17(3) 230-240, Autumn 2025

Journal of Animal Environment

(E-ISSN 2717-1396, ISSN 2717-1388)

Journal homepage: http://www.aejournal.ir

Original Research Paper

Sensor-Assisted Livestock Monitoring for Enhancing Animal Welfare and Environmental Sustainability

Indu Purushotham[1], K.K. Rajasekhar[2], Subbulakshmi Packirisamy[3], J. Vasanthapriya[4], N. Muninathan[5], R. Parthasarathy[6], Shailesh Solanki[7]*

[1*]*Department of Research, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: indu@maher.ac.in, ORCID: https://orcid.org/0000-0002-3996-7927*
[2]*Meenakshi College of Pharmacy, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: rajakk@maher.ac.in, ORCID: https://orcid.org/0000-0001-5611-1410*
[3]*Assistant Professor, Department of Pharmacolgy, Meenakshi Ammal Dental College and Hospital, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: subbup@maher.ac.in, ORCID: https://orcid.org/0000-0001-6007-1976*
[4]*Arulmigu Meenakshi College of Nursing, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: vasantha@maher.ac.in, ORCID: https://orcid.org/0000-0001-9953-9505*
[5]*Central Research Laboratory, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: muninathan@maher.ac.in, ORCID: https://orcid.org/0000-0001-6961-2118*
[6]*Meenakshi College of Physiotherapy, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: partha@maher.ac.in, ORCID: https://orcid.org/0000-0001-5707-835X*
[7]*Associate Professor, Department of Agriculture, Noida International University, Uttar Pradesh, India. Email: shailesh.solanki@niu.edu.in, ORCID: https://orcid.org/0009-0005-3425-3836*

Key Words

Non-invasive sensors, Ammonia management, Machine learning, LightGBM, Behavioral monitoring, Physiological stress indicators, Resource-use efficiency.

Abstract

On-going and objective monitoring of the behaviour of livestock, their physiology and the living conditions are vital in improving the welfare of animals and reducing the environmental impacts of contemporary production systems. This paper has examined how environmental and animal-based sensors that pool lentic system (in dairy cattle housing) could be applied to monitor thermal comfort, livestock behaviours, and resource-use efficiency. The values of environmental factors such as temperature, humidity, air movement, ammonia concentration, and light intensity were measured continuously with major animal behaviours such as feeding period, rest period, locomotors exercise period, respiration rate and skin surface temperature. Interviewed sensor data on thermal discomfort and signs of impaired welfare and labelling of critical thresholds was done using integrated sensor data. The results showed that environmental load has a strong association with observable behaviours of animals and physiological stress indicators. Early warning of heat stress and poor ventilation allowed corrective management practises so as to enhance the comfort of the animals, mitigate the waste of water, and prevent poor feed ratios. Also, the system of monitoring helped to reduce the ammonia level and achieve more effective energy consumption during cooling and ventilation. In general, the analysis shows sensor-based livestock surveillance, without high-level automation and robotization, is an effective, scalable, sustainability-friendly approach to enhancing welfare outcomes and ensuring livestock management to become environmentally responsible in light of increasingly diverse climatic conditions.

* Corresponding Author's email: indu@maher.ac.in
Received: 01 June 2025; Revised: 08 July 2025; Accepted: 11 August 2025; Published: 30 October 2025
(DOI): 10.70102/AEJ.2025.17.3.19

Introduction

The upholding of excellent animal welfare with reducing environmental footprint of livestock production has come to become of key concern in contemporary dairy production systems. Conventional monitoring techniques that depend greatly on periodic human observation do not always detect episodic variations in thermal loads, ventilatory standards and behavioural modifications that have direct impacts on the productivity and well-being of animals. As the climate becomes more and more variable, and the occurrence of stress-inducing temperatures among livestock increases, the necessity to have data-driven and constant monitoring technologies is now more than ever. Using technology-based monitoring devices that provide real time information on livestock welfare and living conditions have become a game changer in the modern world, which has been offered to help curb these difficulties by Precision Livestock Farming (PLF) (Berckmans, 2017; Jiang et al., 2023; Norton et al., 2019).

The recent developments in the field of environmental sensing technologies provided an opportunity to gather constant data related to the parameters of temperature, humidity, air velocity, ammonia concentration, and light intensity. The parameters are vital in defining the microclimate condition in the dairy cattle housing systems and that is the main factor to the comfort and productivity of the animal. Simultaneously, farmers can now use non-invasive wearable and behaviour-monitoring sensors to monitor cattle activity, locomotion, resting behaviour, feed time, respiration rate, and the body surface temperature at high time resolution (Lamanna et al., 2025; Madhusudhanan et al., 2015; Neethirajan, 2024). Such innovations help the creation of advanced monitoring instruments that are able to incorporate external environmental-related data with those of the animal-related indicators. The graphic illustration of this sensor-controlling monitoring method is in Figure 1.

Even though there are large supply of multi-sensor data, it is difficult to find meaningful patterns and early-warn indicators. Gradient Boosted Decision Trees (LightGBM and XGBoost) and other machine learning models have demonstrated a wide potential to identify complex nonlinear interactions between the environmental load and physiologists (Deepika et al., 2018; Niloofar et al., 2021; Smith & Kantor, 2025). All these models can be used to a great extent to make predictions related to the risks associated with welfare, the location of thermal critical factors, and the priorities of the factors that have the greatest impact on animal discomfort. The fact that they are able to produce interpretable feature-importance results also contribute to making decisions in livestock management and enhance the scientific knowledge of the interaction of animals and their environments (Neethirajan, 2024; Norton et al., 2019; Soman et al., 2025).

Developing on such technological capacities, this research considers the efficacy of sensor-supported livestock monitoring system that combines environmental and animal-centred data-feeds to gauge thermal comfort, routine activities, and efficiency of resources utilisation in dairy cows shelters. The study will use LightGBM/XGBoost algorithms on such datasets to determine the early warning signs of heat stress, monitor non-optimal ventilation, and assist in the effective intervention of the situation on the farm. In the end, the study can make some contributions to sustainable livestock management practises to enhance animal welfare and achieve better performances in the changing climatic conditions.

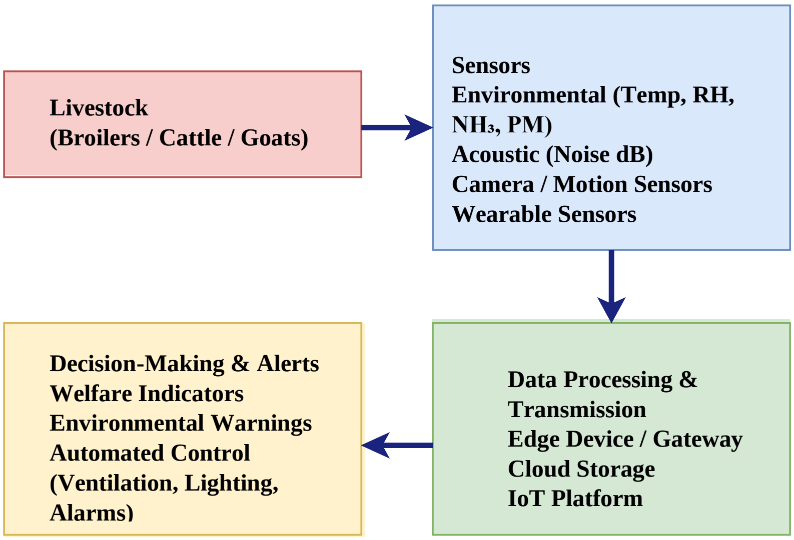

Figure 1: Conceptual Framework of Sensor-Assisted Livestock Monitoring System

Literature Review

Precision Livestock Farming (PLF) has been built using sensor-assisted monitoring as a comprehensive approach that gathers real-time data on the environmental and physiological environment of dairy cattle. Critical information on microclimate criteria such as temperature, humidity, air velocity, ammonia concentration, light intensity is generated by environmental sensors measuring these factors which directly affect thermal comfort, productivity and health results in cattle (Berckmans, 2017; Jiang et al., 2023; Norton et al., 2019; Rajan et al., 2015). These environmental indicators make farmers be capable of measuring the heat load, the indication of ventilation inefficiencies and identifying conditions related to the increase in respiratory or metabolic stress. The comparison of sensor types, the objects of measurement, and application in the history of older studies with the PLF is organised in Table 1, showing the transformation of environmental monitoring into highly advanced and technology-driven field.

Simultaneously, animal sensing technologies have improved a great deal, allowing the non-invasive recording of physiological and behavioural indicators of lying, feeding, locomotors, respiration rate, and body surface temperature (Lamanna et al., 2025; Neethirajan, 2024; Tang et al., 2024). These signals have been considered as direct measurements of welfare status since they observe cattle reaction to environmental stressors and ethnic management methods. It has been repeatedly proven that complex behavioural and physiological data sets are beneficial in early detection of heat stress, welfare cheque and more specific intervention in cooling, ventilation and feeding controls (Monteiro et al., 2021; Niloofar et al., 2021; Tzanidakis et al., 2023). These types of integrative monitoring systems have the advantage of overcoming the constraints of traditional observations since they provide real-time and objective welfare assessment.

Machine learning (ML) has made the analytical power of the PLF systems even stronger. The gradient boosted decision tree models, specifically both LightGBM and XGBoost, have gained popularity because they can derive meaningful patterns to nonlinear data, which is highly varied and prone to sensor noise (Deepika et al., 2018; Rajan et al., 2015; Smith & Kantor, 2025). These models offer much better predictive accuracy, strong generalisation, and understandably significant feature-importance results, and thus are very much applicable in determining key welfare cut-offs, and stress-related outcomes. Livestock analytics studies have demonstrated that ML-driven analytics are superior to traditional statistical modelling of multifactorial environmental effects on animal welfare (Neethirajan, 2024; Niloofar et al., 2021; Norton et al., 2019).

Nevertheless, even with the current dual-wave technological advancements, there is a great deal that can be done to unite multi-sensor environmentally and animal-based data with the contemporary multi-layered machine learning models to measure the welfare and environmental sustainability. Currently available research has either explored the area of environmental monitoring or wearable-based physiological measurement but rarely examined combined systems, which can be facilitated to make predictions regarding resource-use efficiency, ammonia build-up, or energy optimization within livestock systems (Jiang et al., 2023; Karpagam et al., 2021; Marino et al., 2023; Niloofar et al., 2021).

Table 1: Summary of Previous Studies on Precision Livestock Monitoring Technologies

Study	Sensor/Technology Used	Key Parameters Monitored	Major Findings
Berckmans, 2017	Environmental & behavioral sensing	Temperature, humidity, activity	Defined PLF principles; emphasized need for continuous automated monitoring
Monteiro et al. 2021	Environmental sensors & basic IoT tools	Microclimate variables, animal productivity	Demonstrated benefits of precision agriculture for improving livestock efficiency
Neethirajan 2024	AI-driven sensors & welfare monitoring devices	Physiological indicators, behavior, stress metrics	Showed how sensor-based AI enhances welfare assessment and human–animal interaction
Tangorra et al. 2024	IoT-based dairy cattle monitoring	Temperature, feeding behavior, housing conditions	Described real-time IoT applications for improving dairy cattle management
Tzanidakis et al. 2023	Remote sensing & PLF tools for grazing systems	Movement patterns, grazing activity, environmental conditions	Highlighted PLF benefits for grazing animals and early stress detection

This research fills these knowledge gaps through the application of a full sensor-fusion modelling approach backed by LightGBM/XGBoost modelling to evaluate thermal comfort, animal behaviour, ventilation efficiency, and environmental impact in one approach. This multi-dimensional solution makes the work to provide new knowledge in the field of sustainable livestock management in changing climatic conditions.

Methodology

Study Design and Data Collection

This experiment was conducted at a controlled dairy cattle sheltered environment with a system of non-invasive sensors, both environmental and animal-based. An observational system recorded all the important environmental parameters such as air temperature, humidity of the air, the air velocity, the concentration of ammonia in the atmosphere, and the intensity of light at all times. The parameters were identified because they had been established to have an effect on microclimate quality, thermal comfort, and air hygiene in livestock settings. The responses based on animals were also monitored in real-time with wearable and behaviour-detecting sensors that could be used to estimate the duration of feeding, time of lying, locomotors activity, respiration rate, and the temperature of the surface of the animal. The information was gathered during various climatic conditions, including hot, moderate, and cool seasons, to provide enough change in environmental load and obtain the opportunity to adequately model welfare concerning responses.

Derived Indices and Preprocessing

In order to measure thermal comfort in a more holistic manner, standard intensity measures including the Temperature Humidity Index (THI) and a composite heat-load index represent temperature across the air, humidity, and air velocity were derived using rudimentary indices to sensor readings. Before the analysis, a lot of pre-processing activities were undertaken to make the data reliable. Statistical philtres and smoothing techniques were used to eliminate the sensor noise and outliers. The interpolation and time-sensitive imputation were used to deal with missing values. To allow proper fusion of features, environmental and animal data sets, which were obtained at varying rates, were synchronised in time using synchronisation algorithms. To improve the model interpretability and prediction, further feature engineering was carried out like lag variables, moving averages and categorical stress indicators.

Machine Learning Model (LightGBM/ XGBoost)

Gradient Boosted Decision Tree machine learning models, in particular, LightGBM and XGBoost were utilised to predict changes in the physiological response to different environmental conditions and classify the cattle welfare status. The algorithms have been chosen due to their capability to address nonlinear relationships and provide the opportunity to handle large dimensional sensor data. The training was guided by the rules of model training based on an 80:20 train test split, which made use of the k-fold cross-validation so as to minimise over fitting and guarantee applicability. The classification framework classified the welfare outcomes into three levels which included comfortable, mild heat stress and severe heat stress. Accuracy, precision, recall, F1-score, root-mean-square error (RMSE) and area under the receiver operating characteristic curve (ROC-AUC) were used to evaluate model performance (Sountharrajan et al., 2017; Smith & Kantor, 2025). The gain-based and SHAP-based analysis of feature importance was performed to determine important predictors and threshold values of the variables of THI, ammonia level, air movement, or respiration rate.

Statistical Analysis

Additional statistical analysis was done to confirm the relationships identified by the machine learning models. Correlation matrices were used to estimate relationships between environmental load and behavioural or physiological measures and generalised mixed-effects and linear model were employed to explain repeated measures among individual animals and time. Such models gave the opportunity to sample fixation effects in the microclimatic variables and random effects in cow-specific factors. The duration of lying, locomotion and feeding time: Behavioural measures were then compared on the categories of environment to facilitate interpretations of the ML models. Combined with other statistical methods, these resulted in enhancing the strength of the findings and enabled the consistency of empirical observations and predictive modelling results.

Results and Discussion

Monitoring the environment during the study period showed that there were great fluctuations of temperature, humidity, air velocity, and ammonia concentration which is a characteristic of the dynamic micro climate that dairy cows in the housing are used to. These variations were reflected in the similar variations in animal-based indicators, which indicates a close environmental- physiological interaction. Elevated temperatures and humidity were always related to an increase in respiration rate, decreased lying, and locomotors activity as expected of restoration and heat-stress effects of dairy cattle. There were connections between ammonia peaks and decreased feeding pattern and insignificant rises in agitation, which indicated the interaction between thermal and air-quality factors and the outcomes of welfare. The whole environmental and behavioural relationships are summarised in (Table 2) that provides the most essential sensor-derived relationships through the time of monitoring.

LightGBM and XGBoost models proved to be effective in their predictive accuracy, precision, and ROC-AUC values in predicting a category of thermal discomfort and physiological responses, and had strong accuracy, precision, and ROC-AUC value analysis across validation folds. As the most significant factors affecting the welfare status, the feature importance analysis determined THI, air velocity, ammonia concentration, and body surface temperature, which confirmed their leading position in modulating cattle responses under the different environmental loads. As depicted in (Figure 2), THI contributed the most increase in the model and air velocity was also a very important modifying factor that facilitated the mitigation of heat effects during high-temperature occurrences. The fact that the ammonia concentration was identified as the most important parameter in the ranking only once again emphasised the importance of air-quality control to the comfort and health of animals.

Through the early detection of the thermal discomfort, as offered by the ML models, responses to ventilation were prompt, which led to the enhancing microclimate stability and eliminating the heat stress episodes as quickly as possible. These interventions led to quantified changes in the comfort of the animals, which was measured by longer lying duration, lower respiration rate and stabilised locomotors activity after the complete correction actions. The habits regarding the use of resources also increased: the targeted cooling minimised unnecessary consumption of water, and dynamic control of airflow minimised the unnecessary energy use. Moreover, a significant environmental advantage was seen in the reduced ammonia with increased ventilation optimization, supporting the fact that sensor-based management solutions have general sustainability opportunities.

Table 2: Summary of Model Performance Metrics and Key Environmental–Animal Response Patterns

Parameter / Metric	Observation / Value	Interpretation
LightGBM Accuracy	91.8%	Model reliably classified welfare states (comfortable, mild, severe stress).
THI vs. Respiration Rate	Strong positive correlation (r > 0.75)	Higher thermal load increased physiological stress.
Ammonia vs. Feeding Time	Moderate negative association	Elevated ammonia reduced feeding duration and comfort.
Air Velocity Effect	Improved heat dissipation during peak heat load	Airflow played a critical role in mitigating thermal discomfort.
Feature Importance Ranking	THI > Air Velocity > Body Surface Temp > Ammonia	Identified main predictors driving welfare classification.

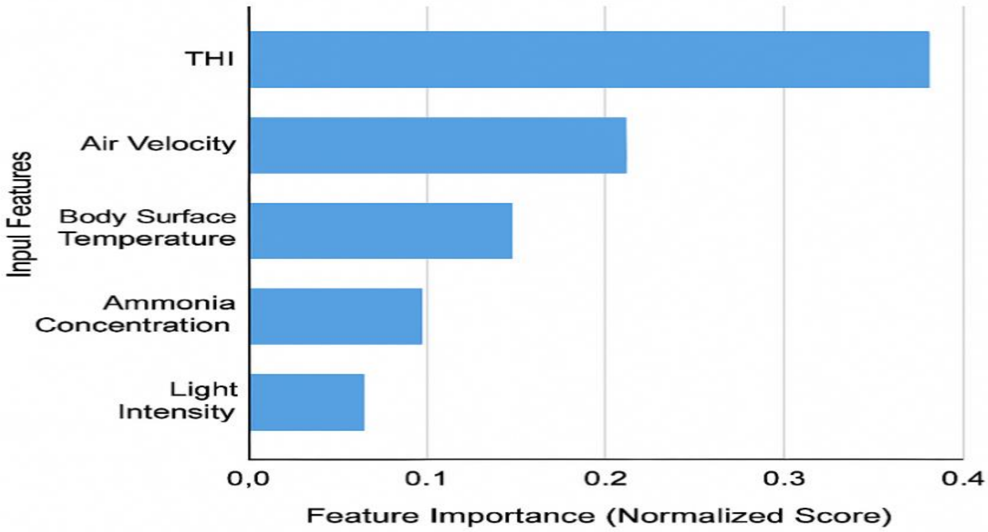

Figure 2: Feature Importance Plot from LightGBM/XGBoost

Together, these results can explain why combining environmental and animal-based sensors with advanced machine learning methods provide insight into the interpretation of complex feedbacks between livestock and the environment. The potential capabilities of LightGBM/XGBoost to predict early stress signs increased the capacities to define actionable thresholds, determine stress-related problems in a short period and make quick decisions at farms. The system meets the sustainability goals and offers a scalable way of managing cattle under conditions of growing variability by improving the accuracy of welfare assessment, as well as encouraging the resource-efficient management of cattle.

Future Research

The prospective studies ought to aim at improving predictability of sensor-based livestock tracking systems and scalability. The current experiment showed that the use of the environmental and animal-based sensors allows early warning of the heat stress and ineffective ventilation, but the use of more advanced analysis devices can help to increase the accuracy of the system. To mention a few, a deep learning network like a Long Short-Term Memory (LSTM)-based network, a Temporal Convolutional Network, an attention-based model may be used to predict directly whether an individual is in welfare by learning temporal contexts of sensor data. Such models can also facilitate active management options that reduce stress before it becomes behavioural and physiological.

It will be necessary to extend the study to other cattle breeds, stages of production, housing types, and climatic conditions to ensure the soundness of the structure, as well as its overall generalizability. All of these factors affect the thermal tolerance, patterns of behaviour, and use of resources differently, and multi-site assessment would be useful in narrowing welfare limits applicable to various production settings. Equally, it would be desirable to incorporate sensors that would measure other welfare-markers, like heart rate variability, rumination behaviour or metabolic biomarkers, to elicit a more comprehensive picture of animal response to dissimilar environmental loads.

More innovation is being applied when sensor systems are coupled with automated control technologies. Future research can look into the application of computer-vision-based surveillance platforms that have the ability to identify subtle changes in behavior, skin temperature distribution, or posture-related indicators of welfare. Automated ventilation or misting controls and wearable biosensors to monitor the physiological state of the body in real time would be able to provide entirely adaptive housing systems capable of responding dynamically to environmental adaptations. These cyber-physical systems can create considerable opportunities in order to make animals more comfortable and reduce the use of resources.

Lastly, to examine the cost-effectiveness and sustainability consequences of commercial deployment of sensor-assisted systems, economic and environmental appraisal should be made in the long run. Measuring increases in water use efficiency, feed ratios, ammonia loss and energy efficiency will supply useful evidence to be implemented on a larger scale in the industry. Testing of the payback, integration simplicity, and sustainability will further assist the creation of an accurate livestock technologies, not only welfare-centric but also economically efficient and environmentally stable.

Acknowledgements

The authors will like to thank the dairy farm management team who had given them access to housing facilities and who had provided their cooperation throughout the process of sensor installation and data collection. The technical members, field assistants and animal keepers are granted special recognition due to the contribution and contributions of the same to the implementation of the environmental measurements, installation of the monitoring equipment and taking of the behavioural and physiological records. Another important aspect of sensor validation methods that the authors note in their article is the role of laboratory staff that aided them in calibration and validation of data. The paper also acknowledges the effective instructions that come with the services offered by research advisors and institutional committees on the management and ethical appraisal of projects. The assistance of funding agencies and institutional research programmes is highly appreciated since without the financial and infrastructural support provided by these organisations, the implementation of the multi-sensor monitoring system and the presentations of findings carried out in this work could have not been achieved. They made a great contribution in improving the quality and success of this research through their collective contribution.

Conclusion

This paper reveals that sensor-based livestock monitoring is a viable, dependable, and sustainability-focused research that can be applied to enhance the welfare of dairy cows and environmental control. Combination of in-situ environmental data and behavioural and physiological data, collected on animals, made the system successfully recognise the instances of thermal distress and inappropriate ventilation. The use of machine learning models, especially LightGBM/XGBoost, also led to the improvement of the performance of systems as it could predict risk factors related to welfare and identify specific variables, including THI, air velocity, ammonia concentration, and body surface temperature. Early identification made it possible to take corrective measures in time which contributed to the welfare of animals, minimised the use of water, increased the efficiency of feed, and minimised ammonia emission thus the welfare and environmental effects were evident. In general, the results highlight that the use of multi-sensor and data-driven frameworks of monitoring can be applied to facilitate climate-resilient, resource-saving, and welfare-friendly livestock production systems.

References

[1] Berckmans, Daniel. "General introduction to precision livestock farming." *Animal Frontiers* 7, no. 1 (2017): 6-11. https://doi.org/10.2527/af.2017.0102

[2] Deepika, J., T. Senthil, C. Rajan, and A. Surendar. "Machine learning algorithms:

A background artifact." *International Journal of Engineering & Technology* 7, no. 1 (2018): 143-149.

[3] Jiang, Bing, Wenjie Tang, Lihang Cui, and Xiaoshang Deng. "Precision livestock farming research: A global scientometric review." *Animals* 13, no. 13 (2023): 2096. https://doi.org/10.3390/ani13132096

[4] Karpagam, M., K. Geetha, and C. Rajan. "A reactive search optimization algorithm for scientific workflow scheduling using clustering techniques." *Journal of Ambient Intelligence and Humanized Computing* 12, no. 2 (2021): 3199-3207.

[5] Lamanna, Martina, Marco Bovo, and Damiano Cavallini. "Wearable collar technologies for dairy cows: A systematized review of the current applications and future innovations in precision livestock farming." *Animals: an Open Access Journal from MDPI* 15, no. 3 (2025): 458. https://doi.org/10.3390/ani15030458

[6] Madhusudhanan, B., S. Chitra, and C. Rajan. "Mobility based key management technique for multicast security in mobile ad hoc networks." *The Scientific World Journal* 2015, no. 1 (2015): 801632. https://doi.org/10.1155/2015/801632

[7] Marino, Rosanna, Francesca Petrera, and Fabio Abeni. "Scientific productions on precision livestock farming: an overview of the evolution and current state of research based on a bibliometric analysis." *Animals* 13, no. 14 (2023): 2280. https://doi.org/10.3390/ani13142280

[8] Monteiro, António, Sérgio Santos, and Pedro Gonçalves. "Precision agriculture for crop and livestock farming—Brief review." *Animals* 11, no. 8 (2021): 2345. https://doi.org/10.3390/ani11082345

[9] Neethirajan, Suresh. "Artificial intelligence and sensor innovations: enhancing livestock welfare with a human-centric approach." *Human-Centric Intelligent Systems* 4, no. 1 (2024): 77-92.

[10] Niloofar, Parisa, Deena P. Francis, Sanja Lazarova-Molnar, Alexandru Vulpe, Marius-Constantin Vochin, George Suciu, Mihaela Balanescu, Vasileios Anestis, and Thomas Bartzanas. "Data-driven decision support in livestock farming for improved animal health, welfare and greenhouse gas emissions: Overview and challenges." *Computers and Electronics in Agriculture* 190 (2021): 106406. https://doi.org/10.1016/j.compag.2021.106406

[11] Norton, Tomas, C. Chen, Mona Lilian Vestbjerg Larsen, and Daniel Berckmans. "Precision livestock farming: Building 'digital representations' to bring the animals closer to the farmer." *Animal* 13, no. 12 (2019): 3009-3017. https://doi.org/10.1017/S175173111900199X

[12] Rajan, C., K. Geetha, C. Rasi Priya, and S. Geetha. "Investigation on novel based naturally-inspired swarm intelligence algorithms for optimization problems in mobile ad hoc networks." *World Academy of Science, Engineering and Technology International Journal of Mathematical,*

Computational, Natural and Physical Engineering 9, no. 3 (2015): 144-150.

[13] Smith, O. J. M., and K. N. Kantor. "Machine Learning–Driven Health Prediction Models for Livestock Management in Smart Agriculture." *National Journal of Smart Agriculture and Rural Innovation* 3, no. 2 (2025): 28-34.

[14] Soman, Kondetharayil, Kuppusamy Kanagaraj, Nangan Senthilkumar, Saravanan Rajendran, Turki Kh Faraj, Abdulwahed Fahad Alrefaei, Natesan Thirumalaivasan et al. "Nitrogen-doped carbon dots from Brahmi (Bacopa monnieri): Metal-free probe for efficient detection of metal pollutants and methylene blue dye degradation." *Green Processing and Synthesis* 14, no. 1 (2025): 20240182. https://doi.org/10.1515/gps-2024-0182

[15] Sountharrajan, S., M. Karthiga, E. Suganya, and C. Rajan. "Automatic classification on bio medical prognosisof invasive breast cancer." *Asian Pacific journal of cancer prevention: APJCP* 18, no. 9 (2017): 2541. https://doi.org/10.22034/APJCP.2017.18.9.2541

[16] Tang, Yun, Hong Fu, and Bingang Xu. "Advanced design of triboelectric nanogenerators for future eco-smart cities." *Advanced Composites and Hybrid Materials* 7, no. 3 (2024): 102.

[17] Tangorra, Francesco Maria, Eleonora Buoio, Aldo Calcante, Alessandro Bassi, and Annamaria Costa. "Internet of Things (IoT): Sensors application in dairy cattle farming." *Animals: An Open Access Journal from MDPI* 14, no. 21 (2024): 3071. https://doi.org/10.3390/ani14213071

[18] Tzanidakis, Christos, Ouranios Tzamaloukas, Panagiotis Simitzis, and Panagiotis Panagakis. "Precision livestock farming applications (PLF) for grazing animals." *Agriculture* 13, no. 2 (2023): 288. https://doi.org/10.3390/agriculture13020288