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Original Research Paper

Data-Driven Livestock Welfare Assessment for Sustainable Environmental Management in Intensive Production Systems

D. Anandhi[1*], Baskaran Kuppusamy[2], K.K. Rajasekhar[3], V. Ramnath[4], Regi Cindrella[5], K. Malar Kodi[6], Varun kumar Sharma[7]

[1]Assistant Professor, Research Scientist, Department of Biochemistry, Meenakshi Ammal Dental College and Hospital, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: anandhid@maher.ac.in, ORCID: https://orcid.org/0000-0002-2863-6671*

[2]Scientist, Central Research Laboratory, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: kjbaskar@gmail.com, ORCID: https://orcid.org/0009-0003-5070-7450

[3]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

[4]Meenakshi College of Allied Health Sciences, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: ramnathv@maher.ac.in, ORCID: https://orcid.org/0000-0001-8592-3637

[5]Tutor, Meenakshi College of Nursing, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: cinderjulius@gmail.com, ORCID: https://orcid.org/0009-0008-8058-2843

[6]Meenakshi College of Physiotherapy, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. Email: malark@maher.ac.in, ORCID: https://orcid.org/0000-0002-8729-152X

[7]Assitant Professor, Department of Biotechnology and Microbiology, Noida international University, Uttar Pradesh, India. Email: varun1.sharma@niu.edu.in, ORCID: https://orcid.org/0000-0001-8575-6939

Key Words

Multivariate analysis, Gradient boosted decision trees (XGBoost/LightGBM), Environmental sustainability, Intensive pig housing, precision livestock farming.

Abstract

Integrated assessment systems which can deliver a measurement of animal welfare and environmental performance in a work-like environment are more and more becoming important in sustainable livestock production. In this research, we developed and used a scientific-based monitoring system on intensive pig housing that integrated standardised microclimatic observations with animal-based welfare outcomes to define essential factors regarding the loss of welfare and ecological efficiency. The environmental variables (air temperature, relative humidity, gaseous pollutants and particulate matter) were recorded continually with the seasons whereas welfare measurements entailed body lesion scoring, posture distribution, activity patterns, frequency of panting and growth performance. It was found through multivariate analysis that an increased Temperature Humidity Index and higher ammonia concentrations were best predictors of behavioural disturbances, greater lesion prevalence, and less gain in weight. These monitoring outputs resulted in targeted management interventions and major decreases in the thermal load, accumulation of pollutants as well as water and energy use. The results indicate the realistic usefulness of data-supported evaluation models in improving the welfare of animals and environmental sustainability despite production systems that lack high-tech automation and digitalisation. It is the evidence based scalable method to enhance management decision making in the contemporary intensive livestock systems.

* Corresponding Author's email: anandhid@maher.ac.in

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Introduction

The environmental performance of livestock production combined with animal welfare is becoming a crucial element of the sustainable livestock production, especially in intensive production systems where the microclimatic instability can quickly undermine both. Temperature, humidity, and air quality fluctuations, consequently resulting to heat stress, respiratory irritation, and behavioural abnormalities especially in modern pig housing environments can be averted only when such factors are effectively monitored and controlled. Combining the constant evaluation of the microclimate to the assessment of welfare, as required, is hence crucial in reducing welfare risks and enhancing environmental sustainability, which adds to the global innovation trends in Agriculture 4.0 and smart farming technologies (Javaid et al., 2022; Subach & Shmeleva, 2022).

Welfare assessment procedures in pig production are traditionally based on the regular visual evaluation of lesions, patterns of activities, and respirations, which does not allow recognising upcoming welfare challenges in their early stages before they worsen. Subjectivity and variability are also introduced by manual observation and there is no way to come up with consistent intervention thresholds. Emerging technologies in the area of precise livestock farming (PLF) have suggested that digital technologies and sensor-gathered measurements should be utilised to improve the exactness, recurrence, and dependability of the safeguarding of creatures within an animal dwelling framework (Aquilani et al., 2022; Neethirajan, 2017; Hostiou et al., 2017). The developments also help the farms become proactive in the management of their welfare as opposed to reactive.

At the same time, the increased access to environmental sensors and Internet of Things (IoT) platforms of data collection has been instrumental in real-time monitoring of the most important microclimatic parameters like temperature, relative humidity, ammonia, and particulate matter. These technologies facilitate automated process of data collection, integration and analytics toward the contribution of better environmental and operation efficiency in livestock farms (Mowla et al., 2023; Misra et al., 2020; Jiang et al., 2023). The environmental housing systems also can be used to emphasise the inefficiency trends in the housing system, including the uneven distribution of ventilation or accumulation of pollutants, which would be challenging to uncover through traditional methods of inspection.

Considering the multivariate and nonlinear quality of welfare environment interactions in pig housing it is necessary to apply advanced methods of analysis to define the most significant predictors of welfare impairment and environmental inefficiency. Machine learning, specifically, Gradient Boosted Decision Tree algorithms including XGBoost and LightGBM provide a powerful schematic infrastructure to model the complex relationships, as well as to discover the underlying patterns in high-dimensional farm data (Rangasamy et al., 2023; Manoharan et al., 2024; Misra et al., 2020;

Karpagam et al., 2020). Driven by these innovations, the given research paper elaborates on the elaboration of a comprehensive, data-based assessment system that integrates environmental surveillance and animal-based welfare measures to investigate the actual situation of farms in intensive pig farming. The framework also uses machine learning to not only measure the most important environmental aspects of welfare deterioration, but also to inform specific management interventions that can be used to enhance sustainability performance.

Literature Review

Intensive pig housing systems determine the outcomes of welfare in dependence on the microclimatic parameters, i.e. temperature, humidity, gaseous emissions, and particulate matter. It has been proven that heat stress which is usually measured in Temperature Humidity Index (THI) is highly related to the occurrence of aggression, increased respiratory effort, decreased feed consumption, and lower growth rates in swine (Javaid et al., 2022; Aquilani et al., 2022). One more significant issue: ammonia exposure may worsen the welfare condition by irritation of respiratory tissues in case of exceeding recommended levels, increasing the load of stress responses and the inability to maintain immunity (Subach & Shmeleva, 2022; Hostiou et al., 2017). These discoveries will focus on the need to conduct ongoing environmental surveys and are aligned with larger scale smart agriculture projects that seek to implement environmental sensors into livestock mobility methods (Javaid et al., 2022; Mowla et al., 2023). Table 1 contains a comparative overview of the environmental stressors that have been reported as per earlier research.

Particulate matter (PM10 and PM2.5) was also reported to be the major cause of lessened respiratory comfort and behavioural instability in pigs. The literature has indicated that feed dust particulates, bedding disturbance particulates and manure agitation particulates have adverse effects on pulmonary health and overall physiological stress (Neethirajan, 2017; Jiang et al., 2023). These exposures are frequently associated with coughing, decrease in lying comfort as well as feed conversion efficiency, especially in mechanically ventilated housing systems. These difficulties are also heightened by seasonal fluctuation where warmer seasons experience high accumulation of THI and pollution levels caused by poor ventilation (Aquilani et al., 2022; Shurson, 2020). All the findings increase the idea of the multidimensionality of environmental stressors affecting pig welfare.

Innovations in the areas of precision livestock farming (PLF) created more possibilities to advance welfare evaluation based on automated and sensor-based technologies. The high-frequency (reading every few hours) monitoring of environmental and welfare variables is now supported through wearable monitoring devices, IoT-based sensing platform, and analytics integrated into the cloud (Neethirajan, 2017; Mowla et al., 2023; Misra et al., 2020). In this digital ecosystem, machine learning models, in particular tree-based ensemble solutions like XGBoost and LightGBM have become a prominent solution because they can estimate nonlinear relationship between environmental inputs and welfare output (Rangasamy et al., 2023; Manoharan et al., 2024; Misra et al., 2020). These algorithms are better than classical linear models and offer explainable information about feature-importance scores, which allows finding the most important predictors of stress, including THI and ammonia.

Since these technologies continue to develop, available literature demonstrates that there exist an absence of integrated, farm-level welfare-environment assessment frameworks that incorporate real-time monitoring with practical managerial advice. Research approaches on PLF technology have given a lot of attention to either welfare measures, or measures of environment alone with little attention to integrating the two streams of measure in order to assist in making sustainability-related choices (Subach & Shmeleva, 2022; Hostiou et al., 2017; Jiang et al., 2023). Moreover, in real-world commercial production systems, operational validation is still underdeveloped, the majority of the ML-based models are experimented under the controlled conditions instead of being experimented under variable conditions. Overcoming these shortcomings, the current research paper will utilise a unified data driven model that incorporates the environmental sensing, welfare metrics as well as machine learning based analytics to inform focused interventions that will further enhance animal welfare and environmental performance.

Table 1: Summary of Previous Studies Linking Microclimatic Factors with Pig Welfare Outcomes

Study / Source	Microclimatic Factor(s)	Observed Welfare Impact	Key Findings
Javaid et al., 2022	Temperature, Humidity	Heat stress, reduced productivity	Elevated THI led to increased panting, lower feed intake, and reduced growth efficiency under intensive housing.
Subach & Shmeleva, 2022	Ammonia (NH_3)	Respiratory irritation, restlessness	High NH_3 exposure was associated with behavioural discomfort and weakened immune function in confined pigs.
Neethirajan, 2017	PM10, PM2.5	Respiratory stress, behavioural disturbance	Increased particulate load contributed to respiratory difficulty and elevated stress responses, affecting welfare stability.
Misra et al., 2020	Temperature–Humidity Index (THI)	Aggression, reduced growth	THI was identified as a major driver of thermal discomfort, behavioural instability, and decreased growth performance.
Jiang et al., 2023	Multi-factor environmental variability	Welfare risk and performance loss	Integrated environmental monitoring showed that combined THI, NH_3, and PM levels strongly predicted welfare deterioration.

Methodology

The research was carried out in a rigorous pig stall facility which had a controlled mechanical ventilation, conventional commercial stocking rates. Multiple seasons were used to monitor housing units to ensure the natural environmental variation and its impact on animal behaviour and physiological responses were recorded. Pens were equally designed so that any confounding effects associated with the space allowance or pen design are minimised. The farm activities were carried on as usual during the study period, and this made sure that all observations were due to the actual production situation and not experimental under practise. The problem of environmental and welfare monitoring was considered a part of everyday management operations to provide a consistent and representative data collection during the course of the study.

The calibrated and digital sensors that were placed at the height of animals were to measure the environmental conditions at the required level to ensure that the microclimatic exposure was taken into account. Such parameters as air temperatures, relative humidity, Temperature Humidity Index (THI), ammonia (NH_3), carbon dioxide (CO_2) and the fractions of the particles (PM2.5 and PM10) were also being measured. Measurements were recorded at present intervals to reflect changing temporal conditions of feeding, manure disturbance, ventilation cycle and diurnal temperature patterns. Animal welfare outcomes were evaluated using the structured scoring schemes which were body lesion scoring, posture classification, analysis of activity pattern, panting frequency, and growth performance in terms of average daily gain (Sountharrajan et al., 2017; Sarumathiy et al., 2020). These signs were chosen regarding their previously determined sensitivity to thermal and air-quality stressors in pig production housings.

Data analysis consisted of cleaning sensor measurements to eliminate missing or inaccurate values, then there was normalisation and summarising into daily pen-level reports. Some correlations and multivariate statistical tests were used to investigate the relations of environmental exposures with welfare outcomes and seasonal variations in microclimatic dynamics. A machine learning system (Gradient Boosted Decision Trees) (XGBoost/LightGBM) was applied to detect the most significant predictors of welfare impairment. Input models were presented as THI, NH_3, CO_2, PM concentration, relative humidity, season, and ventilation fan rate, and output models were given as lesion score, restlessness index, frequency of panting and weight gain, which were the important welfare parameters. A 70/30 training testing split with 5-fold cross-validation was used to develop models. The metrics of evaluation were RMSE, MAE, R^2 in regression tasks and accuracy, and F1-score in classification tasks. The general workflow in the process of the analysis is presented in (Figure 1).

After model interpretation through SHAP based feature importance, management interventions targeted at the identified environmental risk factors, especially high levels of THI and ammonia. Ventilating measures, airflow pattern change, and better manure removal times were introduced to minimise the heat load and pollutants deposit. Comparison of environmental and welfare conditions in the pre- and post-intervention period made through post intervention monitoring enabled assessment of changes in thermal comfort, air quality, behavioural stability and resource efficiency. This mixed methodology approach enabled the study to evaluate both predictive and the feasible effect of data-informed decision-making on the sustainability of the entire farm.

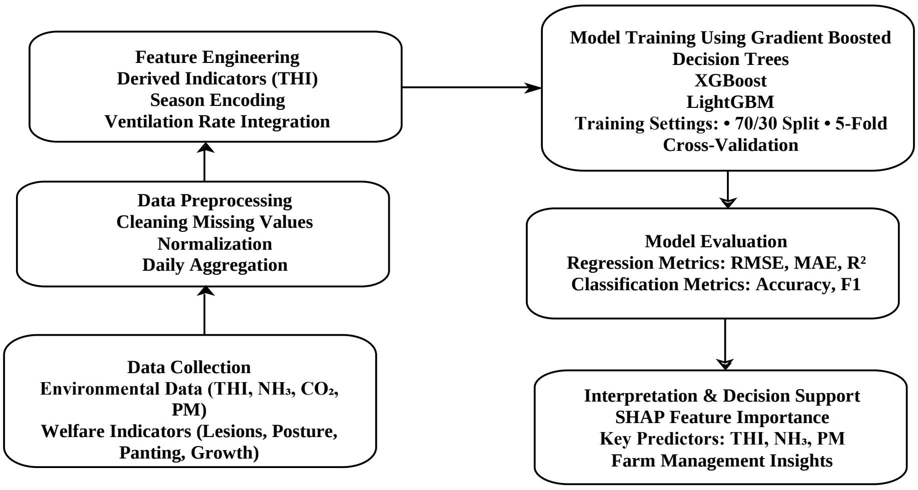

Figure 1: Workflow of Data Collection, Preprocessing, and Machine Learning (XGBoost/LightGBM) Analysis

Results and Discussion

The seasonal variability had significant effect on the indoor microclimatic conditions and a heavy effect of seasonal change to high value of THI and ammonia was recorded during warm seasons. Such higher thermal and gaseous loads had a direct impact on the pig behaviour as manifested by higher panting habits, shorter lying periods, and greater overall activity which are some of the signs of thermal uneasiness and uneasiness. The same seasonal trends were also noted on the concentrations of particulate matter which had a tendency to increase at slower rates in cases with less ventilation efficiency. A summary of such environmental and welfare trends provided as descriptive statistics (Table 2) reveal the apparent correlation between the undesired microclimatic situation and behavioural instability.

Multivariate statistical analysis has also shown that THI and ammonia continued to be the predominant environmental stressors that determined the outcome of welfare. The patterns of PCA loading revealed that these variables were grouped in a tight cluster implying that there was a shared heat-air quality stress factor within the house. To augment these results, LightGBM and XGBoost models showed superior predictive power in the determination of welfare impairment, strongly drawing the nonlinear interactions, which could not be explained exhaustively by classical statistical models. In the model outputs, THI, NH 3 and PM 10 were observed to be uniformly significant predictors of augmented restlessness, high level of lesion scores, and the loss of weight gain. The analysis of SHAP interpretability was also supplementary as it marked that THI was the most powerful predictor with behavioural and performance indicators, which tells about its pivotal position in welfare risk determination.

Based on the model-driven identification of the important stressors, specific management interventions, mostly the ventilation optimization have been introduced and was measured. The interventions produced significant elimination of ammonia concentration and heat load yielding better thermal comfort to the animals. Observations of behaviour confirmed a reduction in the slewing events and restlessness scores whereas lesion scores recorded slight improvements owing to decreased aggression and a rise in resting stability. There was also an improvement in growth performance indicators following these interventions and this means that alleviation of environmental stress directly transfers to increased productivity results in intensive pig housing systems.

In addition to welfare benefits, the sustainability of the production system environmentally also increased after the adjustments of data-driven managements. There was a decrease in water consumption as a result of the low level of heat induced demand to drink and reduction in electricity consumption because scheduling of ventilation became more efficient. Reduced gaseous emission especially ammonia was another indicator of environmental benefits installed by better housing conditions. Altogether, these outcomes prove that even those farms with no completely automated digital systems could reach significant welfare and sustainability progress when assisted by the integrative data analytics and the machine learning-enhanced decision-making instruments. It supports the relevance of a data-based monitoring system to the real-life livestock production facility.

Table 2: Key Environmental and Welfare Descriptive Statistics

Parameter	Mean ± SD	Seasonal Trend	Welfare Impact Observed	Notes
THI (Temperature–Humidity Index)	78.4 ± 4.6	Highest in summer	Increased panting, reduced lying time	Strongest environmental stressor
Ammonia (NH_3) Concentration (ppm)	18.7 ± 3.2	Peaks during warm & humid periods	Elevated restlessness and irritation	Second-most influential predictor
Lesion Score (0–5 scale)	2.1 ± 0.8	Higher under elevated THI	Increased aggression & minor injuries	Behavioural instability evident
Panting Frequency (breaths/min)	58 ± 12	Significant rise in summer	Clear indicator of heat stress	Highly sensitive to microclimate shifts
Weight Gain (g/day)	612 ± 45	Reduced in high THI/NH_3 conditions	Lower feed intake and metabolic stress	Strong negative association with THI

Future Research

The future efforts to broaden the existing data-driven monitoring system to a fully operational real-time system of sensing the environment and welfare should be developed. The inclusion of sensor networks with the IoT capabilities combined with automated sensors to identify when adverse microclimatic conditions appeared would enable immediate response and enhanced welfare results. These real-time features would also provide further data granularity and it would be possible to connect certain management behaviours, such as feeding or manure behaviour to real-time environmental and behavioural responses.

It is also possible to forecastively enhance predictive analytics in livestock surveillance systems with enhanced deep-learning architecture, which has a significant potential. Long Short-Term Memory (LSTM) networks, temporal convolutional networks and attention-based models are the most appropriate models to learn sequential patterns and temporal dependencies in environmental and behavioural information (Nayak, 2024). The use of these algorithms can play a major role in enhancing the development of early warning systems against deficiency of welfare to allow the prediction of heat stress, aggression, or even respiratory distress before it occurs. Furthermore, integrating machine learning models with computer vision would enable uninterrupted behavioural recognition and cut back on the need to perform manual observation and enhance the completeness of welfare measurements.

Lastly, cross-farm validation should be used as a priority in future studies in order to generalise and make the suggested monitoring framework sturdier when emphasising the applicability beyond different climatic conditions, housing systems, and management regimes. It would be possible to increase the dataset so that it included representatives of more than one facility because it would be possible to create the more adaptive and scalable models which would enable them to address different production settings. The development of easily accessible decision-support dashboards may advance the adoption at the farm level also as the decision-maker, farm producers, will be able to see the welfare risks, comprehend the model results, and apply specific interventions more efficiently. All these developments would promote the adoption and evolution of artificial intelligence, environmental sensors, and realistic management applications in contemporary precision livestock production (Janaki & Geetha, 2017).

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Conclusion

This work illustrates that a data-based monitoring system that incorporates data of microclimatic parameters as well as those of animal-based welfare systems provides a useful tool in the process of improving welfare and environmental outcomes in intensive pig production systems. The swift seasonal changes on the index of temperature-humidity and ammonia concentration were found to be the most influential to cause behavioural discomfort, incidence of lesions and decrease in the performance of growth rate, results that were reproducibly consistent with multivariate analysis and Gradient Boosted Decision Tree modelling. The introduction of specific management changes made based on these data, especially ventilation optimization, led to quantitative increases in thermal comfort and the decrease in the pollutant content and improvement in behavioural stability, as well as decreasing the use of water and energy. The results underline the usefulness of implementing semi-automated and data-driven monitoring arrangements even in locations that do not have sophisticated digital systems and their abilities to enable more sustainable, less damaging, and welfare-oriented approaches to livestock rearing.

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