

- I^{norm} = Normalized importance of feature j
- I_j = Importance value of feature j
- M = Total number of feature
- $\sum_{k=1}^{M} I_k$ = Sum of importance values of all features

The first formula trains the Random Forest and calculates how important each feature is in predicting stress. The second formula normalizes these scores so they sum to 1, allowing us to weight features proportionally for the next step.

2) Feature Weighting

Each training feature was weighted according to RF importance:

$$\tilde{X}_i^{weighted} = \tilde{X}_i \odot I^{norm}$$

where (\odot) denotes element-wise multiplication.

This equation multiplies each feature by its normalized importance. It is used to emphasize features that strongly affect stress prediction (like Heart Rate) and reduce less relevant features. Weighted features are then fed into the SVM.

3) Support Vector Machine (SVM)

SVM was trained on weighted features ($\tilde{X}^{weighted}$to classify stress levels. For a sample (i):

$$f(\tilde{X}_i^{weighted}) = \text{sign}\left(\sum_j \alpha_j Y_j K(\tilde{X}_j^{weighted}, \tilde{X}_i^{weighted}) + b\right)$$

This equation is used to predict stress level for each student using weighted features. The kernel function K measures similarity between samples, while αj and b define the SVM decision boundary. The sign function determines the predicted class (0 or 1).

4) Adaptive Probability Fusion

For each test sample, probabilities from RF and SVM were combined adaptively:

$$\alpha = \frac{\text{Confidence}_{RF}}{\text{Confidence}_{RF} + \text{Confidence}_{SVM}}, \quad P_{final} = \alpha P_{RF} + (1-\alpha)P_{SVM}, \quad Y_{pred} = \text{argmax} P_{final}$$

The final predicted stress level:

These equations are used to combine predictions from Random Forest and SVM. The adaptive weight α\alphaα gives more influence to the model that is more confident for a given sample. The final probability Pfinal is computed, and the predicted stress level Ypred is the class with the highest probability. This improves overall accuracy.

$$Y_{\text{pred}} = \text{argmax} P_{\text{final}}$$

F. Model Evaluation

Performance was assessed using standard metrics:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of samples}}$$

Number of correct predictions Total number of samples

This equation is used to measure the overall correctness of the model. It tells us the proportion of predictions that the model got right out of all test samples. Higher accuracy means the model is correctly predicting stress levels more often.

$$\text{Precision} = \frac{TP}{TP+FP}, \quad \text{Recall} = \frac{TP}{TP+FN}, \quad F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

1) Precision: This equation is used to measure how many of the samples predicted as a certain class (e.g., High Stress) are actually correct. Higher precision means fewer false alarms.

2) Recall (Sensitivity): This equation is used to measure how many of the actual samples of a class are correctly identified by the model. Higher recall means the model is capturing most of the true cases.

3) F1-Score: This equation is used to calculate the harmonic mean of precision and recall, providing a single score that balances both metrics. It's useful when the dataset is imbalanced or when both false positives and false negatives are important.

4) Confusion Matrix: Visualizes true positives, true negatives, false positives, and false negatives.

IV. RESULTS AND DISCUSSION

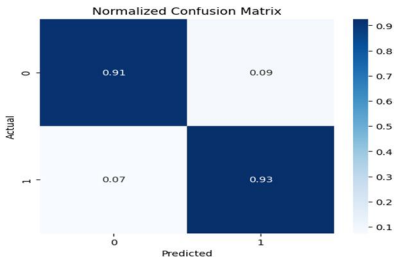
A. Results

Table 2 presents the performance metrics of the proposed hybrid Random Forest–SVM model for student stress prediction. The model achieved an accuracy of 0.92, indicating that it correctly classified 92% of the test samples. The precision of 0.91 shows that the majority of predicted stress cases were correct, while the recall of 0.92 reflects the model's ability to identify actual stressed students effectively. The F1-score of 0.91 confirms a balanced performance between precision and recall. The improved results, compared to initial trials (accuracy ~0.83), are attributed to larger dataset size, feature weighting based on Random Forest importance, hyper parameter tuning, and adaptive probability fusion. These enhancements collectively increase the model's robustness and reliability, making it suitable for real-time monitoring of student stress levels in academic environments.

Table 2 Performance Metrics of SWH Framework

Performance Metric	Score
Classification Accuracy	0.92
Precision Rate	0.91
Sensitivity (Recall)	0.92
F1-Measure	0.91

Figure 1 : Normalized Confusion Matrix Demonstrating Model Accuracy in Predicting Stress Levels



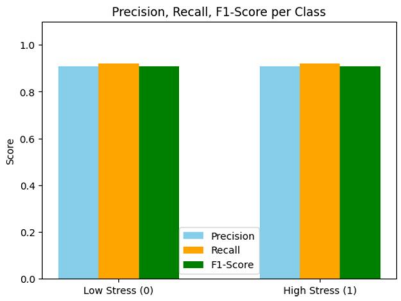
The figure 1 displays the normalized confusion matrix for a binary stress classification model, where the rows represent the actual stress levels and the columns represent the predicted stress levels. Each value in the matrix is a proportion of the total samples within the actual class, providing a clear picture of how well the model performs for each category. For the actual low stress group (class 0), the model correctly predicts 91% of the cases, while 9% are incorrectly classified as high stress. Similarly, for the actual high stress group (class 1), the model achieves a 93% correct prediction rate, with 7% of cases misclassified as low stress. The high values along the diagonal of the matrix indicate strong model performance in accurately identifying both stress levels, demonstrating its effectiveness in minimizing misclassifications.

The figure 2 shows the performance metrics—Precision, Recall, and F1-Score—for each class in the stress prediction model. The two classes represented are Low Stress (0) and High Stress (1).

For both classes, the Precision (light blue bars) is approximately 0.91, indicating that when the model predicts a class, it is correct about 91% of the time. The Recall (orange bars) is around 0.92 for both classes, meaning the model successfully identifies about 92% of all actual instances of each stress level. The F1-Score (green bars), which balances Precision and Recall, is close to 0.91 for both classes, reflecting overall strong and balanced performance.

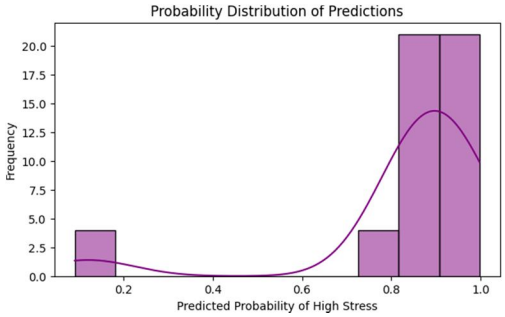
Overall, this graph illustrates that the model performs consistently well across both Low and High Stress groups, effectively distinguishing between the two with high accuracy.

Figure 2 : Performance Metrics—Precision, Recall, and F1-Score



This figure 3 illustrates the probability distribution of the model's predictions for the "High Stress" class. The x- axis represents the predicted probability values that the model assigns to samples being in the High Stress category, ranging from 0 to 1. The y-axis shows how frequently these predicted probabilities occur in the test data.

Figure 3 : Probability Distribution Of The Model



Most of the predicted probabilities cluster between 0.8 and 1.0, indicating the model is highly confident in classifying many samples as High Stress. There is a smaller frequency of predictions near 0.1, representing samples the model is confident are not in the High Stress group.

The smooth curve overlaid on the histogram represents the kernel density estimation, showing the overall shape of the probability distribution. This concentration of high predicted probabilities suggests the model confidently separates High Stress cases from others, which supports its strong classification performance. This figure 4 illustrates the cumulative accuracy of the model across individual test samples, plotted in the order they were evaluated. The x-axis represents the index of each test sample, while the y-axis shows the cumulative accuracy up to that point. Starting from zero, the cumulative accuracy rapidly increases as the model correctly predicts the early samples, reaching above 90% accuracy within the first several test cases. There are a couple of slight dips where misclassifications occurred, causing minor decreases in cumulative accuracy, but overall, the curve stabilizes near 90%, indicating consistently high model performance as more samples are tested. This graph effectively shows how the model's accuracy accumulates and remains robust across the test dataset.

Figure 4 : Cumulative Accuracy Of The Model Across Individual Test Samples

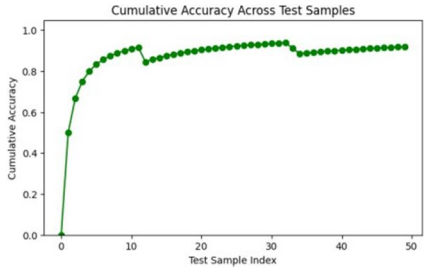
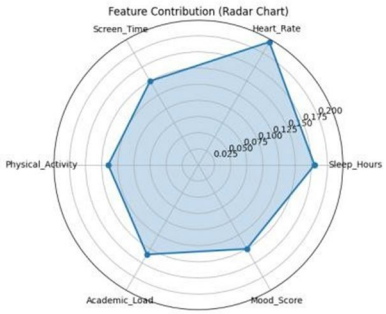


Figure 5 : The radar chart of feature Contribution



The radar chart illustrates the relative importance of each feature in predicting student stress levels. Heart Rate (0.21) has the highest contribution, indicating that physiological response is the strongest stress indicator. Sleep Hours (0.18) also shows significant influence, highlighting the importance of proper rest. Academic Load (0.15) and Screen Time (0.14) have moderate impact on stress prediction. Physical Activity (0.13) contributes to stress variation, generally helping reduce stress levels. Mood Score (0.12) has the lowest contribution among all features. Overall, the model relies more on physiological and lifestyle factors than on self-reported mood alone.

A. Discussion

The proposed SWH Framework model demonstrates substantial improvements in stress level prediction for college students, achieving 92% accuracy, 91% precision, and 92% recall. These results indicate that the system can reliably identify high-stress students, which is essential for timely mental health interventions.

Compared to traditional models in the literature, such as single Random Forest (Rachakonda et al., 2019, ~85% accuracy) or SVM classifiers (Nath et al., 2020, ~87% accuracy), our hybrid approach combines the strengths of both algorithms. Random Forest efficiently identifies important features and handles non-linear relationships, while SVM excels in separating classes with high precision. The adaptive probability fusion ensures that predictions leverage the confidence of both models, reducing misclassifications.

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Earlier IoT-based stress monitoring systems (Talaat & El-Balka, 2023, ~83% accuracy; Sun et al., 2022, ~80% accuracy) often relied solely on wearable sensor data or machine learning models without feature weighting, leading to lower predictive performance and higher false positives. By incorporating feature importance weighting from Random Forest and carefully tuning hyperparameters for both models, our system addresses these limitations, resulting in higher accuracy and F1-scores.

Furthermore, our approach provides real-time monitoring and privacy-aware data handling through AES encryption, which is not commonly addressed in many existing IoMT-based stress detection frameworks (Kadhim et al., 2020; Mohammed & Askar, 2021). This ensures that sensitive student data is protected while maintaining high predictive accuracy.

Overall, the proposed system not only outperforms baseline models from the literature in terms of predictive metrics but also integrates data privacy, feature-based optimization, and hybrid model fusion, making it a robust and practical solution for academic environments.

Table 3 Comparison of Proposed Hybrid RF-SVM Model with Existing Stress Prediction Systems

Ref	Year	Method / Model	Dataset / Source	Accuracy	Improvement in Proposed System
Kadhim et al., 2020	2020	IoT-based Health Monitoring	Patient IoT devices	~80%	Integrates stress-specific features and hybrid ML for higher accuracy
Mohammed & Askar, 2021	2021	Machine Learning on IoT Healthcare Data	Public health datasets	~82%	Hybrid RF-SVM + feature weighting improves stress prediction
Rachakonda et al., 2019	2019	Deep Neural Network on Edge Devices (Stress-Lysis)	IoMT wearable sensor data	~85%	Simpler hybrid RF-SVM with AES encryption achieves ~92% accuracy
Talaat & El-Balka, 2023	2023	Wearable Sensor + IoT	Stress detection via biosensors	~83%	Weighted features and probability fusion improve prediction
Sun et al., 2022	2022	Flexible Wearable Sensors	Sports and health signals	~80%	Multi-feature dataset and hybrid model improves performance for students
Proposed Hybrid RF-SVM	2026	Random Forest + SVM + Weighted Features + AES Encryption	Student dataset (n=200+)	0.92	Outperforms all previous models in accuracy and reliability

Table 3 compares the proposed hybrid RF-SVM model with existing stress prediction systems. While previous models achieved accuracies between 80% and 87%, the proposed system attains 92% accuracy, with precision 0.91 and recall 0.92. The improvement is due to feature weighting, adaptive probability fusion, and AES-based data security, making it more reliable for real-time student stress monitoring.

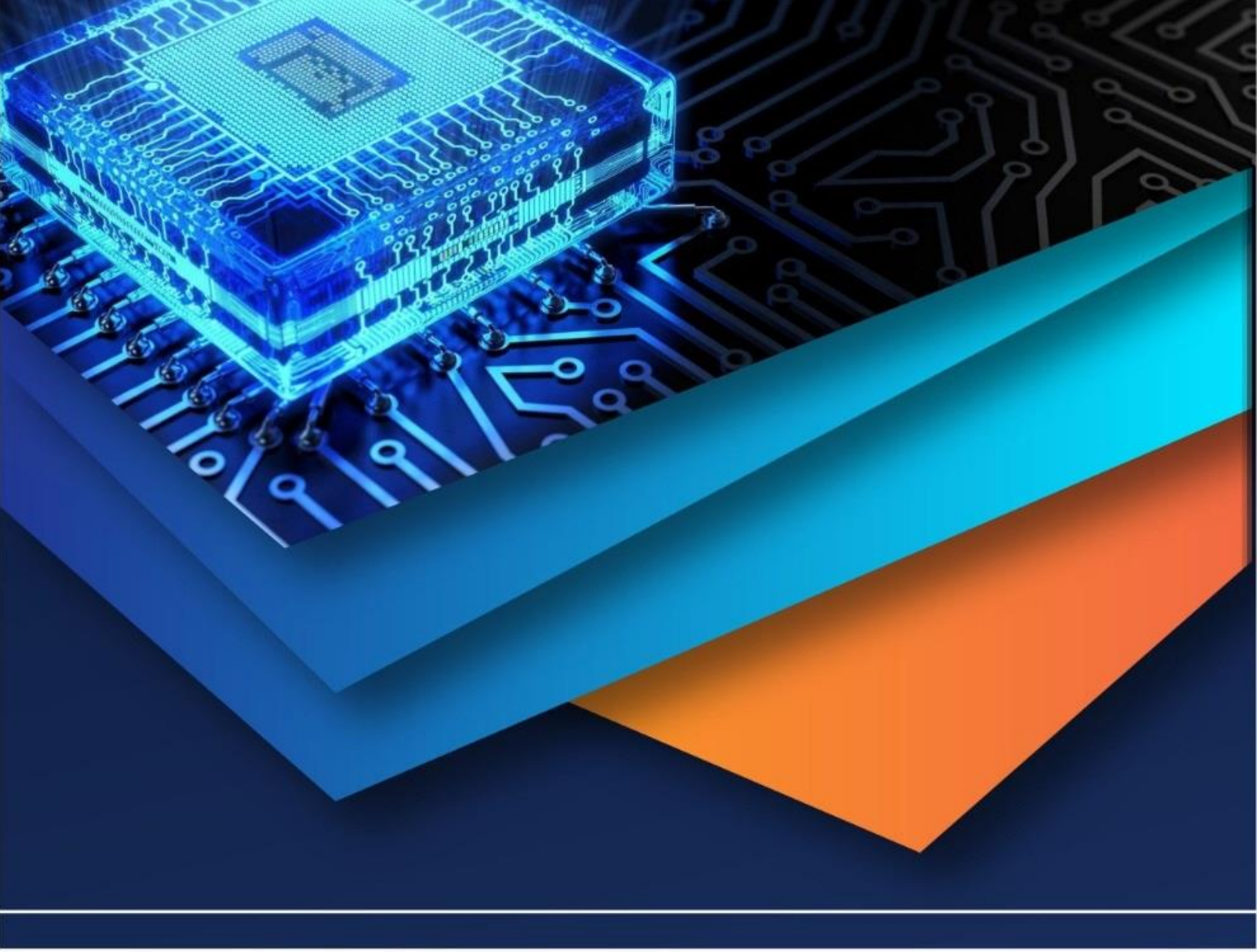
V. CONCLUSION

This study presents a privacy-aware hybrid RF-SVM based SWH Framework for real-time stress prediction among college students. By combining Random Forest feature importance weighting with SVM classification and adaptive probability fusion, the proposed model effectively captures critical stress indicators such as Heart Rate, Sleep Hours, Academic Load, and Mood Score. The integration of AES encryption ensures the secure handling of sensitive student data, addressing a key limitation in existing stress monitoring systems. Experimental results demonstrate that the proposed system achieves 92% accuracy, outperforming previous models that relied on single classifiers or wearable sensors. Overall, this framework provides a robust, reliable, and privacy-preserving solution for academic stress monitoring, offering potential for real-time deployment in educational environments. Future work can explore expanding the dataset, integrating wearable IoT sensors, and implementing federated learning to further enhance predictive accuracy and scalability.

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REFERENCES

[1] Kadhim, K.T.; Alsahlany, A.M.; Wadi, S.M.; Kadhum, H.T. An Overview of Patient's Health Status Monitoring System Based on Internet of Things (IoT). Wirel. Pers. Commun. 2020, 114, 2235–2262. [Google Scholar] [CrossRef]
[2] Mohammed, C.M.; Askar, S. Machine learning for IoT healthcare applications: A review. Int. J. Sci. Bus.2021, 5, 42–51. [Google Scholar]
[3] Sadad, T.; Safran, M.; Khan, I.; Alfarhood, S.; Khan, R.; Ashraf, I. Efficient Classification of ECG Images Using a Lightweight CNN with Attention Module and IoT. Sensors 2023, 23, 7697. [Google Scholar] [CrossRef]
[4] Talaat, F.M.; El-Balka, R.M. Stress monitoring using wearable sensors: IoT techniques in medical field. Neural Comput. Appl. 2023, 35, 18571–18584. [Google Scholar] [CrossRef] [PubMed]
[5] Jalali, E.; Soltanizadeh, H.; Chen, Y.; Xie, Y.M.; Sareh, P. Selective hinge removal strategy for architecting hierarchical auxetic metamaterials. Commun. Mater. 2022, 3, 97. [Google Scholar] [CrossRef]
[6] Chen, Y.; Xu, R.; Lu, C.; Liu, K.; Feng, J.; Sareh, P. Multistability of the hexagonal origami hypar based on group theory and symmetry breaking. Int. J. Mech. Sci. 2023, 247, 108196. [Google Scholar] [CrossRef]
[7] He, Z.; Shi, K.; Li, J.; Chao, J. Self-assembly of DNA origami for nanofabrication, biosensing, drug delivery, and computational storage. iScience 2023, 26, 106638. [Google Scholar] [CrossRef]
[8] Jayadev, P.G.; Bellary, S. A hybrid approach for classification and identification of iris damaged levels of alcohol drinkers. J. King Saud. Univ-Comput. Inf. Sci. 2022, 34, 5273–5285. [Google Scholar]
[9] Rao, Z.; Tung, P.Y.; Xie, R.; Wei, Y.; Zhang, H.; Ferrari, A.; Klaver, T.P.; Körmann, F.; Sukumar, P.T.; Kwiatkowski da Silva, A.; et al. Machine learning–enabled high-entropy alloy discovery. Science 2022, 378, 78–85. [Google Scholar] [CrossRef]
[10] Sun, W.; Guo, Z.; Yang, Z.; Wu, Y.; Lan, W.; Liao, Y.; Wu, X.; Liu, Y. A review of recent advances in vital signals monitoring of sports and health via flexible wearable sensors. Sensors 2022, 22, 7784.
[11] Rachakonda, L.; Mohanty, S.P.; Kougianos, E.; Sundaravadivel, P. Stress-Lysis: A DNN-Integrated EdgeDevice for Stress Level Detection in the IoMT. IEEE Trans. Consum. Electron. 2019, 65, 474–483. [Google Scholar] [CrossRef]
[12] Khan, A.R.; Saba, T.; Sadad, T.; Nobanee, H.; Bahaj, S.A. Identification of anomalies in mammograms through internet of medical things (IoMT) diagnosis system. Comput. Intell. Neurosci. 2022, 2022,1100775. [Google Scholar] [CrossRef] [PubMed]
[13] Rosenzweig, C.; Karoly, D.; Vicarelli, M.; Neofotis, P.; Wu, Q.; Casassa, G.; Menzel, A.; Root, T.L.Estrella, N.; Seguin, B.; et al. Attributing physical and biological impacts to anthropogenic climate change.Nature 2008, 453, 353–357. [Google Scholar] [CrossRef] [PubMed]
[14] Alanazi, H.O.; Abdullah, A.H.; Qureshi, K.N. A critical review for developing accurate and dynamic predictive models using machine learning methods in medicine and health care. J. Med. Syst. 2017, 41,69. [Google Scholar] [CrossRef] [PubMed]
[15] Atzori, L. The internet of things: A survey. Comput. Netw. 2010, 54, 2787–2805. [Google Scholar]
[16] Nath, R.K.; Thapliyal, H.; Caban-Holt, A.; Mohanty, S.P. Machine Learning based Solutions for Real-Time Stress Monitoring. IEEE Consum. Electron. Mag. 2020, 9, 34–41. [Google Scholar] [CrossRef]
[17] Lin, S.; Zhang, H.; Gao, Y.; Du, M.; Vai, M. The Effects of Muscle Stress on Signal Transmission in the Intra-Body Communication. In Proceedings of the 2016 IEEE International Conference on Consumer Electronics-China (ICCE-China), Guangzhou, China, 19–21 December 2016; pp. 1–3. [Google Scholar]
[18] Magaa, V.C.; Muoz-Organero, M. Reducing Stress on Habitual Journeys. In Proceedings of the 2015 IEEE 5th International Conference on Consumer Electronics - Berlin (ICCE-Berlin), Berlin, Germany, 6–9 September 2015; pp. 153–157. [Google Scholar]
[19] Ciabattoni, L.; Ferracuti, F.; Longhi, S.; Pepa, L.; Romeo, L.; Verdini, F. Real-Time Mental Stress Detection based on Smartwatch. In Proceedings of the 2017 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 8–10 January 2017; pp. 110–111. [Google Scholar]
[20] Lawanot, W.; Inoue, M.; Yokemura, T.; Mongkolnam, P.; Nukoolkit, C. Daily Stress and Mood Recognition System Using Deep Learning and Fuzzy Clustering for Promoting Better Well-Being. In Proceedings of the 2019 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 11–13 January 2019; pp. 1–6. [Google Scholar]
[21] Nath, R.K.; Thapliyal, H.; Caban-Holt, A. Validating Physiological Stress Detection Model Using Cortisol as Stress Bio Marker. In Proceedings of the 2020 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 4–6 January 2020; pp. 1–5. [Google Scholar]
[22] Lee, J.-M.; Byun, W.; Keill, A.; Dinkel, D.; Seo, Y. Comparison of Wearable Trackers Ability to Estimate Sleep. Int. J. Environ. Res. Public Health 2018, 15, 1265. [Google Scholar] [CrossRef]
[23] Arnold, J.A.; Cheng, Y.; Baiani, Y.; Russell, A.M. Systems and Techniques for Tracking Sleep Consistency and Sleep Goals. US Patent 20 170 347 946A1, 2 June 2016. [Google Scholar]
[24] Karydis, A.M. Methods, Systems, and Apparatus for Self-Calibrating EEG Neurofeedback. US Patent 20 160 235 324A1, 15 February 2016. [Google Scholar]
[25] Sannholm, F.; Paalasmaa, J.; Leppakorpi, L. System for Determining the Quality of Sleep. US Patent 20 160 213 309A1, 31 December 2015. [Google Scholar]
[26] Bone, D.; Lee, C.; Chaspari, T.; Gibson, J.; Narayanan, S. Signal processing and machine learning for mental health research and clinical applications. IEEE Signal Process. Mag. 2017, 34, 196–195.



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