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

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Introduction

Ensuring dairy cattle welfare and reducing the environmental footprint of farms have become strategic priorities in modern agriculture, driven by societal demand for ethical, low-emission and traceable dairy production. Intensified herd sizes and climate-related stressors, such as heat load, increase the risk of welfare deterioration and productivity losses, while the livestock sector remains a significant contributor to global greenhouse gas emissions. In this context, IoT technologies, AI-based analytics and intelligent monitoring systems offer essential tools for continuous assessment of behaviour, physiology and microclimate, enabling early detection of anomalies, improved health management and more efficient resource use, thereby strengthening both welfare and sustainability.

Introduction

Yet the potential of these digital systems is constrained by the absence of transparent, secure mechanisms to validate data and incentivize environmentally responsible practices. Blockchain technology addresses this limitation by transforming welfare and ecological indicators into verifiable and actionable information. The BIoTa EcoToken platform integrates IoT sensing, deep-learning behaviour recognition and a Proof of Sustainability incentive model, achieving 91.10% accuracy in behaviour classification, early anomaly detection 6–12 hours before onset, and a 30% rise in farmer participation. These results demonstrate the system's capacity to unite animal health, environmental stewardship and economic motivation in a coherent, scalable framework for advancing Dairy 4.0.

Materials and methods

Recent IoT developments enable multimodal monitoring architectures that integrate behavioural, physiological, and environmental data to enhance welfare assessment and farm management. Wearable sensors, vision systems, and gas-microclimate probes support accurate behaviour recognition, health tracking, and emission monitoring, while edge–cloud computing provides efficient real-time analytics despite challenges such as limited datasets, battery constraints, and network instability.

BIoTa EcoToken – Core Features:

- **IoT-based multimodal monitoring** of cattle behaviour, physiology, and barn microclimate.
- **<u>Deep learning detection</u>** for behaviour classification and early anomaly identification.
- **<u>Hybrid blockchain architecture</u>** ensuring secure, transparent, tamper-proof data records.
- **<u>Proof of Sustainability mechanism</u>** that rewards validated eco-friendly actions with EcoTokens.
- **<u>Scalable edge–cloud design</u>** enabling real-time analytics and sustainable farm management.

Results and discussions

A multi-classifier ensemble integrating Random Forest, Support Vector Machines, and Convolutional Neural Networks was developed to improve cattle behaviour recognition, supported by time-windowed sensor matrices and Dynamic Time Warping for temporal alignment across individuals. Model comparisons show a consistent increase in accuracy from feature-engineered to deep learning approaches. Random Forest achieved 82.40% accuracy, performing well for static behaviours, while the SVM model reached 84.60%, capturing subtler distinctions such as feeding versus drinking. The CNN yielded the highest standalone improvement, achieving 88.90% accuracy by learning complex temporal–spatial patterns directly from raw sensor data, demonstrating the superiority of deep learning for behaviour inference.

Results and discussions

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

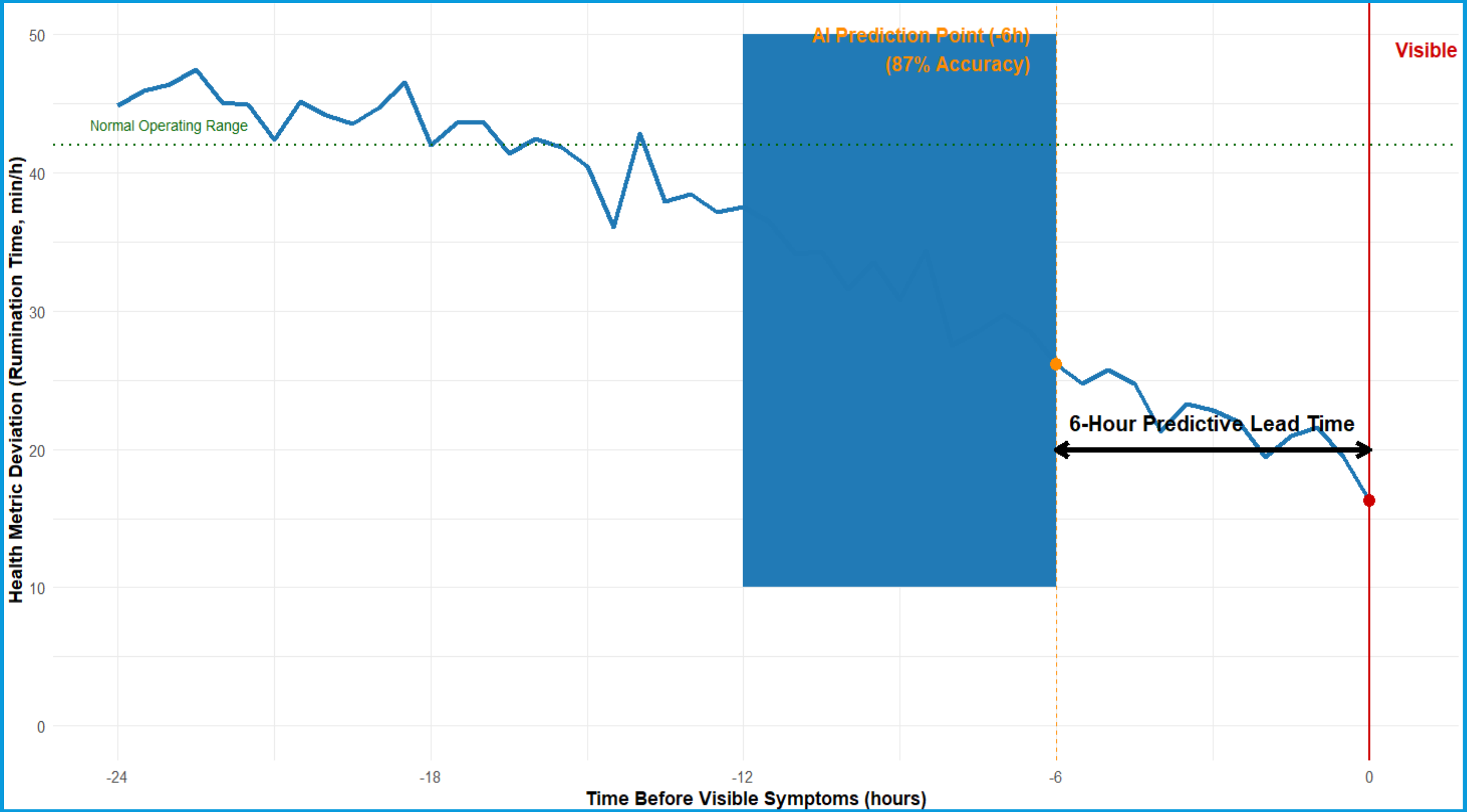
Model	Feature Type	Accuracy (%)	Observations
Random Forest (RF)	Raw sensor features	82.40	Performs well for static behaviours (lying, standing)
Support Vector Machine (SVM)	Statistical movement descriptors	84.60	Strong separation for feeding vs drinking
CNN (Standalone)	Time-windowed sensor matrices	88.90	Learns complex temporal-spatial movement patterns
CNN + DTW Alignment	Time-warped motion sequences	89.80	Improved alignment across cows with different activity levels
RF + SVM (Hybrid Voting)	Combined feature sets	86.70	Reduces individual classifier biases
Full Ensemble (RF + SVM + CNN)	All sensor and temporal features	90.30	Best overall performance across behaviour types
Full Ensemble + DTW	Time-aligned temporal windows	91.10	Highest generalization and cross-animal consistency

Results and discussions

To ensure secure and transparent data governance, all validated eco-actions and sensor-derived events were recorded on a hybrid blockchain combining a public ledger for transparency with a private chain for controlled access. Smart contracts implemented a Proof-of-Sustainability mechanism that rewarded farmers with EcoTokens for verified welfare improvements, emission reductions, and environmentally responsible practices. The system operated for six months on a Romanian dairy farm, generating over 1.2 million multimodal data points across diverse conditions, while human-annotated ground truth ensured reliable validation of the AI models.

Results and discussions

Figure 1. Early anomaly detection timeline for visible symptoms related to rumination



Results and discussions

Environmental monitoring identified strong links between barn microclimate, cattle behaviour, and pollutant emissions: methane levels varied with rumination activity, ammonia increased under high humidity or heat, and nitrous oxide rose with manure buildup or imbalanced nitrogen intake. By combining behavioural and environmental data, the system precisely mapped emission dynamics, as reflected in table 2, figure 2 further shows that reduced rumination during a heat-stress episode coincided with heightened methane variability, indicating that thermal stress disrupts digestion and destabilizes emission patterns.

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**

Results and discussions

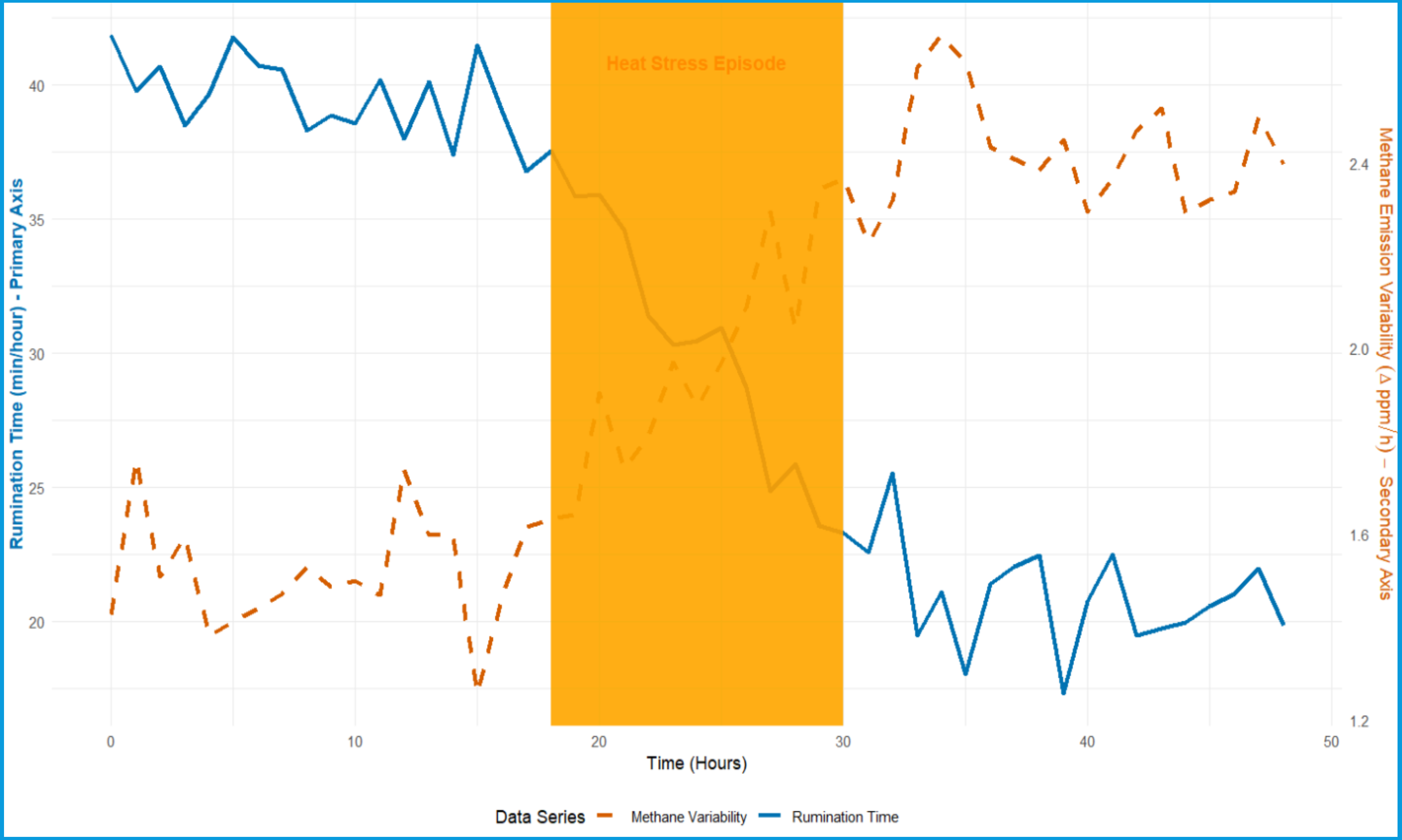


Figure 2. Correlation between rumination time and methane emission variability

Results and discussions

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

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

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

Results and discussions

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.**

Conclusions

- IoT + AI + Blockchain → major improvement in welfare monitoring, early anomaly detection & data reliability.
- Environmental sensing → supports targeted reduction of CH_4, NH_3, N_2O and stabilizes barn microclimate.
- Blockchain layer → full traceability, secure validation, lower redundancy & real-time integrity of records.
- EcoToken incentives → +30% farmer engagement, stronger adoption of welfare & sustainability practices.
- Recommended: scale hybrid digital systems; expand datasets; integrate EcoTokens into sustainability schemes; deploy modularly across farms.

References

- 1. 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
- 2. 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
- 3. 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
- 4. 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.
- 5. 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
- 6. 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
- 7. 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
- 8. 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
- 9. 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
- 10. 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
- 11. 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
- 12. 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

References

- 13. 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
- 14. 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
- 15. 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
- 16. 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
- 17. 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
- 18. 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
- 19. 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
- 20. 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
- 21. Arshad, J., Irtisam, A., Arif, T., Muhammad Shahzaib Rasheed, Sohaib Tahir Chauhdary, Khalid, M., & Rania Almajalid. (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
- 22. 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
- 23. 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

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