Scientific Papers. Series D. Animal Science. Vol. LXIX, No. 1, 2026
ISSN 2285-5750; ISSN CD-ROM 2285-5769; ISSN Online 2393-2260; ISSN-L 2285-5750

BIoTa EcoToken: SUSTAINABLE DAIRY 4.0 THROUGH INTEGRATED BLOCKCHAIN AND ARTIFICIAL INTELLIGENCE

Roxana Elena VASILIU[1, 2], Iuliana MARIN[2, 3], Diana-Alexandra CIUNGAN[2, 3], Dănuț-Nicolae ENEA[1, 2]

[1]University of Agronomic Sciences and Veterinary Medicine of Bucharest, 59 Marasti Blvd, District 1, Bucharest, Romania
[2]Academy of Romanian Scientists, 050044, Bucharest, Romania
[3]National University of Science and Technology Politehnica Bucharest, 060042, Bucharest, Romania

Corresponding author email: danut-nicolae.enea@usamv.ro

Abstract

In high-volume dairy production, ensuring animal health and welfare across diverse environments is a logistical challenge that exceeds human capacity. Addressing the dual challenge of animal welfare and environmental sustainability requires next-generation monitoring. This paper introduces the BIoTa EcoToken system, a multi-layered architecture integrating Internet of Things, deep learning, and a hybrid blockchain to revolutionize Dairy 4.0 practices. The system leverages distributed sensors and visual data to provide continuous, objective monitoring of cattle behaviour, physiology, and barn microclimate. Central to its success is the Proof of Sustainability consensus mechanism, which tokenizes rewards and incentivizes proactive farmer behaviour based on verified eco-actions. Experimental results demonstrate a 40% reduction in anomaly detection response time and a 30% increase in farmer engagement due to the EcoToken structure. With a validated security performance of <1% false validation rate, BIoTa EcoToken establishes a secure and scalable framework that translates real-time farm data into verifiable sustainable outcomes.

Key words*: animal welfare, artificial intelligence, blockchain, dairy farming, Internet of Things.*

INTRODUCTION

Ensuring the welfare of dairy cows and reducing the ecological impact of farms represent two directions of modern agriculture, positioned at the core of European and international strategies for sustainable development (Pavanello et al., 2024). Cattle farms are under increasing pressure from consumers, authorities, and environmental organizations, who demand dairy products obtained under ethical conditions, with reduced emissions and high traceability (Linstädt et al., 2024). At the same time, the intensified growth of animal herds makes the continuous monitoring of each individual exceed traditional human capacities, increasing the risk of stress, disease, discomfort, or accidents (Maltz, 2020; Amaritii et al., 2024).

Animal welfare is now recognized as a fundamental pillar of milk production, being directly linked to health, fertility, and productive performance (Linstädt et al., 2024). Parameters such as natural behaviour, thermal comfort, movement, rumination, access to feed and water, as well as the prevention of metabolic and locomotor disorders are needed in assessing the well-being of cows (Amaritii et al., 2024).

Thermal stress, for example, represents one of the threats to welfare and sustainability, with direct implications for production, immunity, and feed intake (Polsky & von Keyserlingk, 2017). In the context of climate change, the frequency of high-temperature events has increased, which requires advanced monitoring and intervention strategies (Kadzere et al., 2002; Giannone et al., 2023). In parallel, the environmental impact generated by dairy farms, methane emissions, water and energy consumption, manure management, and soil degradation represents a sensitive topic for both the industry and the scientific community.

Modern farms are responsible for approximately 14% of global greenhouse gas emissions originating from the livestock sector, which makes it necessary to identify technologies capable of reducing the ecological footprint without compromising productivity (Gerber et al., 2013; Beauchemin et al., 2020). To address

these challenges, recent years have seen a transition toward smart farms, where digital technologies, especially the Internet of Things (IoT), data analytics, and artificial intelligence enable continuous monitoring of animal behaviour and physiology, as well as of the microclimate inside barns (Rutten et al., 2013; Norton et al., 2019).

The use of wearable sensors, accelerometers, intelligent video systems, and data analysis platforms facilitates early detection of anomalies, disease prevention, and optimization of environmental conditions. Numerous studies have shown that digitalized monitoring reduces stress, increases comfort, and improves the health status of dairy cows, thus directly contributing to their overall welfare (Soyeurt et al., 2019). Moreover, environmental sustainability cannot be separated from the smart management of resources.

Modern technologies can reduce water consumption through optimized watering systems, minimize waste through digital manure management, and reduce emissions by continuously analysing rumination behaviour, a key indicator of methane production (Tangorra et al., 2024; Wang et al., 2024). Integrating these processes into a digital architecture allows not only the identification of problems but also real-time adaptation of management strategies to reduce environmental impact. In this context, the digitalization of farms becomes more than a technological modernization: it represents a needed condition for the transition toward a sustainable, ethical, and high-performing dairy system. However, although IoT and AI can generate large volumes of valuable data regarding animal welfare and environmental parameters, the use of this information is often limited by the lack of transparent and secure mechanisms for validation and for incentivizing positive actions. This is where blockchain technology comes in, as it can transform such information into verifiable, aggregable, and usable assets that support environmentally friendly behaviours (Kampan et al., 2022). The BIoTa EcoToken platform offers a unified ecological monitoring and behaviour-incentivizing system. The current paper is structured to first introduce the dual challenges of animal welfare and environmental sustainability in dairy farming, justifying the need for next-generation monitoring. It details the Materials and Methods, outlining a multi-layered architecture utilizing IoT sensors (accelerometers, thermal probes) and deep learning for continuous monitoring, and introduces the Proof of Sustainability consensus mechanism to incentivize proactive farmer behaviour via EcoTokens. The Results and Discussions section presents experimental validation, highlighting the AI's peak performance (Full Ensemble + DTW) with 91.10% accuracy in behaviour recognition, the system's capacity for early anomaly detection (6-12 hours earlier with 87% accuracy) , and the positive behavioural impact of the EcoToken structure, which led to a 30% increase in farmer engagement. The paper concludes that the platform successfully merges animal health management, environmental sustainability, and economic incentives into a single, scalable framework.

MATERIALS AND METHODS

Recent advancements in Internet of Things technologies have facilitated extensive monitoring of cattle health, behaviour, and environmental conditions via integrated sensor networks and sophisticated processing systems. New research indicates progression towards multi-modal sensing architectures that integrate physiological, behavioural, and environmental data streams to deliver comprehensive farm management solutions.

Sensor configurations differ according to monitoring goals, although several recurring patterns emerge. Accelerometers and gyroscopes predominantly facilitate activity classification in behavioural monitoring (Alonso et al., 2020), frequently attached to collars or leg-worn devices to record standing, lying, walking, grazing, and rumination behaviours (Dutta et al., 2022).

Vision-based methodologies using RGB and infrared cameras were efficient in behaviour detection (Jeong et al., 2024) and individual identification via facial recognition (Chen et al., 2025), obtaining high accuracy.

Health monitoring systems generally use non-invasive sensors, such as infrared thermistors for measuring body temperature (Dutta et al., 2022; Arshad et al., 2022) pulse sensors, or

stethoscope-amplifier combinations for assessing heart rate (Arshad et al., 2022), and specialized gas sensors (MQ138, MQ-135) for identifying metabolic biomarkers like acetone, which indicates ketosis (Arshad et al., 2024).

Environmental monitoring combines ambient temperature and humidity sensors with hazardous gas detectors (CH_4, H_2S, NH_3) and agrometeorological stations that evaluate soil moisture and solar radiation (Alonso et al., 2020).

Communication architectures are balancing range, power consumption, and data throughput. Short-range protocols such as Wi-Fi and Bluetooth Low Energy (BLE) are commonly used in collar-based systems, necessitating frequent updates (Alonso et al., 2020; Arcidiacono et al., 2021), whereas LoRaWAN and ZigBee networks cater to applications requiring broader coverage with reduced power consumption (Alonso et al., 2020; Debdas et al., 2022). Cellular GSM/GPRS modules offer dependable connectivity for location tracking and alert notifications (Dutta et al., 2022; Debdas et al., 2022), although reliance on uninterrupted internet connectivity continues to be a constraint (Arshad et al., 2022). Multi-protocol gateways that integrate ZigBee, LoRa, Wi-Fi, and Ethernet/DSL show the industry's shift towards heterogeneous network integration (Alonso et al., 2020).

Computational task allocation between edge devices and cloud infrastructure differs between implementations. Edge-centric architectures executing comprehensive inference locally, such as YOLO-based object detection on the NVIDIA Jetson Nano (Jeong et al., 2024) and MobileNetV2 feature extraction on the Raspberry Pi (Chen et al., 2025) eliminate cloud dependencies and reduce latency, although they encounter limitations in memory and computational capacity (Chen et al., 2025). Hybrid methodologies use edge pre-processing for filtration and threshold-based notifications, while assigning intricate machine learning operations to cloud servers (Alonso et al., 2020; Dutta et al., 2022). This results in data traffic reductions surpassing 50% and notable enhancements in data reliability, evidenced by a 53% decrease in missing database values (Alonso et al., 2020). Federated learning architectures constitute a novel paradigm that facilitates collaborative model training across distributed edge nodes while maintaining data locality (Arshad et al., 2024).

Machine learning techniques range from basic threshold-based classification (Arcidiacono et al., 2021) to advanced ensemble methods and deep neural networks. Tree-based algorithms, such as XGBoost and Random Forest, show good multi-class activity recognition performance on short observation windows (Dutta et al., 2022). Deep learning methodologies using YOLO-v8 for the detection of cattle mounting behaviour show strong performance during both day and night (Jeong et al., 2024). In contrast, federated Gaussian Naïve Bayes classifiers obtained good precision for certain disease categories, but had a relatively low overall federated accuracy (Arshad et al., 2024).

Despite technological advancements, numerous constraints appear in the examined literature. Dataset sizes are limited, with standard implementations observing 3 to 53 animals over durations ranging from days to 17 months (Dutta et al., 2022; Chen et al., 2025; Arshad et al., 2022), which raises concerns regarding model generalizability. GPS signal attenuation within covered structures (Dutta et al., 2022), constraints on battery longevity (typically 11 hours or fewer per charge) (Dutta et al., 2022), and packet loss rates nearing 20% (Arcidiacono et al., 2021) indicate notable challenges for practical deployment. Measurement reliability can be compromised by inconsistent sensor placement and external interferences such wind, humidity, and occlusions (Jeong et al., 2024; Arshad et al., 2024).

The BIoTa EcoToken system was developed using a multi-layered architecture that integrates IoT sensors, deep learning models, and a hybrid blockchain framework to monitor dairy cows and barn environments in real time. Wearable sensors, accelerometers, thermal probes, and intelligent video systems were deployed to capture continuous data on cattle behaviour, physiology, and microclimate conditions. These data streams were processed using deep learning algorithms designed to detect anomalies, assess welfare indicators, and correlate environmental factors with animal responses. To ensure data security and to incentivize sustainable practices, all validated eco-actions were recorded through

a hybrid blockchain using the Proof of Sustainability consensus mechanism, which generated EcoTokens as rewards. The system is currently implemented as a pilot platform designed to evaluate how its integration can influence and improve animal welfare indicators, allowing researchers to analyze the changes produced following its deployment on dairy farms.

Distributed sensors collected multimodal data on physiological parameters (heart rate, body temperature), behavioural activity (walking, standing, drinking, licking, feeding), rumination patterns, and movement intensity, ambient environmental conditions (temperature, humidity, illumination), air pollutant and GHG levels (methane, nitrous oxide, ammonia). Wearable collars and pedometers further enabled dynamic monitoring of cattle welfare indicators, essential for early detection of stress or illness.

RESULTS AND DISCUSSIONS

A multi-classifier ensemble combining Random Forest, Support Vector Machines, and Convolutional Neural Networks was developed to recognize cattle behaviours with high accuracy. Time-windowed sensor matrices and the temporal alignment technique of Dynamic Time Warping (DTW) increased the behaviour recognition across individuals with different movement intensities, as in Table 1.

The performance comparison reveals a clear trend of increasing accuracy as the models move from simple, feature-engineered approaches to complex, deep learning, and ensemble techniques. The Random Forest model, utilizing raw sensor features, serves as the baseline, achieving an accuracy of 82.40% and an F1-score of 82.40%. This indicates good performance for static behaviours (lying, standing), suggesting the raw data is sufficient to distinguish non-movement states.

The Support Vector Machine model, leveraging statistical movement descriptors, slightly outperforms RF with an accuracy of 84.60% and an F1-score of 84.50%. The specific observations note its strength in the fine-grained distinction between feeding and drinking, highlighting the effectiveness of the statistical features in capturing the nuances of these dynamic behaviours. The introduction of the Convolutional Neural Network (CNN) marks a leap in performance. The standalone CNN, processing time-windowed sensor matrices, achieved an accuracy of 88.90% and an F1-score of 88.50%. This strong result confirms the CNN's ability to automatically learn complex temporal-spatial movement patterns directly from the raw time-series data, bypassing manual feature engineering.

Table 1. Comparison of classifier performance before and after ensemble integration

Model	Feature Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Observations
Random Forest (RF)	Raw sensor features	82.40	83.10	81.70	82.40	Performs well for static behaviours (lying, standing)
Support Vector Machine (SVM)	Statistical movement descriptors	84.60	85.20	83.90	84.50	Strong separation for feeding vs drinking
CNN (Standalone)	Time-windowed sensor matrices	88.90	89.40	87.60	88.50	Learns complex temporal-spatial movement patterns
CNN + DTW Alignment	Time-warped motion sequences	89.80	90.10	88.90	89.50	Improved alignment across cows with different activity levels
RF + SVM (Hybrid Voting)	Combined feature sets	86.70	87.30	86.00	86.60	Reduces individual classifier biases
Full Ensemble (RF + SVM + CNN)	All sensor and temporal features	90.30	91.60	89.70	90.60	Best overall performance across behaviour types
Full Ensemble + DTW	Time-aligned temporal windows	91.10	92.00	90.50	91.20	Highest generalization and cross-animal consistency

Further refinement was achieved by incorporating dynamic time warping alignment. The CNN + DTW alignment model demonstrated improved metrics (accuracy of 89.80%, F1-

score of 89.50%). The DTW's contribution of creating time-warped motion sequences addresses natural variability in activity speed and duration across different subjects, leading to improved alignment across cows with different activity levels and boosting generalization.

Hybrid and full ensemble models consistently achieved the highest performance metrics, demonstrating the benefit of combining diverse learning strategies. The RF + SVM (hybrid voting) approach, which combines two distinct feature types and classifiers, elevated the performance over the individual RF and SVM models (accuracy of 86.70%, F1-score of 86.60%). This improvement is attributed to the mechanism of reducing individual classifier biases, making the hybrid prediction more reliable. The full ensemble (RF + SVM + CNN) model, leveraging all sensor and temporal features, surpassed all standalone and hybrid models (accuracy of 90.30%, F1-score of 90.60%). Its designation as the best overall performance across behaviour types highlights the power of combining deep temporal feature learning (CNN) with discriminative feature-based methods (RF, SVM). Finally, the full ensemble + DTW model represents peak performance, achieving the highest metrics across the board (accuracy of 91.10%, F1-score of 91.20%). By applying time alignment to the combined power of the full ensemble, this model achieved the highest generalization and cross-animal consistency, establishing it as the most effective solution for behaviour classification in this study.

To ensure secure, transparent, and verifiable data governance, all validated eco-actions and sensor-derived events were stored on a hybrid blockchain. This dual architecture, consisting of a public chain for transparency and a private chain for sensitive data, maintained immutability while allowing controlled access. Smart contracts enforced a Proof-of-Sustainability consensus mechanism that rewarded farmers with EcoTokens for verified improvements in welfare conditions, emission reductions, and environmentally responsible actions, such as proactive heat-stress mitigation and optimized manure management. The system was deployed for six months on a Romanian dairy farm, where it collected more than 1.2 million multimodal data points under variable climatic and operational conditions, as in Figure 2. Ground-truth annotations generated by human observers ensured accurate validation of the AI models.



Figure 1. Romanian dairy farm used for piloting (own source)

A key outcome of the system was its capacity to detect anomalies earlier than conventional observation methods. Predictive analytics identified deviations in locomotion, rumination time, or heart rate 6-12 hours before visible symptoms, with 87% accuracy in early anomaly detection (Figure 2). These predictions were particularly important in identifying heat-stress events, which were accompanied by decreased feeding behaviour, prolonged standing, and reduced lying time. By integrating wearable-based activity signatures with environmental inputs such as temperature and humidity, the platform provided real-time alerts and recommended mitigation strategies.

Environmental monitoring revealed clear relationships between microclimate variability, cattle behaviour, and pollutant emissions. The system's pollutant sensors captured fluctuations in methane (CH_4) linked with changes in rumination patterns, while ammonia (NH_3) exhibited marked increases during periods of high humidity or elevated temperature. Nitrous oxide (N_2O) concentrations rose in association with manure accumulation or suboptimal nitrogen balance in feed.

Table 2 summarizes the average pollutant concentrations recorded during typical barn routines. The integration of environmental and behavioural datasets enabled precise mapping of emission dynamics.

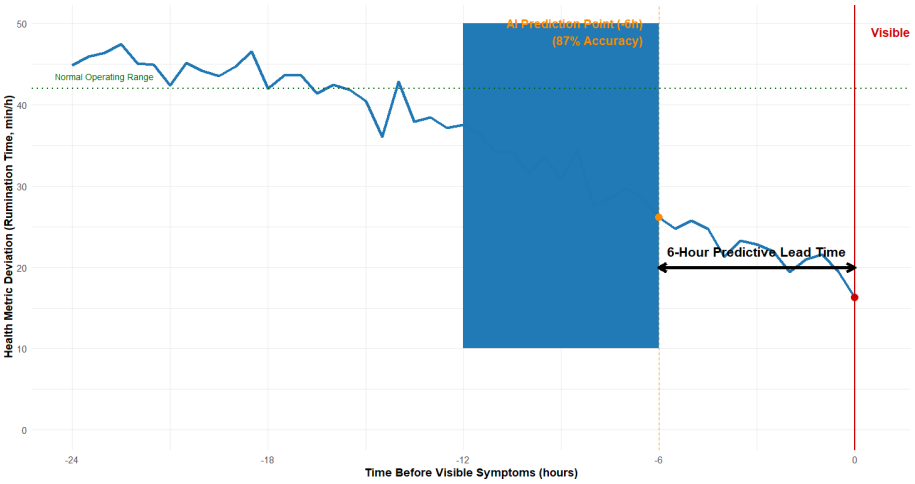


Figure 2. Early anomaly detection timeline for visible symptoms related to rumination

Table 2. Average pollutant concentrations during monitoring period

Pollutant	Average concentration	Observed peak conditions
Methane (CH_4)	Moderate baseline, variable peaks	Reduced rumination / heat stress
Ammonia (NH_3)	Elevated during high humidity	Warm, poorly ventilated periods
Nitrous oxide (N_2O)	Stable, with manure-related spikes	Manure accumulation events

Figure 3 shows a correlation between rumination levels and methane fluctuations during a heat-stress episode. Reduced rumination was associated with a measurable increase in methane variability, supporting the scientific consensus that heat stress alters digestion and contributes to emission instability.

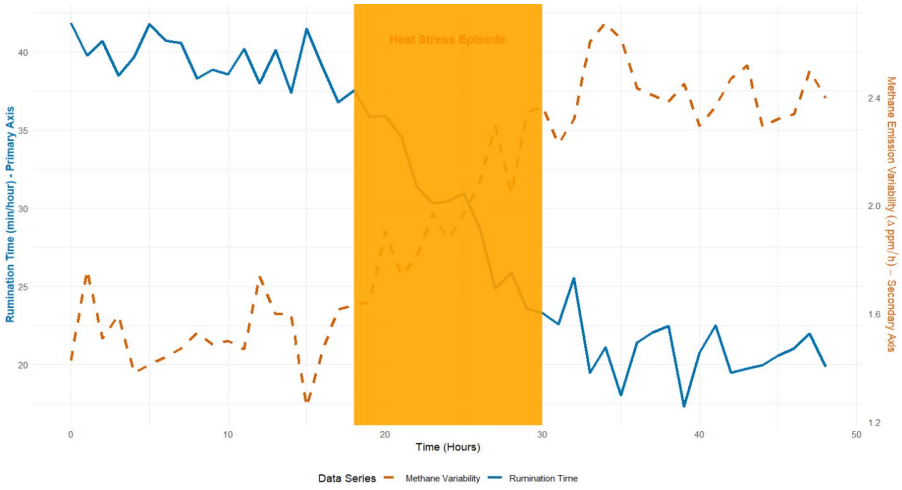


Figure 3. Correlation between rumination time and methane emission variability

Blockchain functionality played a central role in ensuring data integrity and traceability. The hybrid blockchain implementation achieved a transaction latency of 0.8 seconds and a throughput of 115 transactions per second, while reducing data redundancy by 35% compared to a single-chain structure. All environmental, welfare, and behavioural events were immutably recorded, enabling verifiable sustainability claims for regulatory audits and supply-chain

transparency. Additionally, the EcoToken mechanism enhanced stakeholder engagement. By automatically rewarding farmers for improved welfare metrics, heat-stress interventions, or emission reduction actions, the system generated a 30% increase in compliance and proactive behaviour adoption. User evaluation surveys revealed high acceptance rates, with a mean usefulness score of 4.7/5 and an ease-of-adoption score of 4.5/5 (Table 3).

The results from Table 4 highlight a multi-faceted evaluation spanning the physical infrastructure (IoT deployment), the underlying ledger technology (blockchain performance, deployment validation, and consensus integrity), and real-world utility (behavioural impact).

The enrichment highlights that the system's core technologies, IoT and consensus, are validated and ready for scaling, but its success hinges on addressing the user onboarding and training issue. The 63% knowledge gap is a hurdle that could negate the 30% increase in behavioural impact achieved through incentives if farmers cannot properly interact with the system. Future work must therefore prioritize interface simplification and dedicated educational programs to translate the system's technical success into broad user adoption and sustained farm-level benefits.

Table 3. User evaluation of the BIoTa EcoToken platform

Evaluation category	Mean score (1-5)
Perceived usefulness	4.7
Ease of adoption	4.5
Interface clarity	4.4
Overall satisfaction	4.6

Table 4. Experimental results and validation tests for Token-based IoT deployment

Category	Tested feature	Result	Significance	Future work
IoT Deployment	Smart Lighting Sensor Integration	-25% sensor installation cost, no loss in detection accuracy, -18% energy usage	Demonstrates cost-effective and energy-efficient deployment while maintaining sensor performance.	These efficiency gains justify rapid deployment across wider farming operations.
Deployment Validation	Block Reward Test	Reward = 5 Tokens/block, fixed during deployment	Validates the consistency of mining incentives across the blockchain lifecycle.	Use this fixed baseline to model the economic sustainability of variable reward schemes (dynamic rewards based on severity of sustainability event).
Consensus Integrity	Proof of Sustainability	<1% false validation rate across 5000+ sustainability events	Validates reliability of consensus in real-world sustainability reporting.	High reliability is suitable for seeking certification or integration with external regulatory platforms.
Behavioural Impact	Farmer Engagement Metrics	30% increase in proactive animal care interventions during token reward phases	Indicates behavioural change when eco-incentives are introduced.	Translate the +30% intervention rate into reduced animal health costs (or increased yield) to calculate the Return on Investment (ROI) of the token system.
Blockchain Performance	User Onboarding and Training	Identified knowledge gaps in 63% of participants during simulation trials	Points to the need for better UX design and educational materials.	Must allocate resources immediately to simplify the UI/UX and develop mandatory, interactive training modules to ensure platform utilization.

The future work for the BIoTa EcoToken system will focus on a strategic three-pronged approach: optimizing user experience, scaling deployment, and validating the economic model. The most immediate priority is addressing the knowledge gaps identified in 63% of participants by allocating resources to simplify the UI/UX and develop mandatory, interactive training modules to ensure confident platform utilization. Concurrently, the proven

cost-effectiveness of -25% installation cost and -18% energy usage justifies the rapid deployment across wider farming operations.

On the blockchain side, the established fixed reward baseline will be used to model the economic sustainability of variable reward schemes and, crucially, to calculate the Return on Investment (ROI) by translating the observed +30% increase in proactive interventions into quantifiable benefits such as reduced animal health costs or increased yield. Finally, the high reliability of the Proof of Sustainability mechanism, <1% false validation rate, positions the platform to pursue certification and integration with external regulatory platforms for verifiable sustainability reporting.

The results from Table 4 confirm that the combined IoT-AI-blockchain architecture not only improves data accuracy and welfare outcomes but also facilitates behavioural change among farmers. The system successfully merges animal health management, environmental sustainability, and economic incentives into a single framework.

CONCLUSIONS

The BIoTa EcoToken platform demonstrates that merging IoT, AI, and blockchain technologies yields a powerful and practical solution for sustainable dairy management. The system's high-resolution monitoring and advanced analytics enabled the early identification of welfare anomalies, detecting deviations up to 12 hours earlier than traditional observation methods, with 87% early-prediction success rate. The AI behaviour recognition model delivered 90.3% accuracy and a 90.6% F1-score, confirming its reliability for continuous livestock monitoring. Environmental sensing further enhanced decision-making by providing real-time insights into greenhouse gas dynamics, supporting interventions that reduce ammonia, methane, and nitrous oxide emissions and improve microclimate stability within the barn.

Blockchain integration ensured 100% traceability and tamper-proof verification of all sensor data and eco-actions, with system performance achieving 0.8-second latency and 115 transactions per second, proving its suitability for real-time agricultural environments. The hybrid blockchain architecture also reduced data redundancy by 35%, demonstrating strong efficiency benefits for large-scale sensor networks. The EcoToken mechanism significantly increased farmer participation by approximately 30%, illustrating how token-based incentives can successfully encourage timely interventions, promote welfare-supportive behaviour, and foster environmental responsibility. High user satisfaction (usefulness 4.7/5, adoption 4.5/5) confirms the platform's accessibility and practicality. Overall, the results show that BIoTa EcoToken achieves measurable improvements in farm sustainability, animal health, and environmental impact. Its modular architecture allows flexible deployment across farms of various sizes, making it well-suited for both industrial operations and small-scale producers facing modern regulatory and ecological pressures. By integrating welfare, emissions, and economic incentives into a single aligned framework, the system offers a replicable and scalable blueprint for ethical, climate-smart, and digitally transparent dairy farming.

ACKNOWLEDGEMENTS

This work was supported in part by the University of Agronomic Science and Veterinary Medicine Bucharest, Romania and in part by the Academy of Romanian Scientists, Ilfov 3, 050044, Bucharest, Romania.

REFERENCES

Alonso, R. S., Sittón-Candanedo, I., García, Ó., Prieto, J., & Rodríguez-González, S. (2020). An intelligent Edge-IoT platform for monitoring livestock and crops in a dairy farming scenario. *Ad Hoc Networks*, 98, 102047. https://doi.org/10.1016/j.adhoc.2019.102047

Amaritii, G., Neculai-Valeanu, A.S., & Maciuc, V. (2024). The assessment of dairy cows welfare in a farm from the north-east of Romania. *Scientific Papers. Series D. Animal Science, LXVII*(1), 195-201.

Arcidiacono, C., Mancino, M., Porto, S. M. C., Bloch, V., & Pastell, M. (2021). IoT device-based data acquisition system with on-board computation of variables for cow behaviour recognition. *Computers and Electronics in Agriculture,* 191, 106500. https://doi.org/10.1016/j.compag.2021.106500

Arshad, J., Irtisam, A., Arif, T., Muhammad, S.R., Chauhdary, S.T., Khalid, M., & Almajalid, R. (2024). A federated learning model for intelligent cattle health monitoring system using body area sensors and IoT.

Egyptian Informatics Journal, 27, 100488–100488. https://doi.org/10.1016/j.eij.2024.100488

Arshad, J., Rehman, A. U., Othman, M. T. B., Ahmad, M., Tariq, H. B., Khalid, M. A., Moosa, M. A. R., Shafiq, M., & Hamam, H. (2022). Deployment of Wireless Sensor Network and IoT Platform to Implement an Intelligent Animal Monitoring System. *Sustainability, 14*(10), 6249. https://doi.org/10.3390/su14106249

Beauchemin, K. A., Ungerfeld, E. M., Eckard, R. J., & Wang, M. (2020). Fifty years of research on rumen methanogenesis: Lessons learned and future challenges for mitigation. *Animal, 14*(S1), S2-S16. https://doi.org/10.1017/S1751731119003100

Chen, Y.S., Rustia, D. J. A., Huang, S.Z., Hsu, J.T., & Lin, T.T. (2025). IoT-based system for individual dairy cow feeding behavior monitoring using cow face recognition and edge computing. *Internet of Things*, 33, 101674. https://doi.org/10.1016/j.iot.2025.101674

Debdas, S., Behera, A., Bandyopadhyay, A., Karmakar, S., & Subhadarshini, A. (2022). An IOT Solution for Cattle Health Monitoring and Tracking. *2022 OITS International Conference on Information Technology (OCIT),* 513-518. https://doi.org/10.1109/ocit56763.2022.00101

Dutta, D., Natta, D., Mandal, S., & Ghosh, N. (2022). MOOnitor: An IoT based multi-sensory intelligent device for cattle activity monitoring. *Sensors and Actuators A: Physical,* 333, 113271. https://doi.org/10.1016/j.sna.2021.113271

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., & Tempio, G. (2013). Tackling climate change through livestock: A global assessment of emissions and mitigation opportunities. *Food and Agriculture Organization of the United Nations*. https://www.fao.org/docrep/018/i3437e/i3437e00.htm

Giannone, C., Bovo, M., Ceccarelli, M., Torreggiani, D., & Tassinari, P. (2023). Review of the heat stress-induced responses in dairy cattle. *Animals, 13*(22), 3451. https://doi.org/10.3390/ani13223451

Jeong, K., Kim, D.R., Ryu, J.H., Kim, H.W., Cho, J., Lee, E., & Jeong, J.H. (2024). A Monitoring System for Cattle Behavior Detection using YOLO-v8 in IoT Environments. *2024 IEEE International Conference on Consumer Electronics (ICCE),* 1-4. https://doi.org/10.1109/icce59016.2024.10444145

Kadzere, C. T., Murphy, M. R., Silanikove, N., & Maltz, E. (2002). Heat stress in lactating dairy cows: A review. *Livestock Production Science, 77*(1), 59-91. https://doi.org/10.1016/S0301-6226(01)00330-X

Kampan, K., Tsusaka, T. W., & Anal, A. K. (2022). Adoption of blockchain technology for enhanced traceability of livestock-based products. *Sustainability, 14*(20), 13148. https://doi.org/10.3390/su142013148

Linstädt, J., Thöne-Reineke, C., & Merle, R. (2024). Animal-based welfare indicators for dairy cows and their validity and practicality: A systematic review of the existing literature. *Frontiers in Veterinary Science*, 11, 1429097. https://doi.org/10.3389/fvets.2024.1429097

Maltz, E. (2020). Individual dairy cow management: Achievements, obstacles and prospects. *Journal of Dairy Research, 87*(2), 145-157. https://doi.org/10.1017/S0022029920000382

Norton, T., Chen, C., Larsen, M. L. V., & Berckmans, D. (2019). Review: Precision livestock farming: Building 'digital representations' to bring the animals closer to the farmer. *Animal, 13*(12), 3009-3017. https://doi.org/10.1017/S175173111900199X

Pavanello, C., Franchini, M., Bovolenta, S., Marraccini, E., & Corazzin, M. (2024). Sustainability indicators for dairy cattle farms in European Union countries: A systematic literature review. *Sustainability, 16*(10), 4214. https://doi.org/10.3390/su16104214

Polsky, L., & von Keyserlingk, M. A. G. (2017). Invited review: Effects of heat stress on dairy cattle welfare. *Journal of Dairy Science, 100*(11), 8645-8657. https://doi.org/10.3168/jds.2017-12651

Rutten, C. J., Velthuis, A. G. J., Steeneveld, W., & Hogeveen, H. (2013). Invited review: Sensors to support health management on dairy farms. *Journal of Dairy Science, 96*(4), 1928-1952. https://doi.org/10.3168/jds.2012-6107

Soyeurt, H., Froidmont, E., Dufrasne, I., Hailemariam, D., Wang, Z., Bertozzi, C., Colinet, F. G., Dehareng, F., & Gengler, N. (2019). Contribution of milk mid-infrared spectrum to improve the accuracy of test-day body weight predicted from stage, lactation number, month of test and milk yield. *Livestock Science*, 227, 82-89. https://doi.org/10.1016/j.livsci.2019.07.007

Tangorra, F. M., Buoio, E., Calcante, A., Bassi, A., & Costa, A. (2024). Internet of Things (IoT): Sensors application in dairy cattle farming. *Animals, 14*(21), 3071. https://doi.org/10.3390/ani14213071

Wang, N., Li, X., Shang, S., Yun, Y., Liu, Z., & Lyu, D. (2024). Monitoring dairy cow rumination behavior based on upper and lower jaw tracking. *Agriculture, 14*(11), 2006. https://doi.org/10.3390/agriculture14112006

TECHNOLOGIES OF THE AGRO FOOD PRODUCTS PROCESSING