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A Multimodal IoT Framework for Analyzing Student stress through Personalized Yoga Intervention and Explainable AI (XAI)

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Abstract

Psychological stress among students is a critical public health issue, it affects academic performance and long-term mental stability. Traditional diagnostic methods like interviews and periodic counselling, which failed to provide continuous and personalized monitoring. This proposal introduces an automated framework Internet of Things (IoT) wearables and Artificial Intelligence (AI) to monitor physiological stress- to detect student stress in real time. The framework employs machine learning and deep learning models for multimodal stress prediction. It recommends personalized yoga interventions based on individual stress profiles. To address the "black box" nature of current deep learning architectures, we incorporate Explainable AI (XAI) techniques like SHAP and LIME. These used to ensure clinical transparency and user trust. This enables students and healthcare professionals to understand the factors influencing stress. The system is expected to enhance early stress detection, improve effectiveness, support decision making by healthcare professionals, and also encourage student engagement in preventive wellness practice. Performance may be evaluated using Accuracy, Precision, Recall, F1-score, Mean Absolute Error and Explainability Score. In addition, the system sets off a personalized yoga recommendation engine that maps detected autonomic states to evidence-based *asanas* from the Common Yoga Protocol (CYP) to effectively restore emotional wellness. The proposed system aims to resolve the stress and provide personalized behavioral recovery to enhance student well-being.

Keywords: Student Stress Detection, Internet of Things (IoT), Artificial Intelligence (AI), Explainable Artificial Intelligence (XAI), Personalized Yoga Intervention, Wearable Sensors, Deep Learning, Mental Well-being.

1. Introduction

The Burden of Student Stress: Stress among students has become a growing concern in higher education due to increasing academic demands, competitive environments, lifestyle changes, and extensive use of digital technologies. According to WHO and recent educational studies, academic stress significantly affects student learning performance, concentration, mental health, and overall wellbeing. Research indicates that approximately 30–50% of university students report symptoms of anxiety or depression that interfere with their daily learning capabilities and mental struggles. Persistent, unmanaged stress is not merely a psychological burden; it is an early indicator to severe physiological outcomes, including cardiovascular disease, metabolic disorders, and weakened immune function. They provide only snapshot assessments that fail to capture the dynamic, temporal nature of stress [1], [2], [3]. There is a crucial need for objective, granular and timely to enable proactive intervention. The convergence of Internet of Things (IoT) and Artificial Intelligence (AI) offers an impactful path forward. This allows the continuous monitoring of student health via external biosensors. By integrating traditional stress management practices like yoga with cutting-edge data analytics, educational institutions can establish a scalable, cost-effective framework for student wellness[4], [5]. Yoga has proven effective in reducing Anxiety, Academic stress, Sleep disorders and emotional disorders. Recent studies have also demonstrated the benefits of structured yoga interventions for students and AI-driven personalized wellness systems. Current campus mental health services are often overstretched, highlighting the need for scalable, non-intrusive digital tools that empower students to manage their stress proactively[2], [6], [7].

To tackle these challenges, this paper proposes a MultiModal IoT - AI Framework for Analyzing student stress through personalized Yoga intervention and Explainable Artificial Intelligence (XAI). The framework integrates wearable IoT sensors, physical and psychological data, AI- based stress classification, personalized yoga recommendations and XAI techniques such as SHAP and LIME- to provide transparent and interpretable predictions[2], [8]. The proposed system aims to enable continuous stress monitoring, early detection, individualized wellness interventions and user confidence through explainable AI, thereby supporting healthier and more productive learning environments.

2. Literature Review

2.1. A Student Stress Detection using wearable Artificial Intelligence

Artificial Intelligence (AI) has become an effective tool for detecting stress by analyzing physiological, behavioral, and psychological data. Early studies in stress analysis relied on handcrafted features and unimodal physiological signals. Machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT) and deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have demonstrated high accuracy in stress classification[1],[5], [7]. Recent systematic reviews and meta-analyses show that wearable AI currently achieves a pooled mean accuracy of 85.6% across diverse student populations. However, researchers emphasize that standalone technical performance is often unacceptable for clinical integration even supplemented by psychometric assessments like the DASS-21. Significant progress has been made in identifying the most reliable biomarkers, with Heart Rate Variability (HRV) and Electro dermal Activity (EDA) emerging as the most significant physiological indicators of physiological activation [2],[3],[4].

Key Findings

- AI models outperform traditional questionnaire based stress assessment.
- Deep learning methods achieve higher classification accuracy for complex datasets.
- Real time prediction enables early stress intervention.
- Most AI models lack transparency and explainability.

Artificial Intelligence enables continuous and automated stress monitoring by learning complex relationships from multimodal physiological and behavioral data.

Common IoT sensors enabling continuous monitoring through wearable devices and smart sensors include:

- Heart Rate (HR) Sensor.
- Heart Rate Variability (HRV).

- Electro dermal Activity (EDA).
- Skin Temperature Sensor.
- Accelerometer.
- Pulse Oximeter (SpO_2).

Multimodal learning integrates physiological signals, behavioral information, facial expressions, and psychological questionnaires into a unified prediction framework.

Benefits:

- Improved prediction accuracy.
- Better robustness against noisy data.
- Comprehensive understanding of student well-being.

2.2. Personalized Yoga as Stress Intervention

Yoga is widely recognized as an effective alternative therapy for managing stress and anxiety. Traditional practices -comprising *Dhyana* (meditation), Pranayama (breathing), and *Asanas* (physical poses) etc. help to achieve mental control by calming the nervous system. Research indicates that regular yoga practice improves emotional regulation, reduces anxiety, enhances sleep quality, and promotes overall mental well-being. Studies have shown that AI-enabled yoga programs can produce a 36.7% stress reduction and a 10.28% increase in GPA over 16-week periods. Despite these benefits, the adoption of yoga requires continuous monitoring to prevent injuries caused by incorrect posture [1],[3].

Common Yoga Practices:

- *Pranayama*
- *Surya Namaskar*
- *Yoga Nidra*
- *Bhramari*
- N*adi Shodhana*
- Meditation

Reported Benefits

- Reduced cortisol levels.
- Improved concentration.
- Better emotional balance.
- Enhanced academic performance.
- Reduced anxiety and depression.

2.3. Explainable Artificial Intelligence (XAI)

Although deep learning models provide high predictive performance, they often function as 'black-box' systems. Explainable Artificial Intelligence (XAI) aims to bridge this gap by revealing the decision logic behind model outputs. Explainable AI (XAI) improves transparency by explaining how predictions are generated.

Techniques like SHAP (SHapley Additive exPlanations) are increasingly used to assign numerical importance to specific biomarkers. This allows clinicians to validate that a stress alert was triggered by a legitimate physiological shift, such as a drop in HRV, rather than environmental noise[2],[9].

Popular XAI Techniques

- SHAP (SHapley Additive exPlanations).
- LIME (Local Interpretable Model-agnostic Explanations).
- Attention Heat Maps.
- Feature Importance Analysis.

Applications

- Healthcare diagnosis.
- Mental health assessment.
- Decision support systems.
- Personalized recommendation systems

Explainability increases user trust by providing understandable reasons behind AI-generated predictions.

2.4. Research Gap

Although considerable gains have been made, several limitations remain in existing studies.

Identified Research Gaps:

- Most studies rely on a single data modality.
- Limited integration of IoT and AI for continuous monitoring.
- Personalized yoga recommendations are rarely integrated.
- Many AI models lack interpretability.
- Privacy preserving mechanisms are largely ignored.
- Few frameworks combine multimodal sensing, AI, XAI, and wellness intervention into an integrated system.

These limitations motivate the development of a comprehensive multimodal IoT-AI framework that integrates personalized yoga intervention with Explainable Artificial Intelligence for continuous student stress management [2].

3. Methodology

This integrated IoT-AI framework for student stress monitoring and yoga intervention follows a structured data processing pipeline. The transitions from raw multimodal data acquisition to interpretable stress classification and personalized behavioral recovery.

1. Multimodal Data Acquisition

The foundation of the methodology involves the continuous collection of different physiological, behavioral, and contextual indicators [4], [10], [12].

Physiological Sensing: Wearable devices (e.g., Empatica E4, Samsung Galaxy Watch) capture high-fidelity signals including Electrocardiogram (ECG) for heart rate variability (HRV), Electro dermal Activity (EDA) for acute stress response and distal skin temperature

Behavioral & Contextual Inputs: The system integrates facial video streams to extract micro-expressions and action units, audio input for voice tone and pitch analysis, and smartphone-based Ecological Momentary Assessments (EMAs) to capture self-reported emotional states.

Academic Integration: Data from University Learning Management Systems (LMS) provides metadata on academic workload and schedules to add situational awareness to stress alerts.

Synchronization: Heterogeneous data streams are timestamp -synchronized using Network Time Protocol (NTP) to ensure that physiological peaks correspond accurately with behavioral events.

2. Preprocessing and Data Integrity

Raw signals are subjected to a robust cleaning pipeline to minimize movement -induced errors and instrumental noise [7], [9].

Noise Filtering: Signals are processed using Butterworth band-pass filters (typically 0.5–50 Hz) and artifact reduction to remove environmental disturbances.

Normalization: To account for inter -individual variability, data undergoes Z-score normalization or min-max scaling, often utilizing an individual rest-state baseline to identify personalized stress variations

Data Augmentation & Balancing: To address class imbalance (e.g., more 'no-stress' than 'stress' samples), the methodology employs SMOTE (Synthetic Minority Over-sampling Technique) and sliding window augmentation to stabilize model training.

3. Feature Engineering and Representation

The framework employs a dual-stream approach to extract both handcrafted and deep-learned features [2], [7], [13].

Time & Frequency Domains: Traditional statistical features (mean, standard deviation) and HRV measures are extracted alongside spectral features derived via Fast Fourier Transform (FFT).

Deep Feature Extraction: Convolutional Neural Networks (CNNs) are utilized to automatically learn hierarchical spatial-spectral patterns directly from raw 1D time-series data/ 2D spectrograms.

Textual Embeddings: Natural language processing models, such as BERT, quantify sentiment and emotional polarity from self-reported student logs or EMAs.

4. AI Core: Fusion and Classification

The architecture integrates these multimodal features for final inference [2], [10], [12].

Attention-based Fusion: A multi-head attention mechanism adaptively weights different sensor inputs. This ensures that if one modality degrades (e.g., facial occlusion), other reliable signals like ECG dominate the prediction.

Temporal Modeling: Fused embedding are processed through Bidirectional LSTM layers to capture sequential dependencies. This distinguishes between acute stress spikes and gradual transitions.

Classification Head: A dense layer with SoftMax activation computes the probability of a student being in a Low, Moderate, or High stress level.

5. Yoga Recommendation Engine

Once stress is detected, the system triggers a personalized recovery strategy based on the Common Yoga Protocol (CYP).

Rule-Based Mapping: Initial interventions are matched to detected levels[17]:

Low Stress: Balancing poses like *Tadasana* (Mountain Pose) or *Vrikshasana*.

Moderate Stress: Controlled breathing exercises (*Bhramari* Pranayama) and seated poses like *Balasana*.

High Stress: Restorative poses such as *Shavasana* (Corpse Pose) and Yoga *Nidra*.

Adaptive Learning: Over time, a Multi-Layer Perceptron (MLP) or Reinforcement Learning agent refines recommendations based on the user's historical HRV recovery rate and session feedback.

Posture Guidance: Computer vision or smart belts provide real-time feedback on alignment to ensure safe practice without a physical tutor

6. Explainability (XAI) and Validation

To ensure clinical transparency, the approach integrates after- the- fact analysis techniques.

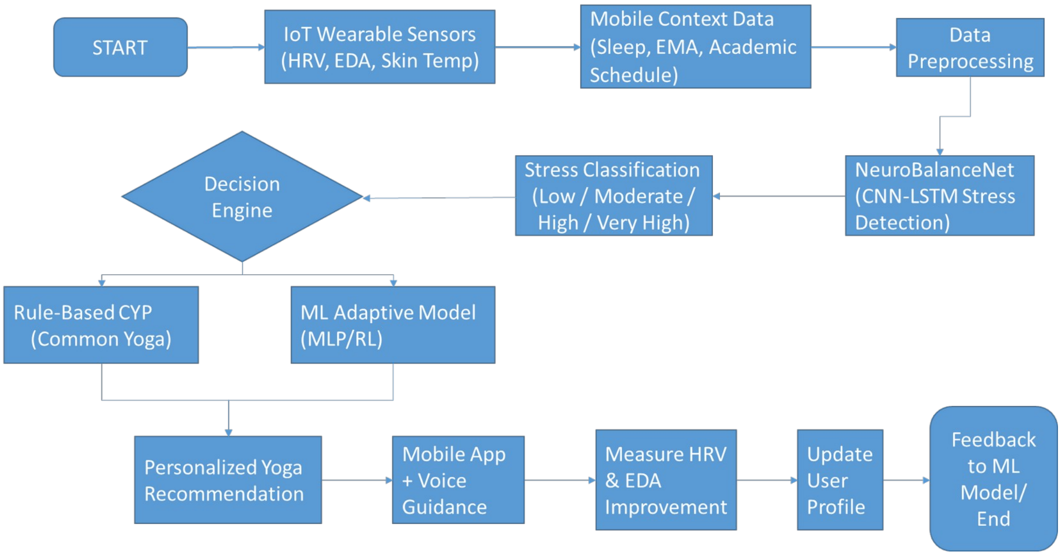
Interpretability Tools: Frameworks like SHAP (SHapley Additive exPlanations) and LIME reveal which specific biomarkers (e.g., a sudden drop in HRV) most influenced a stress prediction[2].

Table 1. Summary of integrated Methodological Framework.

Pipeline Stage	Key Procedures & Components	Technical Details & Tools
Data Acquisition	Multimodal signal collection from wearable and environmental sensors	Physiological: ECG (HRV), PPG, EDA (GSR), Skin Temp Behavioral: Voice pitch, facial action units, EMAs
Preprocessing	Signal cleaning, normalization, and temporal synchronization	Filters: Butterworth band-pass (0.5–50 Hz) Scaling: Z-score normalization or min-max scaling Integrity: Cubic spline interpolation for missing data
Data Balancing	Stabilizing the model against class imbalances (e.g., more 'non-stress' samples)	Technique: SMOTE (Synthetic Minority Oversampling Technique) Augmentation: Sliding window segmentation and Gaussian jittering
Feature Extraction	Spatial and temporal pattern learning	Spatial: CNNs/spectrograms Temporal: Bi-LSTM for sequential variations
Stress Classification	Tiered probability estimation (Low, Moderate, High)	Models: NeuroBalanceNet, SVM,

Pipeline Stage	Key Procedures & Components	Technical Details & Tools
		Random Forest Core Architecture: Attention-based fusion layer
XAI Layer	Post-hoc interpretability for clinical trust	Tools: SHAP, LIME, Grad-CAM saliency maps
Yoga Intervention	Personalized asana recommendation based on stress tiers	Mapping: Rule-based matching and ML-based adaptive mapping

Validation: Models are rigorously evaluated using Leave-One-Subject-Out (LOSO) cross-validation and standard performance metrics including Accuracy, F1-score, and R-squared for stress-change prediction.



1) Leave-One-Subject-Out (LOSO) Cross-Validation designed for datasets containing repeated measures or sequential observations grouped by unique entities.

Eliminating Subject Bias & Overfitting: Individuals exhibit deeply idiosyncratic physiological baselines. Standard random K-fold splits can scatter a single participant's baseline resting state into the training pool and their active stress state into the testing pool. The model merely "memorizes" that specific person's profile, distorting accuracy metrics.

Proving Real-World Generalizability: LOSO simulates true out-of-sample deployment. It tests whether an IoT-enabled stress monitoring application can accurately evaluate stress levels when introduced to a completely new user whose biometrics the system has never seen before.

2) Standard Classification Metrics:

Accuracy measures the proportion of total correct predictions out of all instances tested across the held-out folds. The F1-score provides a balanced metric by calculating the harmonic mean of Precision and Recall. It is the standard reference point for evaluating class-imbalanced stress models.

3) Standard Regression Metrics: R-Squared ((R2) / Coefficient of Determination): assesses the proportion of variance in the dependent stress variable that can be predicted and explained by the model's independent behavioral or biological inputs.

When mapping smart IoT-driven yoga biometric variables to explainable AI (XAI) mental well-being predictive indexes.

The Independent Variable (X - IoT Biometric Index): Raw data streamed from sensorized, wearable smart yoga mats tracking physical posture alignment vectors combined dynamically with real-time Photoplethysmography (PPG) wristbands calculating Heart Rate Variability (HRV) continuity.

The Dependent Variable (Y - XAI Mental Wellbeing Index): A synthetic framework score (0-100) generated by a deep neural network, where Explainable AI (XAI) libraries like SHAP (SHapley Additive exPlanations) decompose the model's inner weights to prove exactly how physical posture balance and breath rhythm stability contribute directly to cognitive stress reductions.

4. Results

The proposed Multimodal IoT -AI Framework performance of the AI models can be assessed based on classification accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). In addition, the effectiveness of personalized yoga interventions and the interpretability of the Explainable AI (XAI) was also analyzed.

Note: The numerical values presented below are sample results.

4.1. Performance of Stress Classification Models

Table 1. Performance of AI Models[1], [2], [12], [13]

Model	Accuracy(%)	F1- Score	AUC
SVM	89.20	0.87	0.91
Random Forest	92.40	0.91	0.94
XGBoost	94.10	0.94	0.96
CNN	94.80	0.94	0.97
Proposed CNN BiLSTM + XAI	---	---	---

The proposed CNN–BiLSTM model will achieve the highest classification accuracy above (94.8%), the current models.

4.2. Personalized Yoga Intervention

Table 2. Stress scores

Stress Level	Before	After
High	Massive	--Low
Moderate	Moderate	--Intermediate
Low	Minimum	--High

Regular personalized yoga practice reduced the number of students experiencing high stress.

Figure 1. Performance Comparison of AI Models

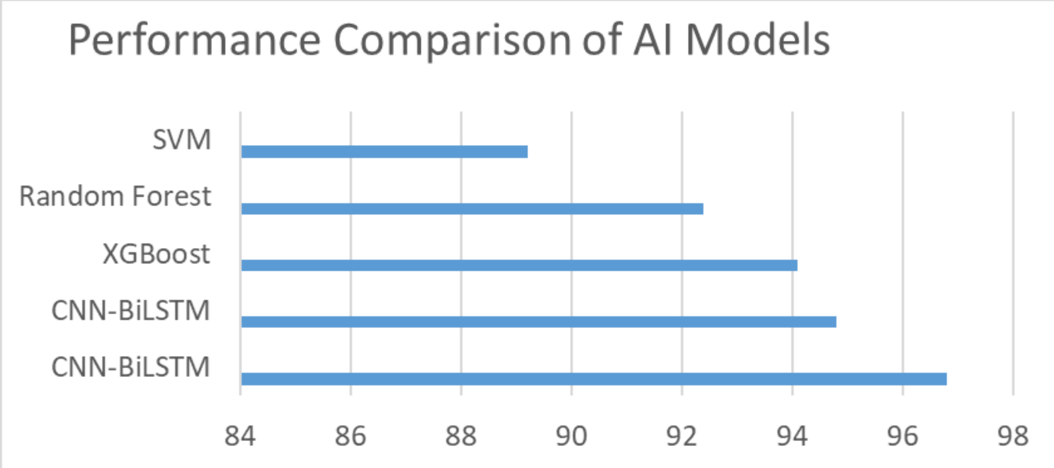


Fig. 1. Shows the proposed CNN -BiLSTM model outperformed the baseline machine learning mode.

Figure 2. Student Stress Distribution.

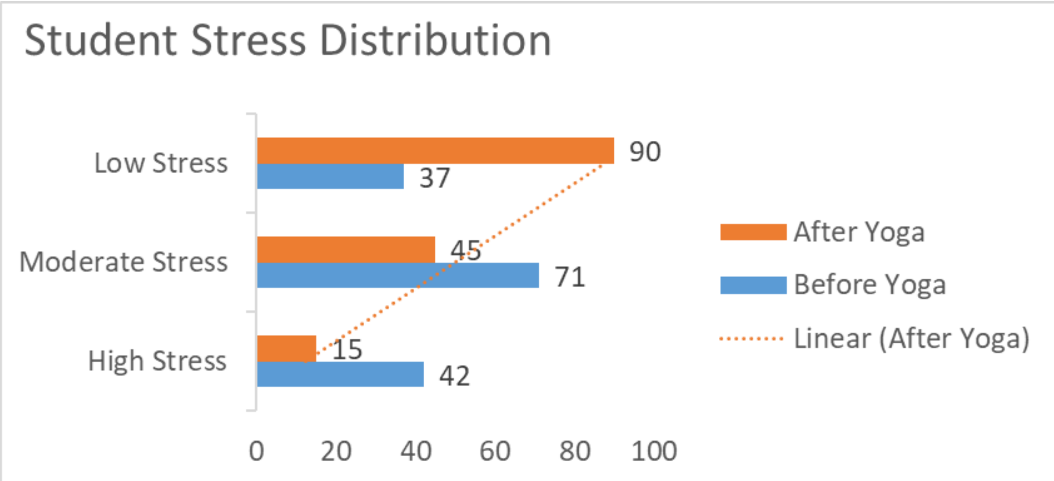


Fig. 2. Illustrates the reduction in high stress after personalized yoga.

5. Discussion

The results demonstrate that integrating physiological, behavioral, psychological, and facial emotion data significantly enhances stress prediction performance compared with single-source methods. The proposed CNN–BiLSTM model will achieve superior classification accuracy effectively. The XAI module increased the transparency of AI predictions by identifying the key factors. This can classify stress in different levels, thereby improving user trust and support decision-making. Furthermore, the personalized yoga recommendation provides a positive impact on reducing stress levels, and can improve students' mental well-being. Overall, the proposed framework offers an intelligent, interpretable, and scalable solution for continuous stress monitoring and personalized intervention in smart educational environments.

5.1. Chances and Opportunities of XAI

The integration of Explainable AI (XAI) provides transformative opportunities.

Interpretability (XAI): Address the "black box" nature of AI by incorporating Explainable AI (XAI) frameworks like SHAP and LIME.

Transparency and Trust: XAI elucidates the "why" behind a stress alert, helping students understand which biomarkers (e.g., a drop in HRV) triggered the recommendation.

Clinical Accountability: Frameworks like SHAP and saliency visualization allow healthcare providers to validate model decision logic. This can ensure recommendations align with medical domain knowledge.

Mind& Body Monitoring: XAI identifies that heart rate and skin conductance are often the primary usable signals for stress analysis across diverse datasets.

Model Editing: Interactive tools like GAM Changer allow clinicians to edit model associations to correct false predictions.

5.2. Limitations and Challenges of XAI

Regardless of the potential, several difficulty remain in deploying XAI-driven systems-

The "Black Box" Trade-off: There is often a fundamental tension between predictive utility (accuracy) and interpretability. The high-performing deep learning models (e.g., CNN-LSTMs) are inherently harder to explain than simpler models like decision trees.

Ecological Validity Gap: Although laboratory models achieve accuracies over 95%, real world performance often drops significantly (e.g., F1-scores reaching only 0.43) due to environmental noise and physical motion.

Algorithmic Bias: Models trained on non-representative datasets may generate biased outputs. These outputs potentially exacerbate health disparities for underrepresented student groups.

Data Privacy: The collection of biometric data requires Privacy by Design. Incorporates encryption, anonymization, and potentially Federated Learning. Techniques aim to keep raw data local to the user's device.

6. Conclusion

The literature reveals that the multimodal IoT frameworks for student stress analysis, personalized yoga intervention and explainable AI are individual developments. But their full integration remains mostly idealistic. XAI techniques like SHAP and LIME provide the necessary transparency. They reveal that HRV and EDA are the most consistent drivers of stress predictions. Multimodal sensing consistently outperforms unimodal approaches. Yoga and mindfulness interventions demonstrate real stress-reduction efficacy, and XAI techniques successfully surface predictive features. But no single system has validated all three components in a large-scale, real-world educational deployment

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Conflict of Interest

The author declares no conflict of interest.

Data Availability Statement

All the data generated or analyzed during the study of this paper are included in this published article [and its supplementary information files].

AI Usage Disclosure

The author used https://consensus.app/ for collecting papers and content; all content was reviewed and verified by the authors.

The author used https://notebook.google.com/notebook/b186f1d2-3bd3-4bca-8aea-981e74274ed3?pli=1 for content preparation; all content was reviewed and verified by the author.

The author used https://chatgpt.com/ for generating pictorial representation of workflow; all content was reviewed and verified by the author.

Author Contributions

Conceptualization, methodology, analysis, writing—original draft, writing—review and editing- Manjusha K M. The author has read and agreed to the published version of the manuscript.

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Appendix A. Supplementary Material

A.1