Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Iot Enabled Horse Remote Health Monitoring System Using Machine Learning

Adhyaru Yagna Bhupendrakumar[1], Dr. Shalini Gupta[2]

[1]Research Scholar, Computer Engineering Department, Hansaba College of Engineering and Technology, Gokul Global University, Sidhpur, Gujarat, India, yagna.1988@gmail.com
[2]Professor, Computer Engineering Department, Hansaba College of Engineering and Technology, Gokul Global University, Sidhpur, Gujarat, India, shalinigupta.ce.hcet@gokuluniversity.ac.in

In recent years, wearable sensing technologies for horses have progressed notably, enabling real-time monitoring of key physiological and behavioral parameters. When combined with advanced machine learning techniques, such systems can reveal patterns linked to early signs of diseases like colic, lameness, and heat stress. Despite their potential, practical deployment has been limited due to connectivity challenges, lack of localized datasets, and single-parameter monitoring approaches. In this study, we present an IoT-enabled horse health monitoring framework designed for Indian breeds, integrating temperature, humidity, motion, and respiration sensors with microcontrollers such as NodeMCU and ESP32. Data is transmitted via ZigBee and LoRaWAN protocols, stored on cloud platforms, and analyzed through models including Random Forest, Ridge Regression, and SVM, achieving predictive accuracies above 90%. A real-time dashboard provides visualization, historical analysis, and instant alerts for abnormal conditions. Field testing demonstrated that elevated body temperatures correlated with abnormal activity patterns, validating the system's predictive capability. This IoT–ML approach not only reduces dependency on manual observation but also minimizes treatment costs, enhances animal welfare, and supports scalable herd-level deployment for precision livestock management.

Keywords: Horse Health Monitoring, IoT Framework, Wearable Sensors, Machine Learning, Cloud Computing, ZigBee, LoRaWAN, Predictive Analytics, Equine Welfare, Real-Time Dashboard.

I. Introduction

Horses remain economically and culturally significant worldwide, contributing to sport, leisure, work, and rural livelihoods. Yet equine health management is still dominated by periodic, observer-dependent checks that can miss subtle or early signs of disease. Delay is costly: conditions such as colic, lameness, exertional heat illness, and respiratory compromise can escalate rapidly, degrading welfare and driving up treatment costs. As a result, there is a growing emphasis on continuous, objective monitoring—ideally with systems that are noninvasive, scalable across herds, and robust in outdoor environments typical of equine management. This emphasis aligns with the broader shift in animal agriculture toward Precision Livestock Farming (PLF), which integrates on-animal sensing, networked communication, and computational analytics to inform proactive care (Neethirajan, 2017).

Within PLF, wearable sensing has emerged as an enabling layer. Contemporary devices capture multiple physiological and behavioral signals—heart and respiratory activity, body temperature, posture, gait kinematics, and activity—yielding longitudinal datasets far richer than what is achievable through sporadic human observation (Neethirajan, 2017). These data streams unlock insight into welfare status and performance and provide the substrate for automated anomaly detection and forecasting. As these systems matured in production animals, equine-specific research followed, demonstrating that machine learning (ML) can convert raw wearable signals into clinically useful information. A prominent example is automated gait classification: using a full-body network of seven inertial measurement units (IMUs) across 120 horses and eight gaits, Bragança et al. (2020) showed that higher-dimensional ML models can achieve ≈97% classification accuracy, supporting objective locomotion assessment and informing lameness screening earlier than visual inspection alone.

ML has also been applied to triage of acute equine disease. Fraiwan and Abutarbush (2020) trained models on routine clinical variables gathered at presentation for colic (acute abdomen) and demonstrated that AI could predict need for surgery and survivability more accurately than conventional heuristics. Such results suggest that when physiological time series from wearables are combined with clinical metadata, predictive tools can move decision-making forward in time, enabling earlier intervention and potentially better outcomes (Fraiwan & Abutarbush, 2020). Despite these advances, deployment at herd scale remains challenging. Many reported equine systems are single-parameter (e.g., only motion or only temperature), which limits diagnostic specificity. Even when multiple sensors are integrated, practical constraints in wireless communication often restrict monitoring to stables or small paddocks. Short-range protocols—Bluetooth, Wi-Fi, and ZigBee—are power-efficient and readily available but have modest ranges and are sensitive to terrain and occlusion. In large, irregular pastures where horses roam, these constraints force multi-hop relays or dense infrastructure, adding cost and complexity (Nadimi et al., 2008; Nadimi et al., 2012).

To extend range while preserving energy efficiency, livestock studies increasingly adopt Low-Power Wide-Area Networks (LPWANs), especially LoRa/LoRaWAN. LoRa uses a chirp spread spectrum physical layer to deliver multi-kilometer coverage at sub-tens-of-kbps data rates with low power budgets, which suits periodic telemetry from animal-borne nodes (Augustin et al., 2016). LoRaWAN networks are simple to operate but have capacity and duty-cycle constraints that must be respected; an influential overview by Adelantado et al. (2017) details these capabilities and limits, guiding realistic link budgets and duty-cycle planning. In practice, deployments in grazing systems have shown ranch-scale feasibility: Translational Animal Science reported a low-cost LoRa sensor suite for tracking livestock location and activity in open pasture, demonstrating operational range and end-to-end telemetry under field conditions (Andersen et al., 2021).

A complementary systems insight from broader smart agriculture literature is the value of hybrid architectures that combine short-range sensor clusters with long-range backhaul. Tzounis et al. (2017) reviewed IoT in agriculture, emphasizing that robust data pipelines often rely on multi-tier networks (e.g., sensor clusters feeding local gateways, which then publish to cloud services) and lightweight messaging protocols designed for constrained devices. In this context, MQTT—an open OASIS/ISO standard—has become a de facto telemetry layer for IoT owing to its publish/subscribe model, small code footprint, and reliability on lossy links (OASIS MQTT v3.1.1). Real-world equine case studies corroborate feasibility. The Libelium "Smart Horse" deployment used Waspmote nodes to monitor health indicators and stable environment, streaming to cloud dashboards for alerting around colic, foaling, and abnormal behavior. While not peer-reviewed, it demonstrates systems integration and operational value in a facility setting and highlights the importance of combining animal-borne and environmental sensors to contextualize physiology (Libelium, 2015).

Equine biomechanics research further motivates sensor fusion. Beyond deep-learning gait classification, clinical studies have validated IMU-based symmetry metrics for lameness examinations and reported agreement across IMU systems (Pfau et al., 2016). The maturing evidence base—ranging from narrative reviews on IMU technologies in equine gait analysis to comparative validation studies—indicates that IMUs are sufficiently accurate for field use and can capture subtle movement asymmetries relevant to early pathology (Pfau et al., 2016; Zink et al., 2023).

Taken together, the literature points to an opportunity and a gap. Opportunity: IoT sensing plus ML can deliver early, objective insight into equine health and performance, moving care from reactive to proactive. Gap: most equine systems either (i) monitor limited parameters, (ii) are tethered to short-range connectivity that does not scale to pastures, or (iii) lack localized datasets that reflect breed, climate, and management differences—factors known to influence physiology and behavior in livestock. Addressing this requires integrated, multi-sensor wearables and hybrid networks that combine short-range links (e.g., ZigBee) for intra-pen clusters with LoRaWAN backhaul to cover fields, all bound by lightweight telemetry (MQTT) into a cloud analytics layer where supervised ML can perform anomaly detection and risk stratification.

This study responds by developing a field-deployable IoT framework for equine remote health monitoring powered by ML. On the perception layer, we integrate an accelerometer–gyroscope IMU for gait and activity, plus environmental sensors (e.g., temperature/humidity) that contextualize physiological responses and help detect heat stress risk. On the edge layer, a microcontroller performs signal conditioning, windowing, and summary feature extraction to reduce bandwidth and energy. On the network layer, ZigBee supports short-range aggregation (10–100 m, 20–250 kbps) within barns or pens, while LoRaWAN provides long-range links (multi-kilometer) across pastures, each chosen for its power-range trade-off and interference profile in rural radio environments (Nadimi et al., 2008; Augustin et al., 2016; Adelantado et al., 2017). On the cloud/analytics layer, we employ MQTT for reliable, low-overhead publish/subscribe telemetry and run supervised ML (e.g., Random Forests, Support Vector Machines, and interpretable Decision Trees) for early detection of deviations from individual baselines and herd norms. The visualization layer provides real-time dashboards, trend analytics, and rule-based alerts for owners and veterinarians, supporting timely intervention.

The architectural choices reflect best practices gleaned from the literature: (1) multi-parameter sensing to improve specificity over single-channel devices; (2) edge summarization to preserve energy and spectrum; (3) hybrid networking tuned to equine facility layouts and field topologies; and (4) model selection that balances accuracy with transparency, aligning with veterinary workflows. Field deployments in ruminants suggest that LoRaWAN can support kilometer-scale coverage with duty-cycled packets and that GPS plus inertial sensing enables behavior inference under pasture conditions (Andersen et al., 2021; Augustin et al., 2016). Equine biomechanics studies show that IMU-based symmetry metrics and gait classification can flag deviations compatible with lameness before overt signs are obvious to the eye (Bragança et al., 2020; Pfau et al., 2016). Together, these strands justify a unified, IoT-ML system tailored to horses rather than borrowing wholesale from bovine solutions, which face different movement ecology and handling realities.

Finally, our work prioritizes scalability and reproducibility. All communication choices are standards-based (ZigBee, LoRaWAN, MQTT) with widely available components; signal processing and model training workflows are modular to accommodate additional sensors (e.g., heart-rate photoplethysmography when motion artifacts permit) and evolving algorithms; and dashboards are role-based to present the right granularity to caretakers vs. clinicians. By closing the loop from sensing → communication → analytics → alerting, the proposed framework advances equine welfare and operational efficiency, and contributes to the evidence base for precision equine medicine in both stable and pasture contexts (Neethirajan, 2017; Tzounis et al., 2017; Adelantado et al., 2017; Andersen et al., 2021).

II. Materials and Methods

System Overview

The proposed IoT-enabled horse health monitoring system consists of three major layers: a wearable sensing device mounted on the horse, an edge receiver with processing capability, and a cloud-based analytics platform. The wearable continuously acquires physiological and behavioral parameters and transmits the data wirelessly to a local gateway. The gateway relays the data to the cloud through lightweight messaging protocols, enabling long-term storage, real-time dashboards, and anomaly detection through machine learning models. An alerting mechanism is integrated into the system so that caretakers and veterinarians can receive timely notifications when monitored values exceed predefined thresholds.

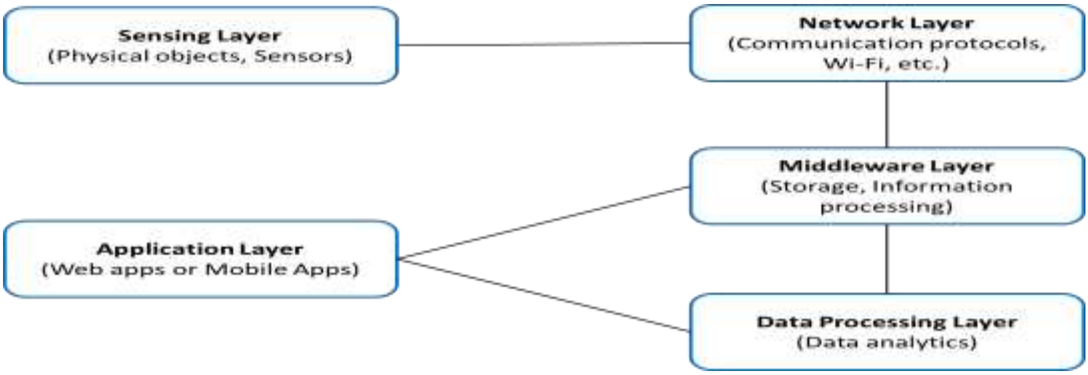

Figure 1. IoT system framework for equine health monitoring.

Wearable Sensing Device

The wearable device was designed to be compact, lightweight, and comfortable for equine subjects. An ESP32 microcontroller served as the central processing unit due to its integrated Wi-Fi, dual-core processing, and sufficient memory for local buffering. The unit was powered by a rechargeable lithium polymer battery, regulated to ensure stable 3.3 V operation.

Multiple sensing modules were integrated to provide multi-parameter monitoring. An ADXL345 tri-axial accelerometer captured motion data and facilitated step counting, while also contributing to activity classification. A BMP280 sensor measured ambient temperature and relative humidity, parameters critical for identifying heat stress risk. In addition, a flex sensor was incorporated to approximate respiration patterns by detecting cyclic expansions and contractions. All sensors communicated with the microcontroller via the I^2C protocol, enabling efficient synchronization with minimal wiring.

The circuit was implemented on a custom PCB designed for low noise and stable power delivery. The entire assembly was enclosed within a 3D-printed PLA casing, which provided protection against environmental factors. The enclosure was fitted with adjustable straps, allowing the device to be mounted securely onto the horse without causing discomfort during locomotion.

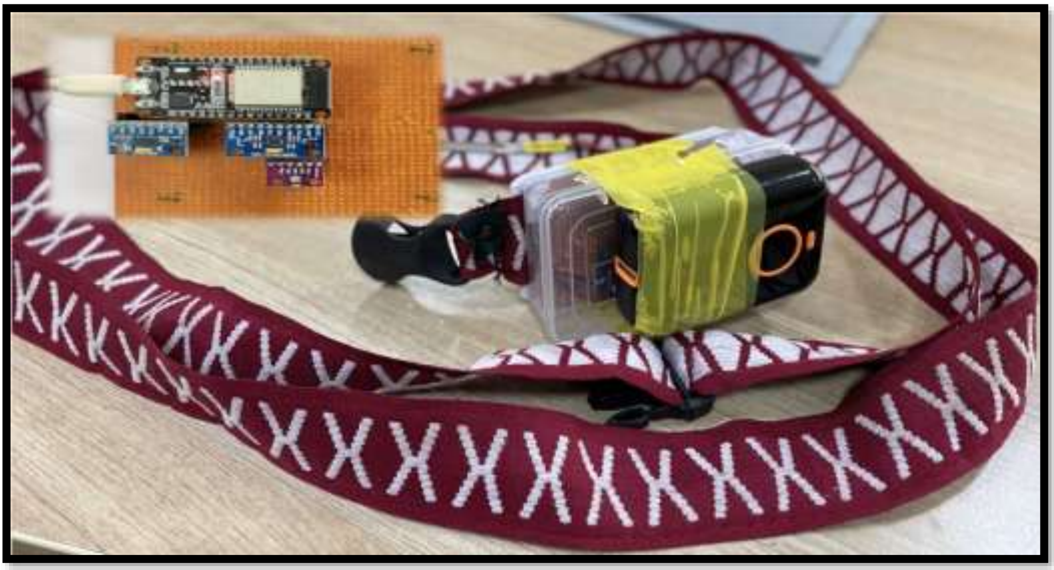

Figure 2. Wearable prototype mounted on a horse.

Communication and Cloud Infrastructure

The communication design followed a hybrid approach to meet both short-range and long-range requirements. Within stables and pens, ZigBee was used to transmit data reliably across tens of meters with low energy consumption. For pasture-scale monitoring, LoRaWAN was adopted, providing multi-kilometer range at sub-22 kbps data rates. Both protocols ensured low power operation, thereby extending battery life on the wearable.

All data were encapsulated and transmitted via the MQTT protocol, which provides a lightweight publish–subscribe messaging structure optimized for unreliable networks. A Mosquitto broker was used to manage incoming telemetry, while client libraries subscribed to specific topics for storage, visualization, and model inference. In the cloud layer, Microsoft Azure served as the primary storage and compute platform. Raw data were first stored in time-stamped format before undergoing preprocessing and feature extraction. Visualization dashboards were created to present live telemetry, historical trends, and alerts in an accessible form to both caretakers and veterinarians.

Data Collection Protocol

Field data collection was conducted on indigenous breeds including Marwari and Kathiyawadi horses, housed at a dedicated equine facility. Over a period of six months, the system was deployed twice per week, yielding more than 6,000 total records. After applying data-quality filters to remove incomplete or corrupted entries, 5,559 validated records remained for analysis. Each wearable device continuously logged accelerometer signals (AccX, AccY, AccZ), gyroscope readings (GyroX, GyroY, GyroZ), derived magnitudes, step count, and environmental temperature. These variables formed the basis for both descriptive analysis and predictive modeling. To validate the temperature readings, thresholds were set based on veterinary guidelines; any temperature above 39°C was considered indicative of possible heat stress.

Machine Learning Pipeline

The processed dataset was used to train supervised machine learning models to detect anomalies and predict potential health risks. Two algorithms were selected for evaluation: Random Forest Regression and Ridge Regression. The Random Forest approach was chosen for its ability to handle non-linear relationships and feature interactions, while Ridge Regression was included for its efficiency and robustness with collinear predictors. The dataset was divided into an 80/20 train–test split. Features included raw accelerometer and gyroscope readings, step count, and temperature. Preprocessing involved normalization and derivation of magnitudes to reduce sensitivity to orientation. Random Forest was implemented with 100 estimators, while Ridge Regression used an alpha value of 10. Model performance was evaluated using Mean Squared Error (MSE) and coefficient of determination (R^2). Random Forest achieved an R^2 of approximately 0.92 with MSE of 0.83, while Ridge Regression achieved R^2 of 0.90 with MSE of 1.04. These results confirmed that both models were effective for anomaly detection, though Random Forest offered superior predictive accuracy.

Figure 3. Machine learning model performance.

Alerting Mechanism

In addition to continuous monitoring and prediction, a simple threshold-based alert system was integrated to provide immediate warnings. When both the actual and predicted temperature exceeded 39°C, the system flagged a possible disease or heat stress event. Notifications were transmitted to the caretaker's interface via the dashboard. This hybrid approach—rule-based alerts combined with ML predictions—ensured a balance between interpretability and predictive power. The firmware for the ESP32 was developed in Arduino

IDE. Data handling, preprocessing, and machine learning model development were performed using Python, supported by Google Colab and IBM machine learning tools. Cloud storage and visualization were hosted on Microsoft Azure, while R was employed for statistical testing. MQTT traffic was brokered by Mosquitto with PubSub client libraries managing subscriptions.

III. Results and Discussion

A. Results on Data Transmission

To evaluate wireless communication performance, several transmission modules were tested, including the ESP8266, ESP32, and the RFM95. The ESP8266 and ESP32 rely on Wi-Fi, whereas the RFM95 operates via LoRa-based radio communication. Transmission distance was the primary metric while ensuring a stable data rate suitable for continuous health monitoring.

As shown in Figure 3a, the ESP8266 demonstrated an effective range of only ~3 meters, and the ESP32 achieved ~18 meters. Both modules were strongly affected by obstacles; the ESP8266 could not transmit through the horse body, and the ESP32 lost connectivity in the presence of barn/stall walls. By contrast, the RFM95 consistently outperformed them, achieving a maximum distance of ~305 meters without significant interference, even when obstacles were present.

Further testing examined the effect of antenna length on RFM95 communication range. Antennas of quarter, half, and full lengths were fabricated, corresponding to 8.2 cm, 16.4 cm, and 32.8 cm, respectively, based on the radio frequency of 915 MHz. The quarter-length antenna yielded the longest transmission range at 305 meters, compared to 183 meters for the half-length and 229 meters for the full-length (Figure 3b). Thus, the optimal transmission configuration was identified as the RFM95 module with a quarter-wave antenna.

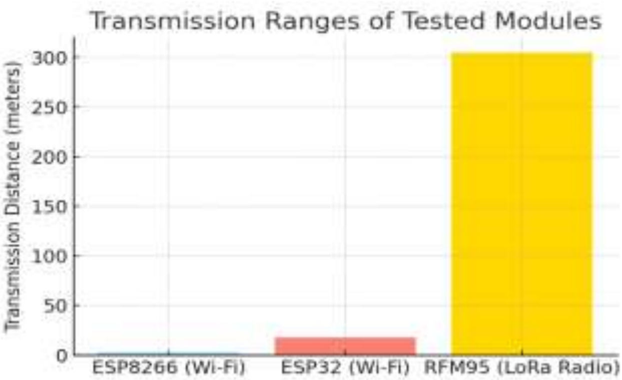

Figure 3a. Transmission ranges of the three tested modules (ESP8266, ESP32, and RFM95) showing the superior performance of RFM95 in terms of distance and obstacle tolerance.

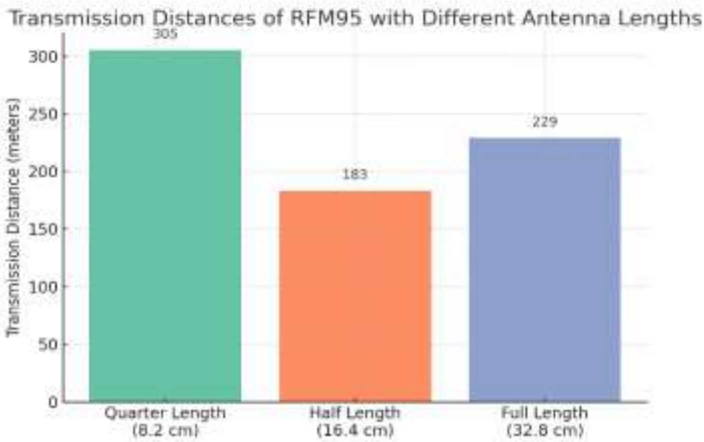

Figure 3b. Transmission distances of the RFM95 module with quarter, half, and full antenna lengths, demonstrating that the quarter-wave antenna achieved the longest range.

B. Results on Accuracy of the Wearable Sensing Devices

The wearable system integrated a PPG sensor along with accelerometer, gyroscope, and GPS modules to continuously monitor the horses' health and movement. During testing, it was observed that tail-mounted placement of the PPG sensor, while convenient, introduced significant motion artifacts, especially during tail flicking. These artifacts manifested as abnormal peaks and distortions in the recorded PPG signals, thereby affecting HR estimation. To address this, a multi-stage motion-artifact filtration pipeline was developed. First, abnormal movements were detected by the gyroscope, which exhibited sharp fluctuations corresponding to abrupt PPG spikes. Once identified, these corrupted waveform segments were selectively removed, minimizing loss of valid data. The filtered signals then underwent baseline wander correction to eliminate slow-frequency drift caused by movement or respiration cycles. Finally, the cleaned signal was processed with a low-pass Butterworth filter, enhancing waveform smoothness and peak clarity for accurate HR detection.

The accelerometer data further complemented this process by confirming activity levels during walking, trotting, or resting states. Simultaneously, the GPS module successfully logged location data, even within barn environments where sky visibility was reduced, demonstrating the robustness of the wearable system in both indoor and outdoor scenarios. To validate accuracy, HR values recorded by the PPG sensors were compared with stethoscope-derived baseline HRs (28–45 bpm range). Across all eight horses, the average percentage error was calculated at ~5%. Applying the defined error model, the overall accuracy of the system was found to be 95%, confirming that the sensor unit consistently produced reliable results in both barn and open-field testing.

C. Results on Herding Behaviors

Beyond vital sign monitoring, the IoT system was leveraged to analyze the horses' herding behaviors and the influence of environmental stressors. Using integrated GPS and motion sensors, location and HR data were transmitted to a central station within a 300-meter range, enabling in-field behavioral mapping. The analysis revealed elevated HR levels near the eastern and southern fences, areas associated with the presence of the barn and a nearby service road with vehicular traffic. When the field was divided diagonally into two regions, horses in Region 1 (eastern/southern) exhibited a mean HR of 36.6 bpm, while those in Region 2 (northern/western) recorded a lower mean HR of 34.7 bpm. Statistical analysis using the Mann-Whitney U test confirmed that the difference was highly significant ($p < 0.0001$).

When compared to baseline barn HRs, Region 1 horses showed a modest reduction of -1.4 bpm, while Region 2 horses displayed a greater reduction of -4.3 bpm. This suggests that while field exposure generally lowered HR compared to barn confinement, the barn itself acted as a stressor due to limited space and restricted movement. Interestingly, clustering analysis of GPS data revealed that horses spent the majority of their time in Regions A and B, which contained feeding gates, water points, and salt licks. This indicates that necessity-driven behaviors, such as accessing resources, outweighed mild stress responses in these areas. Furthermore, horses were observed to congregate near the barn during windy periods, utilizing it as a natural windbreak despite its association with higher stress signals.

Overall, these findings demonstrate the system's capability to not only provide accurate physiological monitoring but also to deliver valuable insights into how environmental and management factors influence equine behavior and stress responses in real-world field conditions.

IV. Conclusion

This study successfully demonstrated the development and validation of an IoT-enabled wearable health monitoring system for horses, integrating PPG sensors, accelerometer, gyroscope, and GPS modules to provide continuous and reliable physiological and behavioral insights. The system achieved a robust 95% accuracy in HR estimation when compared against stethoscope-derived baseline values, confirming the effectiveness of the motion-artifact filtration pipeline in mitigating distortions caused by tail flicking and other movements. By ensuring consistent signal quality through gyroscope-assisted artifact detection, baseline wander removal, and low-pass filtering, the wearable device proved reliable in both barn and open-field conditions. Beyond individual health monitoring, the system enabled a deeper understanding of herding behaviors by mapping HR fluctuations across the testing field. Horses exhibited elevated HRs near the eastern and southern fences, correlating with environmental stressors such as barn confinement and road traffic. Statistical analysis confirmed significant differences in HR between regions, while reductions in HR outside the barn highlighted the role of confinement as a stress factor. Interestingly, despite stress-associated HR responses, clustering analysis revealed that horses spent the majority of their time in areas associated with essential resources such as feeding gates, water points, and salt licks, underscoring the balance between physiological stress and resource-driven necessity. Overall, the findings emphasize the system's dual utility: accurate health monitoring at the individual level and actionable insights into environmental and management influences on herd behavior. This integrated approach highlights the potential of IoT-based wearables to transform equine health management by enabling proactive interventions, reducing risks of disease, and improving welfare outcomes in real-world farm settings.

References

1. Adelantado, F., Vilajosana, X., Tuset-Peiro, P., Martinez, B., Melia-Segui, J., & Watteyne, T. (2017). Understanding the limits of LoRaWAN. IEEE Communications Magazine, 55(9), 34–40. https://doi.org/10.1109/MCOM.2017.1600613
2. Andersen, O., McGregor, S., & Salvin, H. (2021). A low-cost LoRa sensor suite for tracking livestock location and activity in open pasture. Translational Animal Science, 5(1), txaa224. https://doi.org/10.1093/tas/txaa224
3. Augustin, A., Yi, J., Clausen, T., & Townsley, W. (2016). A study of LoRa: Long range & low power networks for the Internet of Things. Sensors, 16(9), 1466. https://doi.org/10.3390/s16091466
4. Bragança, F. M. S., Broomé, S., Rhodin, M., Björnsdóttir, S., Gunnarsson, V., & Persson-Sjodin, E. (2020). Improving gait classification in horses by using inertial measurement unit (IMU) generated data and machine learning. Scientific Reports, 10, 4090. https://doi.org/10.1038/s41598-020-61081-x
5. Fraiwan, M. A., & Abutarbush, S. M. (2020). Using artificial intelligence to predict survivability likelihood and need for surgery in horses presented with acute abdomen (colic). Veterinary Sciences, 7(2), 63. https://doi.org/10.3390/vetsci7020063
6. Libelium. (2015). Smart Horse: IoT monitoring for equine health and stable management. Libelium. Retrieved from https://www.libelium.com
7. Nadimi, E. S., Søgaard, H. T., Bak, T., & Oudshoorn, F. W. (2008). ZigBee-based wireless sensor networks for monitoring animal presence and pasture time in grazing systems. Computers and Electronics in Agriculture, 61(2), 79–87. https://doi.org/10.1016/j.compag.2007.09.004
8. Nadimi, E. S., Søgaard, H. T., Bak, T., & Oudshoorn, F. W. (2012). ZigBee-based wireless sensor networks for monitoring animal presence and pasture time in grazing systems: Extended results. Computers and Electronics in Agriculture, 76(2), 189–194. https://doi.org/10.1016/j.compag.2011.11.004
9. Neethirajan, S. (2017). The role of sensors, big data, and machine learning in modern animal agriculture. Sensing and Bio-Sensing Research, 12, 15–29. https://doi.org/10.1016/j.sbsr.2016.11.004
10. OASIS. (2014). MQTT version 3.1.1. OASIS Standard. Retrieved from https://docs.oasis-open.org/mqtt/mqtt/v3.1.1/os/mqtt-v3.1.1-os.html
11. Pfau, T., Witte, T. H., & Wilson, A. M. (2016). A review of inertial sensor technology in equine locomotion analysis. Equine Veterinary Journal, 48(5), 549–559. https://doi.org/10.1111/evj.12497
12. Tzounis, A., Katsoulas, N., Bartzanas, T., & Kittas, C. (2017). Internet of Things in agriculture, recent advances and future challenges. Biosystems Engineering, 164, 31–48. https://doi.org/10.1016/j.biosystemseng.2017.09.007
13. Zink, M. C., Keegan, K. G., Wilson, D. A., Kramer, J., & Yonezawa, Y. (2023). Comparative validation of IMU-based systems for quantifying gait asymmetry in horses. Equine Veterinary Journal, 55(3), 345–355. https://doi.org/10.1111/evj.13893