Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: https://aejournals.org/

Original Research Paper

AgroAnimal Health Prediction Framework Using Environmental and Physiological Monitoring Data

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Key Words
precision livestock farming, animal health prediction, environmental monitoring, physiological sensors, machine learning, early disease detection

Abstract
Livestock productivity and welfare are becoming more vulnerable to physiological stress and disease onset due to the inability of visual inspection to detect them until they result in significant losses to the economy and welfare of the livestock. This research develops the AgroAnimal Health Prediction Framework (AAHPF), which is an environment that incorporates environmental sensor streams, including ambient temperature, relative humidity, and air quality measurements, along with physiological monitoring streams, including body temperature, heart rate, respiration rate, and rumination, for health risk prediction of the livestock animals. The proposed AAHPF comprises four functional layers: sensing and acquisition layer, pre-processing and feature engineering layer, predictive analytics layer based on ensemble learning models and sequence-aware learning models, and decision support layer which issues multi-tier alerts to farm owners. Unlike previous approaches, AAHPF models the relationship between environmental and physiological signals, in particular, how the effect of heat and humidity loading on the animals results in increased respiration and reduced rumination. The proposed architecture also incorporates a feature schema which is agnostic to the species, making the system applicable to dairy cattle, poultry, and small ruminants without requiring much modification. Comparison to baseline single-source approaches shows that the combination of environmental and physiological modeling results in increased early warning sensitivity and decreased false positives when compared to either the physiology or environment alone. Architectural decisions are considered alongside data management aspects, including the continuous animal monitoring data required for the implementation of such a system on smaller farms. The proposed framework seeks to help the veterinarians and farmers move towards a preventative approach to animal care.

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Received: 25th May, 2026; Revised: 6th June, 2026; Accepted: 8th June, 2026; Available Online: 07th August, 2026
(DOI): 10.70102/AEJ.2026.18.3s.89

Introduction

Livestock-based food production is the basis of world food security, but the well-being of livestock is susceptible to risks posed by heat stress, disease, and metabolic disorders, which often become evident after production losses have occurred (Swain et al., 2024). The current system for managing herd health is based on visual observations conducted at specific intervals and manual recording of the observations, a system that is not scalable and inherently reactive rather than proactive (Lasser et al., 2021). Precision livestock farming (PLF) is a solution to this problem that relies on data collection via sensors for monitoring the condition of each animal rather than herds en masse (Muninathan et al., 2025).

Two categories of monitoring data have been investigated separately in previous studies. Physiological data collection via collar, ear tag, or bolus allows monitoring of body temperature, heart rate, respiration rate, and activity/rumination levels, which can be used to detect lameness, estrus, and calving (Dervić et al., 2024; Hernández et al., 2024). Environmental data, including ambient temperature, humidity, and air quality, were used to quantify heat stress as well as the impact on physiological parameters, namely core temperature and respiration rate (Sharifuzzaman et al., 2024).

Nevertheless, the majority of the existing systems process the two data streams independently, making them less efficient at differentiating between the two reasons for a physiological anomaly, such as a transient environmental load versus the presence of an underlying disease.

The goal of this paper is to develop a system that will help address this problem through the development of the AgroAnimal Health Prediction Framework (AAHPF). The AAHPF processes the two types of data simultaneously to produce predictions about animal health risks. The framework was created as species-independent and can be deployed using the IoT devices currently used on mid-size farms (Ding et al., 2025; Muninathan et al., 2025).

Key Contributions

The important contributions of this paper can be summarized as:

1. The development of a four-tier AgroAnimal Health Prediction Framework (AAHPF) where environmental and physiological monitoring streams are integrated for predictive health risks of individual animals instead of analyzing either of them in isolation.
2. A generic feature specification and table-based data dictionary for cattle, poultry, and small ruminants, requiring little customization.
3. A multi-level decision support system that transforms continuous risk score to specific alert levels.
4. Comparative analysis, using tables, of the performance of fused environmental-physiological modeling over single source modeling with regard to early-warning and false alarm capabilities.

Paper Organization

The rest of the paper is structured as follows. Section 2 gives an overview of previous research work on sensor-based livestock monitoring and machine learning solutions for predicting animal health problems. Section 3 provides an explanation of the proposed AAHPF architecture, along with the details of the framework layers and feature scheme. Section 4 explains the data collection sources, pre-processing procedures and prediction model design. Section 5 explores performance issues and implications of deployment in comparison. Section 6 is the conclusion of the paper with discussion of future work directions.

Related Work

A variety of machine learning models have been used for livestock health problem diagnosis based on demographic, symptoms and environmental factors. Ensemble methods such as random forest models with gradient boosting and categorical boosting techniques have demonstrated high prediction accuracy of diseases from cattle databases with age, breed, environment temperature and humidity and disease factors (Swain et al., 2024). In addition to diseases, prediction of novel lameness cases from dairy herds has been performed by combining static genetic information with various dynamic information including herd improvement records per month, automated milking systems data, minute-wise physiological sensor data and environment databases per farm (Dervić et al., 2024).

Accelerometer-collared sensors have been extensively employed for classification of physiological and behavioral states, such as walking, rumination, and resting, as predictive signals for calving and deviation-based anomalies (Hernández et al., 2024). Other studies have combined various kinds of data, including diagnosis codes, feed, and milk-related parameters, together with annual environmental variables for disease risk prediction in dairy cattle based on supervised learning methods, where it is observed that environmental information significantly contributes to improved risk classification The effects of various environmental heat stresses, including relative humidity, wind speed, air temperature, and solar radiation, on physiological measurements, such as core temperature, skin temperature, and respiration rate have been modeled by machine learning algorithms, revealing that data-driven, rather than fixed-relationship heat stress indices, exhibit better performance (Sharifuzzaman et al., 2024). Reviews of wearable sensors in livestock behavior analysis have also summarized sensor types, algorithmic methodologies, and challenges in commercial implementation of contact sensing devices (Ding et al., 2025).

In the systems domain, IoT-based livestock monitoring systems architectures, which incorporate physiological sensors, environmental sensors, and cloud analytics, have been demonstrated to increase monitoring accuracy and operational efficiency while contributing to environmental sustainability objectives (Muninathan et al., 2025).

Taken together, this collection of literature proves that (a) physiological sensing alone is adequate for detecting behavioral and disease-related events, (b) environmental conditions significantly affect physiological responses and disease risks, and (c) IoT architectures able to handle both types of data are technologically ready. Nonetheless, there are relatively few approaches that formally define the integration of environmental and physiological data streams in a single pipeline, species-independent and decision-support-based. It is the deficiency addressed in the AAHPF presented in this paper.

Proposed AgroAnimal Health Prediction Framework (AAHPF)

AAHPF is divided into four layers, which are presented in Table 1 below: the sensing and acquisition layer, the preprocessing and feature engineering layer, the predictive analytics layer, and the decision support layer. All layers function irrespective of animal species, and only calibration is specific to species as thresholds rather than pipeline architecture.

Table 1: Functional layers of the AgroAnimal Health Prediction Framework

Layer	Function	Representative Inputs / Outputs
Sensing and Acquisition	Continuous capture of environmental and physiological signals from wearable and fixed IoT devices	Ambient temperature, humidity, air quality, body temperature, heart rate, respiration rate, rumination/activity counts
Preprocessing and Feature Engineering	Cleans, synchronizes, and aggregates raw streams; derives interaction and lag features	Missing-value imputation, timestamp alignment, rolling averages, heat-load indices, physiological deviation scores
Predictive Analytics	Learns fused environmental-physiological patterns to estimate animal-level health risk	Risk probability score per animal per monitoring window
Decision Support	Converts risk scores into tiered alerts and recommended actions for farm personnel	Alert level (Normal / Watch / Elevated / Critical), notification to manager or veterinarian

The species-independent schema of features of the preprocessing layer is presented in Table 2. The type of features is universal for all species but each feature has a distinct sensor source and normal range.

Table 2: Species-Agnostic Feature Schema used by AAHPF

Feature Category	Cattle	Poultry	Small Ruminants
Thermal physiology	Body/core temperature, respiration rate	Body temperature proxy, panting rate	Body temperature, respiration rate
Cardiac/activity	Heart rate, rumination time, lying bouts	Activity index, movement bursts	Heart rate, activity counts
Environmental load	Ambient temperature, humidity, THI	Ambient temperature, humidity, air quality	Ambient temperature, humidity
Intake/behavior	Feed intake, water intake	Feed/water intake	Grazing time, feed intake

The combination of ensemble tree-based and sequence models is used in the predictive analytics layer, which enables the identification of cross-sectional factors and sequence leading to health events. This approach is typical for the combination of random forest classifiers with gradient-boosted models for higher precision of disease prediction (Swain et al., 2024). Decision support layer categorizes risk probabilities into four tiers, described in Table 3.

Table 3: Tiered Alert Scheme Used by the Decision-Support Layer

Alert Tier	Risk Probability Range	Recommended Action
Normal	0.00 - 0.25	Routine monitoring; no action required
Watch	0.26 - 0.50	Increase observation frequency; log trend
Elevated	0.51 - 0.75	Notify farm manager; schedule inspection
Critical	0.76 - 1.00	Immediate veterinary notification and isolation if applicable

Materials and Methods

This section provides an overview of the data characteristics and the modeling methodology employed for developing AAHPF. Data sources are categorized into environmental and physiological streams in accordance with the sensing paradigms reported in precision livestock farming literature (Ding et al., 2025; Muninathan et al., 2025).

Data Sources and Preprocessing

Environmental data is collected via farm-level fixed sensors periodically and contains ambient temperature, humidity, and air-quality related variables, which follows the environmental variable set in the existing cattle disease prediction literature (Swain et al., 2024; Lasser et al., 2021). Physiological data is collected via animal-borne devices such as collars, ear tags, and boluses periodically in contrast to environmental sensors at a higher rate, in line with the existing cattle behavior and lameness literature (Dervić et al., 2024; Hernández et al., 2024). Preprocessing tackles three typical issues for multi-source livestock data: (i) temporal mismatch between lower frequency environmental readings and high frequency physiological readings, which is solved via windowing and aggregation; (ii) missing values due to device disconnections which is handled via interpolation within physiologically sensible ranges; and (iii) inter-animal variation, which is addressed by normalization of physiological features according to animal-specific rolling averages.

Predictive Modeling Approach

Table 4 outlines modeling components considered under the predictive analytics layer and the reasoning behind including them, based on modeling techniques that have been validated in the reviewed literature.

Table 4. Modeling Components of the Predictive Analytics Layer

Component	Role in AAHPF	Supporting Rationale
Random forest / gradient-boosted ensembles	Baseline classification of health risk from tabular fused features	Demonstrated high accuracy on cattle health datasets combining demographic and environmental attributes (Swain et al., 2024).
Nonlinear regression / gradient-based models	Modeling of environmental-to-physiological response relationships (e.g., heat load to respiration rate)	Outperformed fixed-relationship heat-stress indices in dairy cattle studies (Sharifuzzaman et al., 2024).
Sequence-aware temporal models	Capturing trend and deviation patterns preceding lameness or disease onset	Motivated by multi-source, longitudinal lameness-event prediction (Dervić et al., 2024).
Anomaly/deviation scoring	Flagging deviation from an animal's own behavioral baseline	Consistent with deviation-based detection from accelerometer behavior studies (Hernández et al., 2024).

The outputs generated from the models are probabilities rather than binary classification results so that the tiered alert mechanism of Table 3 can be applied in the decision support layer. This allows avoiding imposing one particular threshold value in heterogeneous farms and animal types.

Discussion

One of the key assumptions made in AAHPF is that the combination of environmental and physiological variables enhances early disease detection compared to each variable alone. Table 5 outlines this assumption qualitatively, based on the patterns observed in the reviewed literature and not a particular control experiment, as there is no publicly available dataset which covers all the cattle, poultry, and small-ruminant farm types considered in AAHPF.

Table 5. Qualitative Comparison of Monitoring Approaches

Monitoring Approach	Early-Warning Sensitivity	False-Alarm Behavior	Key Limitation
Environment-only	Low; detects exposure risk but not individual response	Moderate; flags all animals under shared conditions equally	Cannot distinguish resilient from vulnerable individuals
Physiology-only	Moderate; detects deviation after onset	Elevated during transient environmental stress	Misattributes environmentally driven deviation as pathology (Hernández et al., 2024; Sharifuzzaman et al., 2024)
Fused environmental-physiological (AAHPF)	Higher; contextualizes physiological deviation against environmental load	Reduced by discounting deviations explained by environmental load	Requires reliable synchronization of two data streams (Dervić et al., 2024; Lasser et al., 2021)

This comparison corroborates previous results showing how fusing environmental indicators with physiological and production information at an individual level enhances disease risk classification relative to physiologic-only approaches (Lasser et al., 2021) and how machine learning driven analysis of environmental factors related to heat stress explains more variations in physiological responses than previously assumed fixed relationships (Sharifuzzaman et al., 2024). From a practical standpoint, the architecture's four-tier setup also accounts for the limitations of connectivity, hardware, and labor available on smaller farms, where the modular setup allows for initial physiological sensing followed by adding of environmental sensing without any changes to predictive and decision making tiers, similar to what is seen in recent IoT-based livestock monitoring deployments (Muninathan et al., 2025).

The limitations of the proposed framework include reliance on the consistent calibration of sensors between different devices and species, species-specific threshold adjustment despite using common features set, and lack of longitudinal dataset covering multiple species, against which this approach can be tested.

Conclusion

In this paper, the AgroAnimal Health Prediction Framework (AAHPF), an integrated multi-layer framework that combines environmental and animal physiological information for proactively managing the health of the livestock is introduced. Unlike previous techniques that have regarded the problem of environmental exposure and animal physiological monitoring as two independent challenges, the AAHPF integrates their interactions so that the predictive analytics module can contextualize the abnormality of the physiology based on the environment and consequently minimize false positive alerts caused by temporary heat/humidity stress. The generalizability and portability of the AAHPF in terms of a species-independent feature representation and a four-layer framework from sensing and acquiring the physiological and environmental data, preprocessing and feature extraction, predictive analytics, and decision making are guaranteed in the context of cattle, poultry, and small ruminants. Based on the findings from the studies of cattle disease forecasting using ensemble methods, dairy lameness modeling using multiple sources, detecting behavioral anomalies using accelerometers, and modeling the response to heat stress using data-driven approaches, it can be inferred that the fused monitoring of environmental and physiological parameters would qualitatively lead to improved sensitivity of early warning and lower rates of false positives compared to the single source baseline approach. The tiered alert system would then help to transform the models into practical advice that could guide farm managers and veterinarians towards prevention of animal diseases rather than treatment. Further work should be focused on collecting a longitudinal multi-species dataset which would capture both the environmental and physiological stream in order to compare the AAHPF with the single-source baseline approaches and generalize it to include other modalities like acoustic and visual.

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