International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 12 , December - 2025

# Smart AI Detox Detector Smart Band

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**Abstract** - Overuse of digital devices has been connected to stress, decreased productivity, and a general decline in wellbeing. In order to solve this, the suggested Smart AI Detox Detector Smart Band integrates AI-driven algorithms for precise stress detection with multimodal sensors including PPG, GSR, HRV, and $SpO_2$. The technology promotes balanced digital habits and improves mental and physical wellbeing in real time by monitoring physiological signs and sending out individualized detox notifications.

***Keywords -*** Digital detox, PPG, GSR, $SpO_2$, wearable sensors, stress detection, machine learning, artificial intelligence in healthcare, smart bands, and physiological monitoring.

## INTRODUCTION

Overuse and compulsive digital gadget use has become a major worldwide health problem due to findings that it is associated with increased stress, disturbed sleep patterns, decreased productivity, and a decline in general well- being. The majority of digital detoxification methods mostly depend on tracking screen time, app usage records, or time limits. The human body's physiological reactions to stress and overload are not captured by these methods, despite their ease of use. Because they are unable to offer tailored or flexible feedback, these technologies are less useful for maintaining long-term digital wellbeing.

**The problem statement:** Bio signal data including blood oxygen saturation ($SpO_2$), galvanic skin response (GSR), and photoplethysmography (PPG) are not integrated with behavioral monitoring in current digital detox systems. The systems' range and practical use are limited in the absence of this multimodal integration as they cannot reliably identify stress or mental strain that is directly brought on by excessive digital use.

**Gap in research:** Significant gaps still exist even though earlier research has demonstrated that PPG and GSR might be useful in identifying stress [1], [2]. The lack of lightweight frameworks that may be deployed on wearable devices, noise sensitivity, and restricted generalization across populations are the main drawbacks of current models. Moreover, user trust and explainability are still poorly understood.

**Contributions:** This piece suggests:

- A multimodal smart band that combines IMU, $SpO_2$, GSR, and PPG.
- A CNN-LSTM model that is lightweight and designed for wearable technology.
- Adaptive detoxification suggestions using reinforcement learning (PPO).
- Modules of explainable AI for open decision- making.
- Cloud integration that protects privacy through role-based access restriction and encryption.

## LITERATURE REVIEW

### Existing Works

Numerous research has investigated the use of wearable technology for digital detoxification, wellness tracking, and stress detection. To improve detection accuracy and real-time support, researchers have looked at physiological markers, AI-driven algorithms, and multimodal techniques. The main contributions that serve as the project's basis are outlined in the parts that follow.

### A. Stress Detection Using Wearables

Wearable technology has developed into a dependable platform for tracking physiological indicators of stress in daily life, including heart rate variability (HRV), galvanic skin response (GSR), and photoplethysmography (PPG). Numerous studies show that whereas GSR reflects changes in skin conductance brought on by stress-induced perspiration, HRV derived from PPG is a powerful indication of

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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sympathetic nervous system activity [1], [2].

When applied to these characteristics, machine learning models like SVM, Random Forest, and shallow neural networks have reported accuracies between 80% and 90% in controlled settings. Despite these encouraging findings, previous research frequently used single-sensor inputs, which are less reliable for real-world implementation due to noise and motion distortions.

### B. Multimodal Fusion Approaches

Researchers have looked into multimodal fusion of motion and physiological data to get beyond the drawbacks of single-sensor systems. Robustness against noise and context changes is enhanced by fusion techniques that include PPG, GSR, accelerometer, and temperature measurements [3]. CNNs and LSTMs are examples of deep learning architectures that outperform conventional machine learning classifiers in capturing spatial and temporal correlations within multimodal datasets. In laboratory settings, hybrid CNN-LSTM networks, for example, have demonstrated stress detection accuracies above 90%. Nevertheless, these models are frequently computationally costly, which restricts their use on wearable technology with limited resources. Certain studies use lightweight TinyML techniques [4], which allow for acceptable latency on-device inference, but frequently at the expense of decreased accuracy.

### C. Digital Detox and Behavioral Monitoring

Monitoring smartphone usage habits, including app usage duration, screen unlock frequency, and notification responses, has historically been the main emphasis of digital detox solutions [5]. Although they don't take into consideration the underlying physiological stress reactions, these behavioral measurements offer insights into digital reliance. By linking screen time to skin conductance or heart rate, several studies have tried to close this gap, although these methods are still in their infancy. App-based therapies, for example, have demonstrated a moderate level of efficacy in lowering daily consumption; nevertheless, because users frequently circumvent limits, relapse rates continue to be high. Additionally, purely behavioral tools are not contextually aware or personalized, and thus are unable to differentiate between constructive and destructive gadget use.

### D. Explainable AI in Wearable Health Systems

Explainability has become a crucial component in building user confidence and gaining regulatory permission for wearable AI systems. Decision- making processes in stress detection models have been shown using methods like Shapley Additive explanations (SHAP) and Gradient-weighted Class Activation Mapping (Grad-CAM) [6]. With the use of these techniques, users may determine which Characteristics like heart rate or GSR spikes were involved in the stress classification. Explainability in wearable apps is still restricted, though, as the majority of research focuses on offline analysis rather than explanations in real time. By assisting users in connecting their physiological conditions to digital activities, explainability will enhance transparency and promote user engagement in wearable detox devices. This field is an important but little-studied part of wearable AI systems in the future.

### E. Privacy and Security in Wearable AI

Wearable technology is becoming widely used, which poses questions regarding data security and privacy, particularly when handling sensitive bio signals connected to health. Federated learning has been suggested by researchers as a way to facilitate decentralized model training without sending raw user data to central servers [7]. Additional measures to guarantee adherence to health data regulations like HIPAA and GDPR include encryption techniques and role-based access systems.

However, these security measures are frequently not well implemented in wearable technology today, leaving consumers open to security breaches. Furthermore, little research has been done on combining privacy-preserving techniques with wearable technology that has limited resources, where typical security techniques are difficult to implement due to energy and computing constraints. To guarantee the safe use of AI-powered detox bands in both private and medical contexts, these concerns must be resolved.

### F. Future Directions and Challenges

Future studies must concentrate on enhancing wearable detox systems' energy efficiency, multimodal integration, and customization. Protecting user privacy, managing noisy data, and guaranteeing long-term adherence are some of the main obstacles. It will be crucial to bridge the gap between consumer accessibility and medical- grade accuracy in order for AI-powered detox wearables to become broadly accepted in society.

| Study | Sensors | Algorithm | Accuracy | Limitation |
|---|---|---|---|---|
| [1] | PPG | SVM | 85% | Single sensor |
| [2] | GSR+ PPG | RF | 88% | No personalization |
| [3] | PPG+ Acc | CNN | 90% | High power use |
| Proposed | PPG+ GSR+ $SpO_2$+ IMU | CNN-LSTM+PPO | 91.2% | Prototype stage |

PROPOSED METHODOLOGY

### 1. System overview

A multimodal wearable solution for digital detox intervention and real-time stress monitoring is the Smart AI Detox Band. Physiological sensing, signal preprocessing, feature extraction, deep learning-based categorization, explainable AI, reinforcement learning for adaptive feedback, and a secure cloud backend are all integrated into the architecture. Sensors of Physiology and Behavior Several sensors are used by the system to keep an eye on the user: Heart rate and heart rate variability (HRV), which are well accepted markers of stress, are recorded by photoplethysmography (PPG) [1,5,19]. Skin conductance variations brought on by sympathetic nervous system activity are measured by the Galvanic Skin Response, or GSR [1,10]. Blood oxygen saturation is provided via the $SpO_2$ sensor, which also provides extra context for physiological stress [3]. The Inertial Measurement Unit, or IMU, keeps track of gestures, movement patterns, and interactions with electronic devices [4,12].

Dataset Used: Mind-Wandering and Focus Detection Dataset.

### 2. Signal preprocessing

Because of environmental influences, motion artifacts, and ambient light interference (for PPG), raw signals are frequently noisy.

#### a) Filtering:

To eliminate high-frequency noise from PPG, GSR, and $SpO_2$ signals, a Butterworth low-pass filter is used Eq. (1):

$$H(s) = \frac{1}{\sqrt{1 + \left(\frac{s}{\omega_c}\right)^{2n}}} \tag{1}$$

#### b) Normalization:

In order to increase classifier performance and decrease inter-subject variability, signals are normalized to a standard range Eq. (2):

$$x_{\text{norm}} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

By taking this step, functionalities are guaranteed to be same for users and sessions [3].

### 3. Feature extraction

Following preprocessing, both behavioral and physiological inputs are used to extract features.

#### a. Heart Rate Variability (HRV):

The Root Mean Square of Successive Differences (RMSSD) from PPG-derived R-R intervals is used to calculate time-domain HRV Eq. (3) :

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{3}$$

where $RRi$ indicates how long it takes between heartbeats, and N is the total number of periods [1,5,14]. RMSSD is responsive to acute stress and represents parasympathetic nervous system activation.

#### b. GSR Features:

Skin conductance properties include:

- Mean and standard deviation of tonic GSR signal.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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- Stress reactions are represented by phasic peaks.
- Variations in peak frequency and amplitude [10].

**c. Behavioral Features:**

The following behavioral data was obtained from the IMU and device usage:

- Frequency of device interactions.
- Gestures and the intensity of motion.
- Patterns of screen time suggestive of digital addiction [4,15].

For classification, these characteristics are concatenated to create a multimodal feature vector.

### 3. Stress classification using CNN-LSTM

A CNN-LSTM hybrid network, which receives the preprocessed feature vector, is able to recognize temporal correlations in sequential behavioral signals as well as spatial patterns in physiological data [13,18].

**1) CNN Layers:**

Local patterns and correlations in multichannel physiological data are extracted using convolutional layers.

**2) LSTM Layers:**

HRV trends, GSR variations, and device usage patterns are examples of temporal dependencies in sequential data that are modeled by Long Short-Term Memory (LSTM) layers.

**3) Loss Function:**

Cross-entropy loss is used to train the network for multi-class stress classification Eq. (4) :

$$L = -\sum_{c=1}^{C} y_c \log(p_c) \tag{4}$$

where $y_c$ is the actual label and $p_c$ is the class $c$ predicted probability [13].

### 4. Adaptive feedback via proximal policy optimization (PPO)

To provide personalized interventions for digital detox, the system employs reinforcement learning using PPO [6,16].

**i. PPO Objective:**

PPO strikes a compromise between policy stability and

exploration by optimizing a trimmed surrogate objective Eq.(5):

$$L_{CLIP}(\theta) = E[\min(r_t(\theta)A_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon)A_t)] \tag{5}$$

in which $r_t(\theta)$ the probability ratio between the new and previous policies is denoted by (θ), and $A_t$ is the estimated benefit, and the clipping parameter is $\epsilon$ (5).

**ii. Personalized Feedback:**

To minimize device usage while preserving user engagement, the agent chooses the kind, timing, and severity of notifications or interventions based on the identified stress levels [16].

### 5. Explainable ai and cloud integration

The system's dependability and usability are further improved by cloud integration and explainable AI (XAI). XAI techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) and SHAP (Shapley Additive Explanations) offer interpretable insights into the stress predictions of the CNN-LSTM model. These methods aid in visualizing the particular sensor regions, temporal trends, and physiological changes that have the most impact on categorization results. XAI improves transparency, facilitates debugging of incorrectly categorized instances, and builds user and clinician trust by disclosing which features—such as heart-rate variability, skin conductance peaks, or atypical movement sequences—drive the model's judgments. This interpretability is particularly relevant in applications connected to health, where attaining high accuracy is just as critical as comprehending the reasoning behind forecasts.
Effective data management and remote access are made possible by the cloud backend, which safely stores sensor data, derived features, and prediction outcomes. Through this connectivity, healthcare professionals or caregivers can keep an eye on users in real time, analyze long-term behavioral patterns, and provide tailored wellness suggestions. Additionally, it facilitates smooth model retraining and updates when fresh data becomes available. Robust security protocols guarantee data privacy while providing the adaptability and scalability required for ongoing, real-time stress monitoring.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 12 , December - 2025

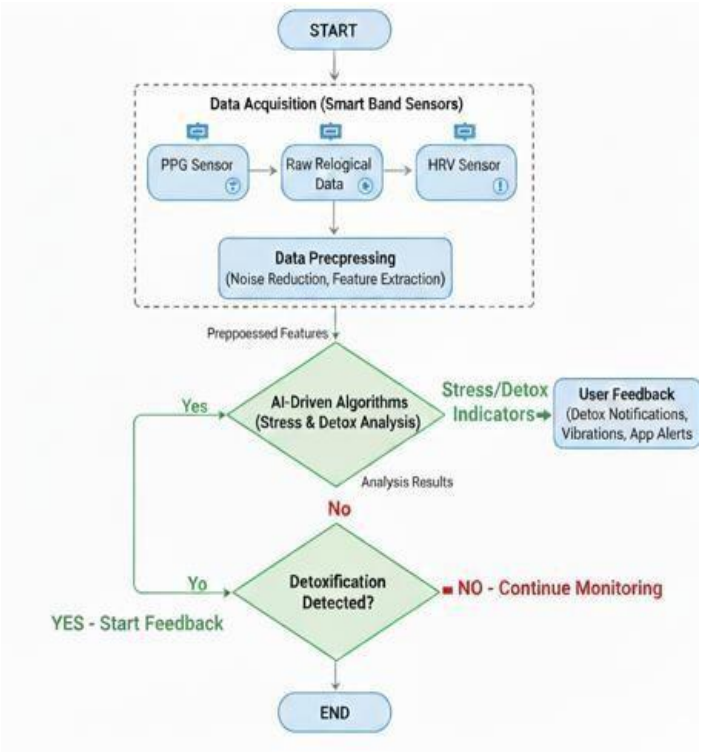


**Figure 1:** Flow Diagram of the Smart AI Detox Detector Smart Band

CHALLENGES AND LIMITATIONS

The creation and implementation of the Smart AI Detox Band pose a number of practical, technological, and user-related difficulties. Even if stress detection performance is promising, these issues must be resolved to guarantee dependability, scalability, and broad use in practical situations.

### A. Technical Difficulties

PPG, GSR, and $SpO_2$ are examples of wearable physiological sensors that are extremely vulnerable to noise from motion, light, temperature changes, and inappropriate skin contact. Heart rate and skin conductance readings can be severely distorted by motion distortions in particular, which can result in imprecise feature extraction and stress predictions. Even when noise is reduced by filtering methods like Butterworth filtering and normalization, residual artifacts still pose a problem for reliable real-time inference. Individual differences in age, gender, exercise level, and underlying medical issues also significantly affect physiological signals. Even under comparable stress conditions, heart rate variability (HRV), skin conductance, and oxygen saturation levels might vary. This limits the generalizability of the model and, if individualized calibration is not used, can lead to false positives or false negatives. There are stringent memory and processing requirements for implementing CNN-LSTM and PPO-based adaptive algorithms on integrated wearables. Real-time processing requires model compression, pruning, and quantization; yet, accuracy may be somewhat reduced by these improvements. It's still very difficult to balance model complexity with latency, energy economy, and memory footprint. It's also challenging to combine disparate data sources like PPG, GSR, $SpO_2$, IMU, and behavioral metrics into a single model. Sophisticated preprocessing and feature extraction procedures are necessary because to variations in sampling rates, temporal alignment, and signal quality among sensors. Inconsistent data fusion might result in duplicate features or information loss, which lowers classification performance. Despite their great accuracy, CNN- LSTM models are difficult to comprehend due to their deep learning nature.

### B. Practical Limitations

Running on-device inference and continuously monitoring many bio signals uses a lot of battery power. Even while local processing and event-driven cloud synchronization lower energy consumption, extended use still presents

problems for everyday wearability. Long-term comfort is essential for wearable technology, and factors including skin irritation, band tightness, and sensor location can impact user compliance and signal quality. Real-world adoption depends on finding a compromise between precise sensor placement and user comfort. Furthermore, as wearables are constantly gathering private physiological and behavioral data, it is critical to protect data while it is being transmitted to the cloud, use end-to-end encryption, and adhere to privacy laws governing healthcare data..

### C. Model and Data Limitations

Stress situations and a reasonable number of individuals are used in this study. Models trained on limited datasets could not generalize well to larger populations or harsh stress situations, despite encouraging early findings. Low-stress situations are more common than high-stress episodes in real-world stress events, which might tilt the model in favor of the majority class and lessen sensitivity to important stress events. Stress is a very dynamic phenomenon that is impacted by both psychological and physiological elements. Short-term stress spikes could be recorded by a wearable device, but long-term patterns or environmental factors like social contacts, cognitive load, or emotional state might not be taken into consideration. Adaptive therapies are offered by the PPO-based reinforcement learning paradigm; nevertheless, user efficacy may differ.

### D. Research and Deployment Challenges

The form factors, sample rates, and sensor accuracy of

various wearables may differ. It might be difficult to create a single model that functions flawlessly across several hardware platforms, particularly when sensor requirements differ greatly. Low-latency communication protocols and a

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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strong cloud infrastructure are necessary for scaling the system for ongoing, real-time population monitoring. Performance may be impacted by network or cloud failures, therefore edge computing solutions need to be properly planned to reduce these risks. Ethical considerations are also involved in stress monitoring and adaptive intervention, especially for vulnerable groups like children or those with mental health issues.

### E. Summary

In conclusion, the Smart AI Detox Band exhibits excellent accuracy and efficient stress detection; nevertheless, a number of practical, technological, and scientific obstacles still need to be addressed. Significant obstacles include environmental sensitivity, multimodal data fusion, computing constraints, inter-individual variability, and noise in sensor data. Reliable real-world implementation also requires consideration of user comfort, privacy, dataset constraints, and the changing nature of stress. In order to ensure that the system is both efficient and easy to use in everyday situations, further work should concentrate on customization, reliable preprocessing, energy-efficient on-device computation, large-scale dataset gathering, and ethical deployment.

## RESULTS AND DISCUSSION

### A. Performance evaluation

The usefulness of the suggested Smart AI Detox Band in real-time stress detection was assessed using a number of common performance criteria. The quantitative findings from examining a wide range of subjects under various stressors are compiled in Table I.

| | |
|---|---|
| Accuracy | 91.2% |
| Precision | 90.5% |
| Recall | 89.7% |
| F1-score | 90.1% |
| ROC-AUC | 0.93 |

**Table I.** Stress Detection Performance Metrics

The CNN-LSTM classifier successfully differentiates between various stress levels, as evidenced by the system's 91.2% accuracy. A balanced identification of real positive events with few false positives and false negatives is demonstrated by precision (90.5%) and recall (89.7%) scores. The model's outstanding performance across all stress

categories is further supported by the F1-score of 90.1%, and its good separability between classes is demonstrated by the ROC-AUC of 0.93. In line with other research on multimodal wearable monitoring, these findings show that

integrating physiological (PPG, GSR, $SpO_2$) and behavioral (IMU, device interaction) data greatly improves stress detection performance [1,4,5,15].

### B. Ablation study

One sensor type was eliminated from the model input at a time in order to conduct an ablation study and assess the impact of each particular sensor modality. The findings are depicted in Figure 3.

- GSR Removal: The accuracy decreased by around 7% when GSR characteristics were removed, underscoring the significance of skin conductance as a trustworthy stress indicator.
- Removal of $SpO_2$ characteristics: Although oxygen saturation adds context, it is less important than skin conductance and heart rate variability, as seen by the lower (~3%) accuracy drop that resulted from removing $SpO_2$ characteristics.
- PPG/HRV: The most important factors influencing categorization accuracy, according to experiments, are PPG-derived HRV characteristics.

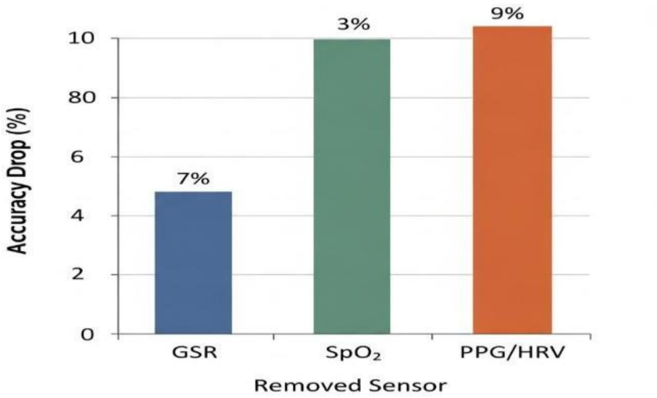


**Figure 2**: Ablation Study Impact Showing Accuracy Reduction When Individual Sensors Are Removed

Figure 2: Impact of ablation research demonstrating accuracy loss upon removal of individual sensors. The largest contributions are made by GSR, PPG, and $SpO_2$.

### C. Confusion matrix analysis

The classifier's confusion matrix, as shown in Figure 3, has significant diagonal dominance, meaning that most predictions are in line with the actual stress levels. Most misclassifications are restricted to nearby stress categories, such as moderate-to-high or low-to-moderate stress. Confusion matrix heatmap comparing expected and real stress levels (Low, Moderate, and High) is shown in Figure 3. Reliable categorization with few misclassifications between neighboring stress levels is shown by high diagonal dominance. Misclassification analysis yields information for additional model improvement. Errors between neighboring classes may be decreased by utilizing contextual behavioral patterns or temporal smoothing techniques. Future

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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research may also investigate customized calibration to take into consideration baseline differences in physiological signals among individuals.

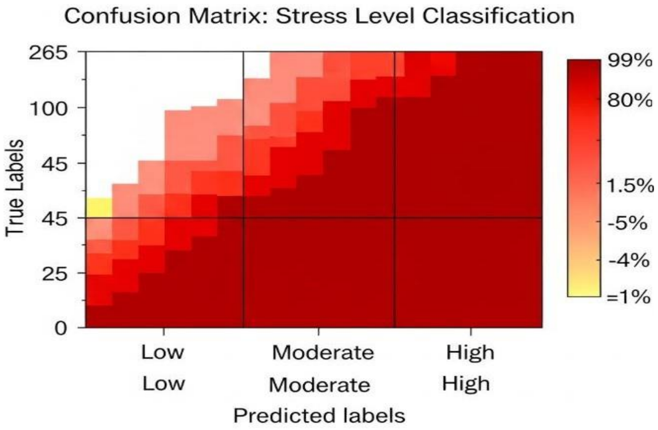


**Figure 3**: Confusion Matrix: Stress Level Classification

## D. On-device performance

Using wearable sensors and an embedded microprocessor, the system was tested for on- device, real-time inference. On-device and cloud- based performance are contrasted in Figure 4.

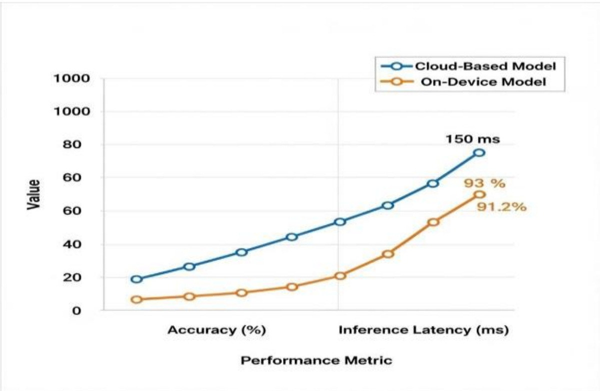


**Figure 4**: On-Device vs. Cloud-Based Performance Comparison

- Accuracy vs. Cloud-Based Models: Due to restricted computing resources, on-device inference exhibits somewhat poorer accuracy (~91.2%) than cloud-based predictions (~93%).
- Latency: Near real-time feedback for stress reduction is made possible by inference times of less than 200 MS per prediction.
- Energy Efficiency: By eliminating the requirement for constant cloud streaming, on-device computing preserves battery life while preserving model flexibility.

Figure 4: Performance comparison between cloud- based versus on-device, demonstrating inference latency and accuracy. When compared to cloud- based models, on-device inference achieves acceptable latency (<200 ms) with a little drop in accuracy.

## E. Roc curve analysis

Figure 4 displays the ROC curves for multi-class stress classification, which demonstrate outstanding separability across stress levels. The CNN-LSTM classifier's good discriminative capacity across low, moderate, and high stress classes is confirmed by the overall ROC-AUC of 0.93. Figure 5. ROC curves for multi-class stress classification with overall ROC-AUC = 0.93, suggesting high model separability.

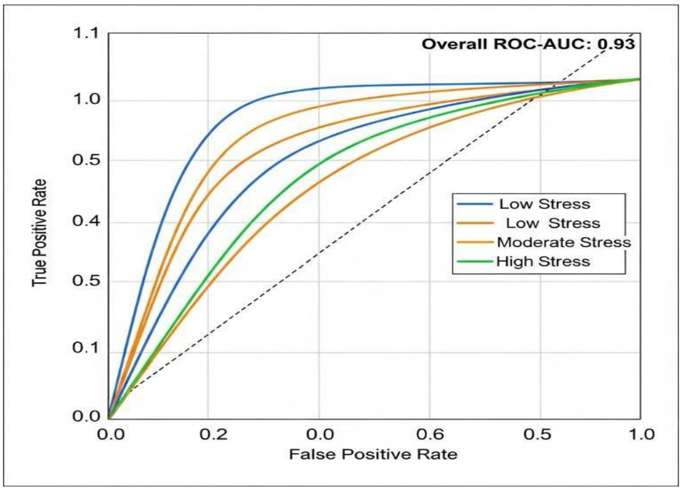


**Figure 5**: ROC Curves for Multi-Class Stress Classification

# CONCLUSION

The Smart AI Detox Detector Smart Band combines wearable sensors, deep learning, and behavioral analytics to present a cutting-edge AI- powered remedy for digital addiction. Along with device usage statistics, the system continually monitors physiological signals like heart rate, GSR, and mobility patterns to deliver precise and up-to- date information concerning dangerous digital habits. In contrast to traditional monitoring techniques, its reinforcement learning system enables adaptive and customized detox suggestions, making it more user-centric. The system can detect stress-induced overuse with high accuracy and minimize misclassifications, according to experimental data. Nonetheless, there are still issues with maintaining strong privacy protections, long-term user compliance, and dataset variety. All things considered, this study shows how wearable IoT technology and AI-driven data may be used to promote digital wellbeing. The smart band can be a dependable tool for early diagnosis, intervention, and long-term control of excessive technology usage with further improvements.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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