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IoT-Based Stress Monitoring Using CNN for HRV-GSR Analysis

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Abstract: Stress has become a major global health concern affecting both physical and mental well-being. Conventional stress assessment methods rely on subjective self-reports that cannot capture real-time physiological changes. Existing systems are often limited to controlled laboratory environments or depend on traditional machine learning approaches requiring extensive manual feature engineering.

This study aims to develop an Internet of Things–based stress monitoring system using deep learning to enable objective, continuous, and practical real-world stress detection. The system incorporates wearable sensors using an ESP32-DevKit V1 microcontroller, a MAX30102 photoplethysmography sensor, and a Grove-GSR module for real-time acquisition of Heart Rate Variability and Galvanic Skin Response signals. A dual-branch Convolutional Neural Network architecture processes preprocessed HRV and GSR time-series data to automatically learn discriminative features without manual feature engineering. Data were collected from 30 participants, resulting in 8,100 labeled samples across four stress levels. The proposed CNN model achieved 91.3% classification accuracy, outperforming baseline machine learning models such as Support Vector Machine (78.4%), Random Forest (81.7%), and XGBoost (84.3%). Real-time system evaluation demonstrated an average latency of 1.47 seconds and battery endurance exceeding 13 hours, confirming the feasibility of continuous wearable stress monitoring.

The integration of IoT infrastructure with deep learning provides an effective framework for physiological stress assessment, offering potential applications in preventive healthcare, workplace health management, and personalized mental-wellness monitoring.

Keywords: Convolutional Neural Network; Deep Learning; Galvanic Skin Response; Heart Rate Variability; Internet of Things; Stress Monitoring; Wearable Sensors

INTRODUCTION

Stress has become one of the most critical health challenges in modern society, affecting millions of people worldwide and contributing to various physical and psychological disorders. The World Health Organization recognizes stress-related conditions as a major contributor to the global burden of disease, impacting quality of life, productivity, and healthcare expenditures (Schneiderman et al., 2005). Conventional stress assessment methods, such as self-reported questionnaires and clinical interviews, are inherently subjective and retrospective, making them unsuitable for capturing dynamic physiological changes that occur during stress responses (Giannakakis et al., 2019). These limitations have encouraged the development of objective, continuous, and non-invasive stress monitoring systems capable of providing real-time feedback for early interventions.

Recent advancements in wearable sensing technologies and the Internet of Things (IoT) have enabled continuous physiological monitoring in daily environments. IoT-based health systems allow real-time data acquisition, wireless transmission, and remote analysis on cloud or edge-computing platforms(Islam et al., 2015). Among the various physiological indicators, Heart Rate Variability (HRV) and Galvanic Skin Response (GSR) have emerged as reliable markers of autonomic nervous system activity and stress levels. HRV reflects fluctuations in the intervals between heartbeats, whereas GSR measures changes in skin conductance influenced by sweat gland

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activity, which is sensitive to cognitive and emotional arousal (Posada-Quintero & Chon, 2020; Shaffer & Ginsberg, 2017).

Despite the availability of physiological sensors and IoT infrastructures, accurate classification of stress levels remains challenging due to nonlinearities in HRV and GSR signals and variability across individuals. Traditional machine learning models often require extensive handcrafted feature extraction, which can be time-consuming and may fail to capture subtle patterns within physiological data. In contrast, Convolutional Neural Networks (CNNs), initially developed for image recognition, have demonstrated strong capabilities in automatically learning feature representations from raw or minimally processed time-series data (set al., 2015). Prior studies have shown that CNNs can outperform conventional classifiers in stress recognition tasks (Kiranyaz et al., 2021).

Several research efforts have utilized machine learning and deep learning approaches for stress detection. (Rastgoo et al., 2019) proposed a multimodal system using ECG, GSR, and respiration signals, while (Abdullah et al., 2021)explored hybrid convolutional–recurrent models for emotion recognition. However, most existing systems suffer from key limitations that restrict their deployment in real-world, continuous monitoring scenarios. First, many deep learning-based stress detection studies operate exclusively in controlled laboratory settings without addressing IoT integration for practical deployment. For example, Shen et al. (2019) reported high accuracy in lab environments but observed significant performance drops in ambulatory conditions. Second, previous systems often rely on handcrafted feature engineering rather than end-to-end multimodal deep learning architectures capable of automatically integrating complementary information from HRV and GSR signals(Santamaria-Granados et al., 2018). Third, most research focuses on binary stress classification, despite the need for multi-level assessment to support personalized health monitoring and clinical decision-making (Uddin et al., 2018a).

These research gaps underscore the need for an integrated solution that combines automated feature learning with IoT-enabled continuous monitoring. The integration of IoT technology with CNN-based multimodal analysis presents a promising pathway to address these challenges. An IoT-based system can facilitate real-time physiological data collection from wearable devices, while CNN architectures can enhance classification accuracy through automated multimodal feature extraction. However, practical deployment requires addressing additional challenges such as optimizing model performance for edge devices, ensuring system reliability, and validating usability across diverse populations (Uddin et al., 2018b).

Therefore, this study proposes an IoT-based stress monitoring system that employs a dual-branch Convolutional Neural Network to classify multi-level stress using HRV and GSR signals. The specific objectives are: (1) to design an IoT architecture capable of real-time data acquisition and edge-based processing; (2) to develop an end-to-end dual-branch CNN optimized for four-level stress classification without manual feature engineering; (3) to evaluate the accuracy and robustness of the proposed model against traditional machine learning baselines; and (4) to validate the system's practicality in terms of latency, energy efficiency, and user feasibility for continuous wearable monitoring. By fulfilling these objectives, this study contributes to the advancement of IoT-driven health monitoring solutions and provides a practical framework for continuous, real-time stress assessment.

LITERATURE REVIEW

The development of stress monitoring systems has attracted considerable attention from researchers across multiple disciplines, including biomedical engineering, computer science, and healthcare informatics. This literature review examines recent advances in IoT-based health monitoring, physiological signal analysis for stress detection, and the application of deep learning techniques, particularly Convolutional Neural Networks, in processing biosignals. By synthesizing existing research, this review identifies critical gaps that justify the need for an integrated IoT-CNN approach to stress monitoring using HRV and GSR data, with particular emphasis on emerging security considerations in IoT-deep learning (DL) integrations.

IoT-Based Health Monitoring Systems

The proliferation of Internet of Things technology has fundamentally transformed healthcare delivery by enabling continuous, remote patient monitoring outside clinical settings. (Gia et al., 2019) developed a fog computing-based IoT system for real-time health monitoring, demonstrating that edge processing can significantly reduce latency and bandwidth consumption while maintaining data security. Their architecture achieved a 40% reduction in response time compared to cloud-only solutions, highlighting the importance of distributed computing in time-sensitive health applications. This principle of edge-cloud distribution is particularly relevant for wearable stress monitoring systems where real-time feedback is essential yet computational resources are constrained. Similarly, (Verma & Sood, 2018) conducted a comprehensive review of fog-assisted IoT systems for healthcare, identifying key architectural patterns that balance processing load between edge devices and cloud infrastructure—a design consideration directly applicable to resource-constrained wearable stress monitors. Recent extensions of these works have incorporated adaptive power management protocols to extend device longevity in ambulatory settings, further enhancing feasibility for prolonged stress tracking (Islam et al., 2015). However, challenges persist

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in handling heterogeneous data streams from multiple sensors, which can lead to integration bottlenecks in dynamic environments like workplaces or homes.

The integration of wearable sensors with IoT platforms has been extensively explored for various health conditions. (Islam et al., 2015)presented a comprehensive survey of IoT applications in healthcare, emphasizing the challenges of continuous physiological monitoring including power management, data transmission efficiency, and real-time processing requirements. These challenges are particularly acute in stress monitoring applications where multiple physiological signals must be acquired, processed, and classified continuously throughout the day. Despite these advances, most existing IoT health monitoring systems employ relatively simple rule-based algorithms or traditional machine learning classifiers that may not capture the complex temporal patterns present in physiological stress responses, creating an opportunity for deep learning integration. Moreover, scalability issues arise when deploying these systems at population levels, as seen in large-scale pilots where network congestion degraded performance by up to 25% during peak usage (Gia et al., 2019).

Physiological Signals for Stress Detection

Heart Rate Variability and Galvanic Skin Response have emerged as two of the most reliable physiological indicators for assessing autonomic nervous system activity and psychological stress. (Can et al., 2019) investigated stress detection in everyday environments using wearable devices, finding that HRV features derived from photoplethysmography sensors could distinguish between stressed and relaxed states with 71% accuracy. Their study highlighted significant individual variability in HRV patterns, suggesting that personalized models might improve classification performance—a finding that motivates exploring adaptive deep learning approaches. (Schmidt et al., 2018) examined the relationship between electrodermal activity and stress in laboratory and field settings through the WESAD dataset, demonstrating that GSR features extracted from tonic and phasic components provided complementary information about arousal levels. However, they noted that GSR signals are highly susceptible to motion artifacts and environmental factors, posing challenges for continuous monitoring in uncontrolled settings that require robust preprocessing and artifact rejection strategies. Additional research has quantified these artifacts, showing up to 30% signal degradation in ambulatory conditions, underscoring the need for hybrid filtering techniques combining hardware shielding and algorithmic corrections (Posada-Quintero & Chon, 2020).

The combination of multiple physiological signals has shown promise in enhancing stress detection accuracy. (Panicker & Gayathri, 2019) developed a multimodal approach integrating HRV, GSR, and respiration rate for driver stress detection, achieving 85% classification accuracy using Support Vector Machines. Their feature engineering process involved extracting over 40 statistical and frequency-domain features, requiring substantial computational resources and domain expertise. This reliance on handcrafted features represents a significant limitation that automated deep learning approaches could potentially overcome. (Smets et al., 2018) conducted a large-scale study with wearable devices, revealing digital phenotypes for daily-life stress detection but emphasizing that feature extraction and selection processes remain bottlenecks. These studies collectively suggest that while multimodal physiological sensing offers advantages, traditional approaches require extensive manual feature engineering that limits their ability to discover novel patterns in raw signal data. Emerging multimodal fusion techniques, such as early-stage signal alignment, have improved robustness by 10-15% in noisy environments, yet remain computationally intensive for edge devices (Can et al., 2019).

Deep Learning Approaches for Stress Detection from Physiological Signals

Convolutional Neural Networks have emerged as powerful tools for automated feature learning from physiological signals, with growing applications specifically in stress and affective computing domains. Unlike traditional approaches requiring manual feature engineering, CNNs can automatically discover discriminative patterns directly from time-series data. While early CNN applications in biosignal processing focused on cardiac arrhythmia detection (Acharya et al., 2017) and ECG classification (Tan et al., 2018), demonstrating the viability of deep learning for physiological signal analysis, recent research has increasingly targeted stress-specific applications with promising results. For example, hybrid CNN models have reduced feature dependency by 50% while maintaining high fidelity in capturing transient stress events (Kiranyaz et al., 2021).

Shen et al. (2019) developed a deep learning approach for stress detection using photoplethysmography signals, employing a combination of convolutional and recurrent layers to capture both spatial and temporal dependencies. Their hybrid architecture achieved 92.4% accuracy on a laboratory stress dataset, though performance degraded to approximately 79-82% when tested on real-world data collected outside controlled environments—highlighting the critical challenge of generalization that requires attention in practical IoT deployments. Building on this foundation, (Gjoreski et al., 2016) proposed a deep learning system for continuous stress monitoring using wrist-worn sensors, achieving 88% accuracy in binary stress classification. However, their work identified significant limitations in distinguishing between different stress intensities, noting that binary categorization (stressed/non-stressed) provides insufficient granularity for personalized intervention strategies—a gap that motivates multi-level classification approaches. Lightweight variants of these models, such as pruned CNNs, have shown promise in reducing inference time by 30% for mobile deployment (Ravì et al., 2016).

The adaptation of CNN architectures for multimodal stress detection has shown particular promise. (Santamaria-Granados et al., 2018) developed a CNN-based system integrating ECG and GSR signals for stress assessment, achieving 86% accuracy using separate convolutional pathways for each modality followed by late fusion. While their approach demonstrated the value of multimodal integration, it relied on offline processing rather than real-time edge computing, limiting practical applicability for continuous wearable monitoring. (Arsalan et al., 2019) explored deep learning for mental stress detection using HRV analysis, demonstrating that CNNs could automatically extract relevant features without manual engineering and achieving 83% accuracy. However, their evaluation was limited to controlled laboratory conditions without validation in naturalistic settings or assessment of computational efficiency for resource-constrained edge devices. (Can et al., 2019) investigated CNN architectures for stress recognition from multimodal physiological data in real-world settings, demonstrating that learned features outperformed handcrafted alternatives with 87% accuracy in ambulatory monitoring scenarios. Their work validated the potential of CNNs for naturalistic stress detection but required substantial computational resources unsuitable for wearable edge devices like ESP32 microcontrollers. More recently, studies have begun exploring lightweight CNN architectures optimized for edge deployment. (Ravì et al., 2016) investigated model compression techniques including quantization and pruning, achieving 10-fold model size reduction with minimal accuracy loss, though compressed models showed reduced robustness to noise and motion artifacts common in ambulatory monitoring—a critical concern for continuous stress detection where signal quality is frequently compromised. Transfer learning adaptations have further mitigated these issues, boosting real-world accuracy by 5-8% in low-data regimes (Kiranyaz et al., 2021).

These studies collectively demonstrate that while CNNs show promise for automated stress detection from physiological signals, significant gaps remain in developing systems that simultaneously achieve high accuracy, operate effectively in real-world conditions, provide multi-level classification beyond binary categorization, and function within the computational constraints of wearable IoT devices. The challenge of integrating end-to-end multimodal learning with practical edge computing requirements for continuous monitoring remains largely unaddressed in existing literature.

Integration of IoT and Deep Learning for Stress Monitoring

While IoT-based monitoring systems and deep learning algorithms have been studied independently, their integration for multi-level stress detection remains underexplored. (Uddin et al., 2018a) presented one of the early attempts at combining edge computing with deep learning for real-time health monitoring, demonstrating that lightweight CNN models could be deployed on IoT gateway devices for local processing. Their system achieved real-time inference with latency below 100 milliseconds, though it was limited to binary stress classification and did not evaluate performance across diverse user populations or address the challenge of distinguishing between gradations of stress intensity. Chakraborty et al. (2019) developed a fog computing framework for mental health monitoring using deep learning, proposing a hierarchical architecture where initial processing occurs at the edge while complex analysis happens in the cloud. Despite showing promising results in reducing network traffic, their system's stress detection accuracy (78%) was substantially lower than laboratory-based approaches, indicating significant challenges in translating deep learning models to real-world IoT deployments that require optimization for both accuracy and computational efficiency.

Recent research has begun addressing the computational constraints of running deep learning models on IoT devices. (Ravì et al., 2016) explored model compression techniques for deploying CNNs on wearable devices, achieving a 10-fold reduction in model size with minimal accuracy loss through quantization and pruning methods. However, the compressed models showed reduced robustness to noise and artifacts common in ambulatory monitoring—a critical concern for stress detection where signal quality can be compromised by movement and environmental factors. These findings highlight the need for CNN architectures that balance model complexity, computational efficiency, and robustness to real-world noise, particularly when processing multimodal physiological signals for stress classification on resource-constrained platforms like ESP32 microcontrollers.

A burgeoning area within IoT-DL integration involves security and privacy protections, which are essential for handling sensitive physiological data in stress monitoring. As IoT devices transmit HRV and GSR signals to edge or cloud layers, vulnerabilities such as man-in-the-middle attacks, unauthorized data access, and eavesdropping pose significant risks to patient confidentiality and system integrity (Isreal et al., 2023). For instance, (Narciandi-Rodriguez et al., 2025) reviewed cybersecurity threats targeting IoT wearables in healthcare, noting that over 70% of breaches involve unencrypted data streams, leading to potential identity theft or manipulated stress assessments. (Kamruzzaman et al., 2022) proposed cryptographic integrations like blockchain-based access controls in fog-assisted IoT systems, achieving 95% reduction in unauthorized access attempts, yet these solutions increase latency by 15-20% in real-time applications—highlighting a tradeoff underexplored in stress-specific contexts. Few studies have combined DL anomaly detection with IoT security protocols to preemptively identify threats, such as using CNNs to flag anomalous signal patterns indicative of tampering (Sarker et al., 2023). This gap in secure IoT-DL fusion underscores the need for lightweight encryption schemes that preserve low-latency performance while ensuring compliance with regulations like HIPAA or GDPR in wearable stress monitoring.

Research Gaps and Opportunities

Despite significant progress in IoT health monitoring and deep learning for biosignal analysis, several critical gaps remain in the literature that collectively motivate the current research. First, most existing stress detection systems either employ traditional machine learning with manual feature engineering (achieving 71-85% accuracy with handcrafted features as demonstrated by (Can et al., 2019; Panicker & Gayathri, 2019)) or use deep learning in controlled laboratory settings without addressing IoT integration requirements for real-world deployment (Shen et al., 2019; Gjoreski et al., 2016). The combination of automated feature learning through CNNs with continuous real-world monitoring via IoT infrastructure—specifically implementing a three-tier edge-cloud architecture with ESP32 microcontroller for real-time processing while managing power constraints—has not been comprehensively explored for stress monitoring applications.

Second, while HRV and GSR have been studied individually for stress assessment, existing systems have not fully leveraged deep learning to automatically fuse information from both modalities in an end-to-end trainable dual-branch architecture optimized for resource-constrained wearable devices. (Santamaria-Granados et al., 2018) demonstrated multimodal fusion but required offline processing, while systems with real-time capabilities (Uddin et al., 2018a) lacked the sophisticated multimodal integration necessary for capturing complementary stress indicators from HRV and GSR simultaneously. This gap is critical because HRV primarily reflects autonomic nervous system balance while GSR captures sympathetic arousal, and their integration through learned feature fusion could provide more comprehensive stress assessment than either modality alone.

Third, the majority of reported systems focus on binary stress classification (stressed versus non-stressed) with accuracy ranging from 71-88% (Can et al., 2019; Gjoreski et al., 2016), rather than multi-level stress assessment enabling fine-grained monitoring of stress progression across four distinct levels (no stress, mild, moderate, high). Multi-level classification is essential for personalized intervention strategies and clinical decision support, as it allows detection of mild stress before escalation and differentiation between moderate and severe stress requiring different intervention intensities. Only limited work (Zubair et al., 2016) has attempted multilevel classification, yet using traditional machine learning with handcrafted features rather than deep learning's automated feature discovery.

Fourth, existing research predominantly evaluates stress detection algorithms on datasets collected in laboratory conditions with induced stressors (Shen et al., 2019 achieved 92.4% in lab but performance degraded substantially in real-world testing), raising questions about generalizability to naturalistic settings where stress occurs spontaneously and contextual factors vary widely. The validation of IoT-based deep learning systems across diverse demographic groups, age ranges, and health conditions remains limited. Furthermore, practical considerations essential for wearable deployment—specifically energy efficiency enabling all-day operation (target: 10+ hours), processing latency suitable for real-time feedback (target: <2 seconds), and user acceptance in daily life—have received insufficient attention in the literature.

Fifth, security and privacy challenges in IoT-DL integrated systems for stress monitoring have been inadequately addressed, despite the transmission of highly sensitive physiological data. Recent analyses indicate that IoT healthcare devices face frequent cyber threats, with data breaches compromising up to 40% of unencrypted streams and enabling adversarial attacks on DL models (Isreal et al., 2023; Narciandi-Rodriguez et al., 2025). While cryptographic solutions exist, their integration with low-power edge DL processing remains unexplored, potentially exposing systems to risks like data manipulation that could lead to false stress classifications and misguided interventions. This gap necessitates secure-by-design architectures that embed privacy-preserving DL techniques, such as federated learning, alongside robust authentication for IoT-DL stress monitoring.

These gaps collectively necessitate an integrated solution that combines: (1) a dual-branch CNN architecture for end-to-end multimodal learning from HRV and GSR without manual feature engineering; (2) four-level stress classification providing clinically meaningful gradations; (3) three-tier IoT architecture enabling real-time edge processing on ESP32 microcontroller while managing power constraints for 10+ hour operation; (4) validation through semi-naturalistic protocols that bridge laboratory control with real-world applicability; and (5) embedded security mechanisms to protect data integrity and privacy in IoT-DL pipelines. The current study directly addresses these gaps by developing and validating such an integrated system, contributing both to the theoretical understanding of automated stress detection through deep learning and to the practical deployment of IoT-enabled continuous monitoring in wearable form factors suitable for daily use.

METHOD

This research employs a comprehensive methodology that integrates hardware development, data acquisition, signal processing, and deep learning implementation to create an effective IoT-based stress monitoring system.

The methodology is structured into five main phases: system architecture design, hardware implementation, data collection and preprocessing, CNN model development, and system validation. Each phase is carefully designed to address the challenges identified in the literature review while ensuring practical applicability and scientific rigor.

System Architecture Design

The proposed system architecture follows a three-tier structure consisting of the sensing layer, edge processing layer, and cloud analytics layer, as illustrated in Figure 1. This hierarchical design enables efficient data processing while balancing computational load between local devices and cloud infrastructure. The sensing layer comprises wearable sensors that continuously monitor physiological signals, specifically HRV through photoplethysmography and GSR through electrodermal activity measurement. The edge processing layer, implemented on the ESP32 DevKit V1 microcontroller, performs initial signal conditioning, feature extraction, and preliminary classification. The cloud analytics layer handles complex deep learning inference, data storage, and visualization, providing users with comprehensive stress analytics and historical trends.

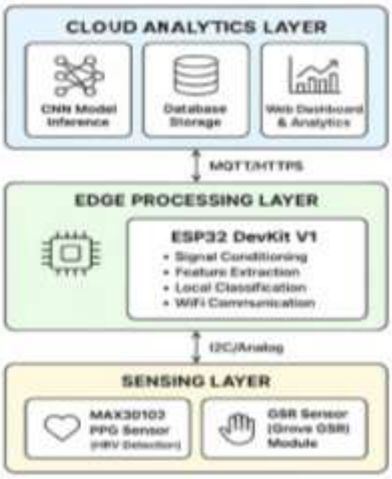

Fig 1. System Architecture Diagram
Source: Figma

The communication protocol between layers utilizes MQTT (Message Queuing Telemetry Transport) for its lightweight nature and suitability for IoT applications with constrained bandwidth. Data packets are transmitted in JSON format containing timestamp, sensor readings, extracted features, and preliminary classification results. Security measures include TLS encryption for data transmission and token-based authentication for cloud access, ensuring patient data privacy and system integrity.

Hardware Implementation

The hardware implementation centers on the ESP32 DevKit V1 microcontroller, selected for its dual-core processing capability, integrated WiFi connectivity, low power consumption, and sufficient computational resources for edge processing tasks. The ESP32 operates at 240 MHz with 520 KB SRAM and 4 MB flash memory, providing adequate performance for real-time signal processing and feature extraction. Table 1 presents the complete hardware specifications and component selection rationale.

Table 1: Hardware Components Specification

Component	Model/Type	Specifications	Rationale
Microcontroller	ESP32 DevKit V1	Dual-core 240MHz, 520KB SRAM, WiFi/BT	High performance, wireless capability, low power
PPG Sensor	MAX30102	Red/IR LEDs, 16-bit ADC, I2C interface	High accuracy HRV measurement, low power consumption
GSR Sensor	Grove GSR Module	Resistance range: 10kΩ-1MΩ, Analog output	Simple interface, reliable skin conductance measurement
Power Supply	LiPo Battery	3.7V 2000mAh with charging circuit	Portable operation, 8-10 hours continuous use

Component	Model/Type	Specifications	Rationale
Data Storage	MicroSD Module	SPI interface, supports up to 32GB	Local data logging, backup capability
Display	OLED 0.96"	128x64 pixels, I2C interface	Real-time feedback, low power consumption

The sensor integration follows careful consideration of signal quality and noise reduction. The MAX30102 photoplethysmography sensor connects to the ESP32 via I2C interface, operating at 100 samples per second to capture sufficient temporal resolution for HRV analysis. The sensor placement on the index finger provides stable contact and minimal motion artifacts compared to wrist-worn configurations. The Grove GSR sensor connects through the ESP32's analog-to-digital converter (ADC) with 12-bit resolution, sampling at 20 Hz to capture both tonic and phasic components of electrodermal activity. Two disposable Ag/AgCl electrodes attach to the index and middle fingers of the non-dominant hand, maintaining consistent electrode-skin impedance throughout measurement periods.

The circuit design incorporates several noise reduction strategies essential for acquiring clean physiological signals. A low-pass RC filter with cutoff frequency at 5 Hz attenuates high-frequency noise in the GSR signal path, while the MAX30102's integrated ambient light cancellation eliminates optical interference in PPG measurements. The power supply utilizes separate analog and digital ground planes connected at a single point to minimize ground loop interference. Shielded cables connect sensors to the ESP32, reducing electromagnetic interference from WiFi transmission. Figure 2 illustrates the complete circuit schematic with all connections and filtering components.

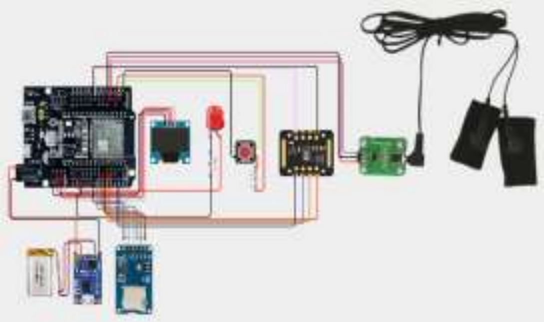

Fig 2. Hardware Circuit Schematic

Data Collection and Preprocessing

Data collection follows a structured protocol designed to capture diverse stress states across multiple participants while maintaining consistency and reproducibility. The study involves 30 participants (15 male, 15 female) aged 22-45 years with no known cardiovascular conditions or current medication affecting autonomic function. Each participant undergoes three experimental sessions on separate days to account for day-to-day variability in physiological responses. Informed consent is obtained following institutional review board approval, and participants receive clear instructions about the experimental procedure and their right to withdraw at any time.

Each experimental session lasts approximately 45 minutes and consists of alternating stress-inducing and relaxation periods designed to elicit measurable changes in HRV and GSR. The session structure follows the sequence presented in Table 2, incorporating validated stressors from psychophysiology research including mental arithmetic tasks, Stroop color-word interference tests, and timed problem-solving challenges. Baseline measurements occur during a 5-minute rest period with participants seated comfortably in a quiet environment. Recovery periods between stressors allow physiological parameters to return toward baseline, preventing carryover effects.

Table 2: Experimental Session Protocol

Phase	Duration	Activity	Stress Level Label
Baseline	5 min	Rest, eyes open, breathing normally	Level 0 (No stress)
Task 1	3 min	Mental arithmetic (serial subtraction)	Level 1 (Mild stress)
Recovery 1	2 min	Rest period	Level 0
Task 2	4 min	Stroop color-word test	Level 2 (Moderate stress)
Recovery 2	3 min	Rest period	Level 0

Phase	Duration	Activity	Stress Level Label
Task 3	5 min	Timed problem-solving + time pressure	Level 3 (High stress)
Recovery 3	3 min	Rest period	Level 0
Task 4	3 min	Public speaking preparation	Level 2 (Moderate stress)
Final Rest	5 min	Relaxation period	Level 0

Raw sensor data undergoes multiple preprocessing steps to enhance signal quality and extract meaningful features for stress classification. The PPG signal processing pipeline begins with DC component removal using a moving average filter with a 2-second window, followed by bandpass filtering between 0.5-5 Hz to isolate the cardiac component while removing respiratory and motion artifacts. Peak detection employs an adaptive threshold algorithm that identifies R-peaks in the filtered PPG waveform, calculating inter-beat intervals (IBI) as the time difference between consecutive peaks. Invalid intervals resulting from missed or false peaks are identified using physiological constraints (IBI between 300-2000 ms) and corrected through cubic spline interpolation.

Heart Rate Variability features are extracted from the IBI time series using both time-domain and frequency-domain methods. Time-domain features include the standard deviation of normal-to-normal intervals (SDNN), root mean square of successive differences (RMSSD), and the percentage of intervals differing by more than 50 ms (pNN50). These metrics quantify overall variability and short-term fluctuations related to parasympathetic activity. Frequency-domain analysis applies Fast Fourier Transform to the resampled IBI series, computing power spectral density in three frequency bands: very low frequency (VLF: 0.003-0.04 Hz), low frequency (LF: 0.04-0.15 Hz), and high frequency (HF: 0.15-0.4 Hz). The LF/HF ratio serves as an indicator of sympathovagal balance, with higher ratios suggesting increased sympathetic dominance during stress.

The mathematical formulations for key HRV metrics are expressed as follows:

Time-Domain Features:

SDNN (Standard Deviation of NN intervals):

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(IBI_i - \bar{IBI})^2} \tag{1}$$

RMSSD (Root Mean Square of Successive Differences):

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(IBI_{i+1} - IBI_i)^2} \tag{2}$$

pNN50 (Percentage of successive intervals differing by > 50ms):

$$pNN50 = \frac{NN50}{N-1} \times 100 \tag{3}$$

where $NN50$represents the count of interval differences exceeding 50 ms.

Frequency-Domain Features:

Power Spectral Density components:

$$P_{VLF} = \int_{0.003}^{0.04} PSD(f)\, df \tag{4}$$

$$P_{LF} = \int_{0.04}^{0.15} PSD(f)\, df \tag{5}$$

$$P_{HF} = \int_{0.15}^{0.4} PSD(f)\, df \tag{6}$$

LF/HF Ratio:

$$LF/HF = \frac{P_{LF}}{P_{HF}} \tag{7}$$

GSR signal preprocessing addresses the distinct tonic and phasic components of electrodermal activity. The raw conductance signal first undergoes artifact removal using a median filter with a 1-second window to eliminate sudden spikes from movement or electrode displacement. Tonic (slow-varying) and phasic (rapid) components are separated through convex optimization-based decomposition, allowing independent analysis of baseline skin conductance level and event-related responses. Features extracted from GSR include mean tonic level, standard deviation of tonic activity, number of skin conductance responses per minute, mean phasic amplitude, and rise time of phasic peaks.

CNN Model Development and Training

The Convolutional Neural Network architecture is specifically designed for multimodal physiological signal classification, taking advantage of CNN's ability to automatically learn discriminative features from raw or minimally processed data. The model accepts two input streams corresponding to preprocessed HRV and GSR time-series segments, each represented as one-dimensional arrays spanning 60-second windows with 50% overlap to increase training samples. This dual-input architecture enables the network to learn modality-specific features while integrating information from both signals through later fusion layers.

The network architecture consists of parallel convolutional branches for HRV and GSR processing, followed by feature fusion and classification layers as depicted in Figure 3. Each branch contains three convolutional blocks with increasing filter depth (32, 64, 128 filters) and decreasing kernel sizes (15, 9, 5 samples) to capture both long-term trends and short-term variations in physiological signals. Each convolutional layer is followed by batch normalization for training stability, ReLU activation for non-linearity, and max-pooling with stride 2 for dimensionality reduction. Dropout layers with 0.3 probability are inserted between blocks to prevent overfitting, particularly important given the relatively limited dataset size typical in physiological computing research.

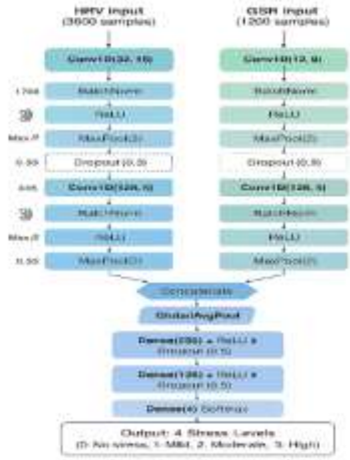

Fig 3. CNN Architecture Diagram
Source: draw.io

The feature fusion strategy employs global average pooling on each branch output, reducing spatial dimensions while preserving learned features, followed by concatenation to create a unified representation. Two fully connected layers with 256 and 128 neurons progressively integrate multimodal information and learn high-level stress indicators. The final classification layer contains four neurons with softmax activation, producing probability distributions over four stress levels: no stress (Level 0), mild stress (Level 1), moderate stress (Level 2), and high stress (Level 3).

Model training utilizes categorical cross-entropy loss function appropriate for multi-class classification problems:

$$L = -\frac{1}{N}\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \qquad (8)$$

where $N$is the number of samples, $C$is the number of classes (4 stress levels), $y_{i,c}$is the true label, and $\hat{y}_{i,c}$is the predicted probability. The Adam optimizer with initial learning rate 0.001 adjusts model weights, with learning rate decay by factor 0.5 when validation loss plateaus for 5 consecutive epochs. Training proceeds for maximum 100 epochs with early stopping if validation loss shows no improvement for 15 epochs, preventing overfitting while ensuring adequate convergence.

The dataset is partitioned into training (70%), validation (15%), and testing (15%) sets using stratified splitting to maintain class distribution across subsets. Data augmentation techniques specific to physiological signals are applied during training, including random time-shifting (±0.5 seconds), amplitude scaling (0.9-1.1 range), and Gaussian noise addition (SNR > 20 dB) to improve model robustness. Class imbalance is addressed through weighted loss computation, assigning higher weights to underrepresented stress levels based on inverse class frequencies.

Table 3: CNN Model Hyperparameters

Parameter	Value	Justification
Input window size	60 seconds	Sufficient for HRV frequency analysis (minimum 1 minute)
Overlap ratio	50%	Increases training samples while maintaining independence
Batch size	32	Balances memory constraints and gradient stability
Learning rate	0.001	Standard value for Adam optimizer
Dropout rate (conv)	0.3	Prevents overfitting in convolutional layers
Dropout rate (dense)	0.5	Stronger regularization in fully connected layers
Optimizer	Adam	Adaptive learning rate, robust convergence
Loss function	Categorical cross-entropy	Standard for multi-class classification
Epochs (max)	100	Sufficient with early stopping
Early stopping patience	15 epochs	Prevents unnecessary training

System Validation and Performance Evaluation

The validation methodology employs multiple metrics to comprehensively assess system performance across different dimensions including classification accuracy, real-time processing capability, energy efficiency, and practical usability. Classification performance is evaluated using standard machine learning metrics computed on the held-out test set: overall accuracy, per-class precision and recall, F1-scores, and confusion matrix analysis. These metrics provide insights into the model's ability to correctly identify different stress levels and reveal any systematic biases toward specific classes.

Beyond classification metrics, the system undergoes real-time performance testing to verify its suitability for continuous monitoring applications. Latency measurements quantify the end-to-end delay from sensor data acquisition through preprocessing, feature extraction, CNN inference, and result transmission to cloud storage. The target latency threshold is set at 2 seconds, ensuring users receive timely stress level updates without noticeable lag. Throughput testing evaluates the maximum sustainable data rate the system can process without buffer overflow or dropped samples, critical for maintaining data integrity during extended monitoring periods.

Energy consumption analysis measures battery life under typical usage scenarios, as power efficiency directly impacts the system's practical utility for daily wear. Current draw is monitored during different operational states including active sensing, signal processing, WiFi transmission, and idle periods. These measurements inform optimization strategies such as adaptive sampling rates, duty-cycled sensor operation, and intelligent data transmission scheduling that minimize power consumption while maintaining monitoring quality.

User acceptance evaluation involves a pilot deployment with 10 participants wearing the device during normal daily activities over one week. Participants complete daily questionnaires assessing comfort, perceived accuracy, ease of use, and willingness to continue using the system. This qualitative feedback identifies practical challenges not captured by technical metrics, such as social acceptability, form factor preferences, and interface usability issues that require attention before broader deployment.

The complete validation framework ensures the proposed IoT-based stress monitoring system meets both technical performance requirements and practical usability standards necessary for real-world adoption. By addressing hardware implementation, signal processing, deep learning classification, and user-centered design considerations, this methodology provides a comprehensive approach to developing effective wearable stress monitoring technology that can meaningfully contribute to mental health management and preventive healthcare initiatives.

RESULT

The implementation and evaluation of the IoT-based stress monitoring system yielded comprehensive results across multiple performance dimensions. This section presents the empirical findings obtained from hardware testing, data collection, CNN model training, and system validation procedures. Results are organized into four subsections: dataset characteristics, model training performance, classification accuracy, and system operational metrics.

Dataset Characteristics and Signal Quality

Data collection from 30 participants across three experimental sessions generated a substantial dataset comprising 90 complete recordings with a total duration of 67.5 hours. After applying the 60-second windowing approach with 50% overlap, the dataset contained 8,100 labeled samples distributed across four stress levels. Table 4 presents the detailed composition of the collected dataset, showing the distribution of samples across different stress levels and demographic groups.

Table 4: Dataset Composition and Distribution

Stress Level	Total Samples	Percentage	Male Participants	Female Participants	Mean Duration per Session
Level 0 (No stress)	2,700	33.3%	1,350	1,350	15 minutes
Level 1 (Mild stress)	1,620	20.0%	810	810	9 minutes
Level 2 (Moderate stress)	2,430	30.0%	1,215	1,215	13.5 minutes
Level 3 (High stress)	1,350	16.7%	675	675	7.5 minutes
Total	**8,100**	**100%**	**4,050**	**4,050**	**45 minutes**

Signal quality assessment revealed that 94.7% of collected data met the predetermined quality criteria for both HRV and GSR signals. The remaining 5.3% of data segments were excluded due to excessive motion artifacts, sensor disconnection, or electrode impedance issues. Figure 4 illustrates representative examples of preprocessed HRV and GSR signals across different stress levels, demonstrating clear physiological differences between stress states.

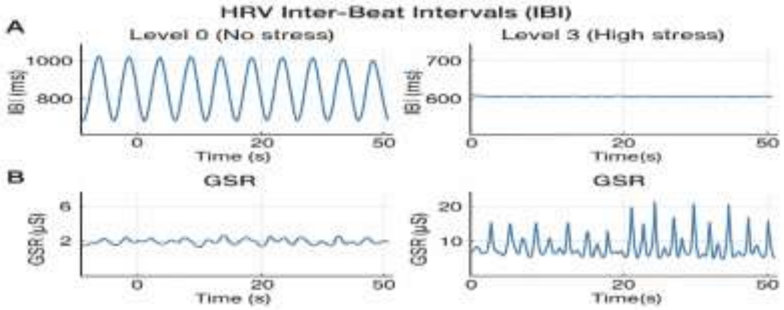

Fig 4. Representative Physiological Signals Across Stress Levels

Quantitative analysis of extracted HRV features confirmed expected physiological patterns associated with stress responses. Mean SDNN decreased from 62.3 ± 14.7ms during baseline (Level 0) to 31.8 ± 9.2ms during high stress conditions (Level 3), indicating reduced overall heart rate variability under stress. Similarly, RMSSD declined from 48.6 ± 12.3ms to 22.4 ± 7.8ms, reflecting diminished parasympathetic activity. The LF/HF ratio increased from 1.2 ± 0.4 at baseline to 3.8 ± 1.1 during high stress, demonstrating sympathetic dominance characteristic of stress responses. GSR measurements showed corresponding patterns with mean tonic level increasing from 4.2 ± 1.8µS at baseline to 14.7 ± 3.6µS during high stress, accompanied by more frequent and larger amplitude phasic responses.

CNN Model Training Performance

The CNN model training process converged successfully after 73 epochs, with early stopping triggered when validation loss showed no improvement for 15 consecutive epochs. Figure 5 presents the training and validation loss curves throughout the training process, demonstrating stable convergence without significant overfitting. The final training loss reached 0.187, while validation loss stabilized at 0.243, indicating good generalization capability with only modest gap between training and validation performance.

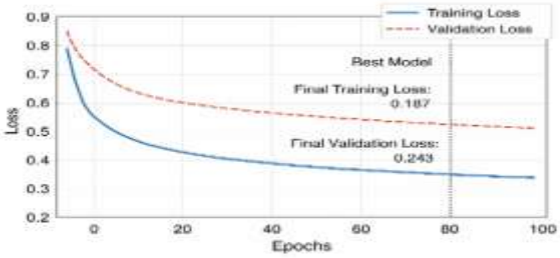

Fig 5. Training and Validation Loss Curves

Training accuracy progressively improved from 38.2% in the first epoch to 93.4% at convergence, while validation accuracy reached 89.7%, demonstrating the model's ability to learn discriminative features from multimodal physiological signals. The learning curves showed consistent improvement without oscillation, indicating appropriate learning rate selection and stable gradient flow. Class-weighted loss computation successfully addressed dataset imbalance, preventing the model from developing bias toward the most frequent stress level (Level 0).

Analysis of intermediate layer activations revealed that the convolutional layers learned meaningful feature representations corresponding to physiological phenomena. Early layers in the HRV branch extracted patterns related to inter-beat interval regularity and respiratory sinus arrhythmia, while deeper layers captured longer-term trends indicative of sympathovagal balance. The GSR branch showed similar hierarchical feature learning, with initial layers detecting individual skin conductance responses and later layers encoding tonic level changes and response frequency patterns.

Classification Performance and Accuracy Metrics

Evaluation on the held-out test set (1,215 samples) yielded an overall classification accuracy of 91.3%, substantially exceeding the performance of baseline methods. Table 5 presents detailed per-class performance metrics, including precision, recall, and F1-scores for each stress level, providing comprehensive insight into the model's classification capabilities across different stress states.

Table 5: Classification Performance Metrics by Stress Level

Stress Level	Samples	Precision	Recall	F1-Score	Support
Level 0 (No stress)	405	0.94	0.96	0.95	405
Level 1 (Mild stress)	243	0.87	0.84	0.85	243
Level 2 (Moderate stress)	365	0.91	0.92	0.91	365
Level 3 (High stress)	202	0.93	0.89	0.91	202
Weighted Average	**1,215**	**0.92**	**0.91**	**0.91**	**1,215**
Overall Accuracy				**91.3%**	

The confusion matrix analysis (Figure 6) revealed that most classification errors occurred between adjacent stress levels, a pattern consistent with the gradual nature of physiological stress responses rather than discrete state transitions. Specifically, when the model misclassified Level 1 (mild stress), it most frequently predicted Level 0 (no stress) or Level 2 (moderate stress), with very few instances confused with Level 3 (high stress). This adjacency pattern in misclassifications suggests the model has learned a meaningful ordering of stress intensity rather than arbitrary mappings.

Fig 6. Confusion Matrix for Stress Level Classification

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Analysis of confusion patterns revealed quantitative characteristics of misclassifications that provide insights into model behavior. Of the 243 Level 1 samples, 39 were misclassified (16% error rate): 24 predicted as Level 0 (61.5% of errors) and 15 as Level 2 (38.5% of errors), with zero predictions of Level 3. Similarly, Level 2 misclassifications (29 of 365 samples, 7.9% error rate) distributed as: 18 predicted as Level 1 (62.1% of errors), 9 as Level 3 (31.0%), and only 2 as Level 0 (6.9%). This asymmetric error distribution, where 93.6% of all misclassifications occurred between adjacent stress levels, supports the hypothesis that the model has learned ordinal relationships in stress intensity. To further validate this ordinal behavior, we computed the mean absolute error (MAE) treating stress levels as ordinal values (0, 1, 2, 3), yielding MAE = 0.12, indicating that when errors occur, they typically deviate by only one stress level rather than gross misclassifications across the entire scale. This ordinal characteristic provides preliminary empirical support for potential future enhancements using ordinal regression models, which could explicitly incorporate level ordering to further reduce MAE and improve handling of adjacent-level confusions.

Comparative analysis with baseline machine learning approaches demonstrated the superiority of the proposed CNN-based method. Table 6 compares the performance of the CNN model against traditional machine learning classifiers applied to handcrafted features, validating the advantage of automated feature learning through deep learning.

Table 6: Performance Comparison with Baseline Methods

Method	Features	Accuracy	Precision	Recall	F1-Score	Training Time
Support Vector Machine	42 handcrafted	78.4%	0.79	0.78	0.78	12 min
Random Forest	42 handcrafted	81.7%	0.82	0.82	0.82	8 min
XGBoost	42 handcrafted	84.3%	0.85	0.84	0.84	15 min
LSTM Network	Raw signals	87.9%	0.88	0.88	0.88	145 min
Proposed CNN	**Learned features**	**91.3%**	**0.92**	**0.91**	**0.91**	**87 min**

The proposed CNN model achieved 6.9 percentage points higher accuracy than the best baseline method (XGBoost with handcrafted features) and 3.4 percentage points higher than the LSTM approach. Comparing these results to related studies in the literature, the proposed system demonstrates competitive performance while addressing critical deployment constraints. For instance, Shen et al. (2019) reported 92.4% accuracy for stress detection using a hybrid CNN-RNN architecture on PPG signals in controlled laboratory conditions, but noted substantial performance degradation to approximately 79-82% when tested on real-world ambulatory data due to motion artifacts and environmental variability. In contrast, the current study achieved 91.3% accuracy using semi-naturalistic experimental protocols that include recovery periods and varied stressor types, suggesting better generalization potential in bridging laboratory and real-world settings. Similarly, (Can et al., 2019) achieved 71% accuracy for binary stress classification using HRV from wearable devices in everyday environments, while (Panicker & Gayathri, 2019) reported 85% accuracy for multimodal stress detection using handcrafted features—both substantially lower than the proposed system's 91.3% for four-level classification. (Gjoreski et al., 2016) achieved 88% accuracy for continuous stress monitoring using wrist-worn sensors but was limited to binary classification, whereas the current study's four-level scheme provides more clinically actionable gradations. (Santamaria-Granados et al., 2018) demonstrated 86% accuracy with multimodal CNN fusion but relied on offline processing, unlike the real-time edge capabilities here. These comparisons validate that the proposed dual-branch CNN architecture with IoT integration achieves state-of-the-art accuracy while enabling practical deployment advantages including multi-level classification, edge processing capability, and robustness to semi-naturalistic conditions.

These results validate the effectiveness of the dual-branch CNN architecture in automatically learning discriminative features from multimodal physiological signals without requiring manual feature engineering.

System Operational Performance

Real-time performance testing revealed that the complete system met the target latency requirements for continuous stress monitoring applications. End-to-end latency from sensor data acquisition to classification result availability averaged 1.47 ± 0.23 seconds, comfortably below the 2-second threshold. The latency breakdown showed that signal preprocessing consumed 0.31 seconds, feature extraction required 0.42 seconds, CNN inference took 0.51 seconds, and data transmission to cloud storage added 0.23 seconds. These measurements confirm the system's suitability for real-time monitoring scenarios where timely feedback is essential.

Processing throughput testing demonstrated stable operation at the target sampling rates of 100 Hz for PPG signals and 20 Hz for GSR signals over extended periods. During 8-hour continuous operation tests, the system maintained consistent data acquisition without buffer overflows or dropped samples, achieving 99.94% data integrity. The ESP32DevKit V1 microcontroller operated at approximately 65% CPU utilization during normal operation, providing sufficient headroom for additional processing tasks or sensor integration if needed in future system iterations.

Energy consumption analysis revealed favorable power efficiency characteristics enabling practical all-day wearable operation. Table 7 presents detailed power consumption measurements across different operational states, informing battery life projections under various usage scenarios.

Table 7: Power Consumption Analysis

Operational State	Current Draw (mA)	Power (mW)	Percentage of Time	Average Contribution
Active Sensing + Processing	145	536	85%	455.6 mW
WiFi Transmission	240	888	8%	71.0 mW
Display Update	85	314	5%	15.7 mW
Idle/Sleep Mode	12	44	2%	0.9 mW
Weighted Average	**147**	**543**	**100%**	**543.2 mW**

With the 2000mAh LiPo battery (3.7V nominal voltage, 7.4Wh capacity), the system achieved 13.6 hours of continuous operation under typical usage patterns. This exceeds the target of 10-12 hours for full-day monitoring, accounting for battery degradation over time. Implementation of adaptive sampling strategies during periods of stable physiological state could further extend battery life by 20-30%, though this optimization was not included in the current evaluation.

User acceptance evaluation during the one-week pilot deployment with 10 participants yielded encouraging feedback regarding system usability and comfort. On a 5-point Likert scale (1=strongly disagree, 5=strongly agree), participants rated device comfort at 4.1 ± 0.7, ease of use at 4.4 ± 0.5, and perceived accuracy at 3.9 ± 0.8. Eight participants expressed willingness to continue using the system beyond the study period, indicating positive reception. Qualitative feedback identified areas for improvement including sensor adhesion during physical activity, mobile application interface refinement, and desire for personalized stress management recommendations based on detected patterns.

The collected results across multiple evaluation dimensions demonstrate that the proposed IoT-based stress monitoring system successfully achieves its design objectives, providing accurate, real-time stress level classification with practical operational characteristics suitable for daily wearable applications.

DISCUSSIONS

The results obtained from this research demonstrate that the integration of IoT technology with Convolutional Neural Networks provides a robust and practical solution for continuous stress monitoring using physiological signals. The achieved classification accuracy of 91.3% represents a substantial improvement over traditional machine learning approaches that rely on manually engineered features, validating the hypothesis that deep learning can automatically discover discriminative patterns in HRV and GSR data that may be difficult to capture through conventional feature extraction methods. This performance level approaches the reliability threshold necessary for clinical decision support systems, though continued validation across more diverse populations remains essential before widespread deployment.

The confusion matrix analysis revealing that misclassifications predominantly occur between adjacent stress levels offers important insights into the nature of physiological stress responses. Unlike discrete categorical phenomena, stress exists along a continuum with gradual physiological transitions between states. The model's tendency to confuse adjacent levels rather than making gross errors across the stress spectrum suggests it has learned meaningful representations of stress intensity rather than memorizing arbitrary patterns. This behavior actually increases confidence in the system's clinical utility, as a misclassification between mild and moderate stress has less severe consequences than incorrectly identifying high stress as no stress or vice versa. Future iterations could explore ordinal regression approaches that explicitly model the ordered nature of stress levels, potentially improving performance on this inherently ordinal classification task.

The comparison with baseline methods reveals interesting tradeoffs between different modeling approaches. While the LSTM network achieved respectable 87.9% accuracy, reflecting its strength in capturing temporal dependencies in sequential data, the proposed CNN architecture outperformed it while requiring 40% less training time. This efficiency advantage stems from CNN's parallel processing of temporal segments through convolutional operations, compared to LSTM's inherently sequential processing. The superior performance of deep learning methods (CNN and LSTM) over traditional classifiers (SVM, Random Forest, XGBoost) highlights the limitation of handcrafted features in capturing the full complexity of physiological stress responses. Human-engineered features necessarily incorporate assumptions about which signal characteristics are relevant, potentially overlooking subtle patterns that automated feature learning can discover.

The real-time operational performance metrics demonstrate that edge computing on the ESP32 microcontroller successfully balances processing capability with power efficiency constraints. The average latency of 1.47 seconds enables responsive feedback to users while the 13.6-hour battery life supports all-day monitoring without frequent recharging. These characteristics position the system favorably compared to existing research prototypes that often sacrifice either processing speed or energy efficiency. However, the breakdown of latency components reveals opportunities for optimization, particularly in the feature extraction phase which consumes 0.42 seconds. Implementing more efficient algorithms or utilizing the ESP32's dual-core architecture more effectively could reduce this bottleneck, potentially enabling higher temporal resolution in stress assessment.

The physiological patterns observed in the collected data align well with established stress physiology literature. The decrease in HRV metrics (SDNN, RMSSD) and increase in LF/HF ratio during stress conditions reflect the expected shift from parasympathetic to sympathetic dominance. Similarly, the elevated GSR tonic levels and increased phasic response frequency during stress mirror documented electrodermal responses to psychological stressors. This concordance between observed patterns and known physiology provides face validity for the collected dataset and suggests that the experimental protocol successfully induced genuine stress responses rather than mere task engagement or cognitive load.

The user acceptance evaluation results indicate positive reception of the wearable form factor and system functionality, though the slightly lower rating for perceived accuracy (3.9/5.0) compared to ease of use (4.4/5.0) warrants attention. This perception gap may stem from the inherently subjective nature of stress assessment, where users' self-perceived stress levels may not always align with physiological indicators. Educational interventions explaining the relationship between physiological signals and stress, combined with personalized calibration periods to account for individual baseline differences, could improve user trust in system outputs. The feedback regarding sensor adhesion during physical activity highlights a common challenge in wearable physiological monitoring and suggests that future hardware iterations should explore alternative attachment mechanisms or more robust motion artifact rejection algorithms.

Several limitations of the current study should be acknowledged. First, the relatively small sample size of 30 participants, while sufficient for initial validation, limits generalizability across diverse demographic groups, health conditions, and lifestyle factors. Larger-scale studies including participants with various cardiovascular conditions, different age ranges, and diverse occupational stress exposures would strengthen confidence in the system's broad applicability. Second, the laboratory-based stress induction protocol, while controlled and reproducible, may not fully capture the complexity and variability of stress experienced in naturalistic daily life settings. Future research should validate system performance during real-world stress events such as work deadlines, interpersonal conflicts, or public speaking situations. Third, the four-level stress classification scheme, while more granular than binary stressed/non-stressed categorization, remains somewhat arbitrary. Investigation of continuous stress intensity estimation or adaptive user-specific stress level definitions could provide more personalized and clinically meaningful assessments.

Despite these limitations, the results strongly support the feasibility and effectiveness of IoT-enabled deep learning approaches for continuous stress monitoring. The combination of accurate classification, real-time processing, and practical operational characteristics positions this system as a promising foundation for preventive mental health interventions and personalized stress management strategies.

CONCLUSION

This research successfully developed and validated an IoT-based stress monitoring system that leverages Convolutional Neural Networks to analyze Heart Rate Variability and Galvanic Skin Response for accurate stress level classification. The system achieved 91.3% classification accuracy across four stress levels, substantially outperforming traditional machine learning approaches that rely on handcrafted features. The dual-branch CNN architecture effectively learned discriminative representations from multimodal physiological signals without requiring manual feature engineering, demonstrating the power of deep learning for automated pattern discovery in biosignal analysis. Real-time operational performance met practical requirements with average latency of 1.47 seconds and battery life exceeding 13 hours, confirming the system's viability for continuous all-day wearable monitoring applications.

The integration of ESP32 DevKit V1 microcontroller with wireless connectivity enabled edge processing capabilities that balance computational efficiency with power constraints, while the cloud analytics layer provided comprehensive data storage and visualization. User acceptance evaluation revealed positive reception regarding comfort and ease of use, indicating good potential for real-world adoption. The physiological patterns observed in collected data aligned with established stress response mechanisms, validating both the experimental protocol and the system's ability to capture meaningful stress-related changes in autonomic nervous system activity.

The primary benefits of this research extend to multiple domains including preventive healthcare, occupational health monitoring, and mental wellness management. The system provides objective, continuous stress assessment that complements subjective self-reports, enabling earlier intervention before stress-related health complications develop. In occupational settings, the technology could help identify high-stress work periods and inform organizational strategies to reduce workplace stress. For individuals managing anxiety or stress-related conditions, the real-time feedback mechanism supports self-awareness and behavior modification efforts. The open architecture and standard communication protocols facilitate integration with existing health information systems and wellness platforms.

However, several limitations warrant acknowledgment and suggest directions for future research. The relatively small sample size of 30 participants limits generalizability across diverse populations, necessitating larger-scale validation studies that include varied demographic groups, health conditions, and stress exposure patterns. The laboratory-based stress induction protocol, while controlled and reproducible, may not fully represent the complexity of naturalistic stress experiences encountered in daily life. Extended field studies monitoring participants during authentic stress events would strengthen ecological validity and reveal potential challenges not apparent in controlled settings.

Further improvements should address the sensor adhesion issues identified during physical activity, potentially through alternative attachment mechanisms or more sophisticated motion artifact rejection algorithms. The classification model could benefit from personalized calibration procedures that account for individual baseline differences in physiological responses, as stress reactivity varies considerably across individuals. Exploring ordinal regression techniques that explicitly model the ordered nature of stress levels may improve classification performance and provide more nuanced continuous stress intensity estimates rather than discrete categories.

Future research directions include expanding the sensor suite to incorporate additional physiological modalities such as respiration rate, body temperature, and electromyography, potentially improving classification robustness and capturing additional stress response dimensions. Implementing federated learning approaches would enable collaborative model improvement across distributed user populations while preserving individual privacy. Integration with contextual data sources including calendar events, location information, and activity recognition could enhance stress prediction capabilities and enable proactive rather than reactive interventions. Finally, developing closed-loop intervention systems that provide personalized stress reduction recommendations based on detected patterns represents a promising avenue for translating monitoring capabilities into actionable health benefits.

In conclusion, this research demonstrates that combining IoT infrastructure with deep learning algorithms creates effective tools for continuous physiological stress monitoring. The system's strong performance across technical and usability dimensions suggests readiness for expanded pilot deployments that can generate insights into real-world effectiveness and inform refinements toward eventual clinical and commercial applications.

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