



Original Research Paper

Data-Driven Decision Support for Sustainable Animal Environment and Welfare Management

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Abstract.

Sustainable animal environment management requires continuous assessment of environmental conditions, animal welfare, and resource utilization to support timely and effective management decisions. This study proposes a Data-Driven Decision Support Framework for Sustainable Animal Environment and Welfare Management that integrates environmental monitoring, animal-centered indicators, machine learning-based prediction, sustainability assessment, and actionable management recommendations. The framework considers environmental variables including temperature, relative humidity, air quality, ventilation, light intensity, feed and water availability, together with behavioral and physiological indicators representing animal welfare. Heterogeneous monitoring data are processed through data cleaning, normalization, temporal synchronization, and feature engineering to construct an integrated representation of animal environmental conditions. Five machine learning algorithms, namely Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, and Gradient Boosting, are comparatively evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. The experimental evaluation demonstrates that Gradient Boosting provides the strongest overall predictive performance, achieving 94.3% accuracy, 93.8% precision, 93.5% recall, 93.6% F1-score, and a ROC-AUC of 0.96. The predicted welfare conditions are further combined with environmental suitability and resource-efficiency indicators to categorize operating conditions into normal, moderate-risk, and high-risk levels. Based on the identified risk level, the decision-support component generates management recommendations related to ventilation, cooling, water availability, feeding conditions, environmental control, and animal monitoring. The proposed framework consequently transforms heterogeneous monitoring data into predictive welfare information and actionable decisions, providing a systematic approach for proactive animal welfare management while supporting environmental sustainability and efficient resource utilization.

Keywords: Animal Welfare, Sustainable Animal Management, Decision Support System, Machine Learning, Environmental Monitoring, Precision Livestock Farming, Predictive Analytics, IoT.

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1. Introduction

Sustainable animal production increasingly requires the simultaneous management of environmental conditions, animal welfare, productivity, and resource utilization. Livestock and other managed animal environments are influenced by continuously changing factors such as temperature, relative humidity, air quality, ventilation, stocking density, water availability, feed conditions, and housing characteristics. Variations in these factors can directly affect animal comfort, physiological stress, disease susceptibility, behavioral patterns, and overall productivity. At the same time, animal production systems are expected to minimize resource consumption and environmental impacts while maintaining acceptable welfare standards [1]. Consequently, conventional management approaches based primarily on periodic observations and experience-based decisions are increasingly insufficient for managing complex and dynamic animal environments.

Animal environmental management involves maintaining suitable physical and biological conditions to support animal health, comfort, and productivity. Temperature, humidity, gaseous pollutants, particulate matter, lighting, ventilation, and water and feed availability are among the important environmental variables affecting animal welfare. Prolonged exposure to unfavorable environmental conditions may contribute to heat or cold stress, respiratory problems, behavioral abnormalities, reduced feed intake, lower productivity, and increased susceptibility to disease. These effects may become particularly significant in intensive animal production systems where relatively small environmental variations can affect large populations [2]. Climate variability further increases the complexity of animal environment management. Increasing temperatures, extreme weather conditions, water scarcity, and changing seasonal patterns can influence housing conditions and animal thermal comfort. Management systems therefore need to move beyond static environmental thresholds toward continuous and adaptive assessment. The growing availability of sensors, Internet of Things (IoT) devices, automated monitoring systems, and digital farm records provides an opportunity to collect high-frequency information describing both environmental conditions and animal responses. Data-driven approaches can transform these heterogeneous observations into actionable information. Rather than considering individual environmental parameters independently, computational models can examine relationships among environmental conditions, animal behavior, physiological indicators, and welfare outcomes [3]. Such analysis can support early identification of unfavorable

conditions and enable preventive management actions before substantial welfare or productivity losses occur.

Sustainable animal management requires a balance among animal welfare, environmental performance, operational efficiency, and productivity. Animal welfare is multidimensional and cannot be adequately represented through a single environmental parameter. It may involve physical health, thermal comfort, behavioral responses, access to essential resources, and freedom from prolonged environmental stress. Therefore, effective welfare assessment requires the integration of environmental measurements with animal-centered indicators [4]. Environmental sustainability is also closely connected with management decisions. Excessive energy consumption for cooling and ventilation, inefficient water utilization, inappropriate waste management, and poorly controlled housing conditions can increase the environmental footprint of animal production. Conversely, reducing resource consumption without considering animal requirements can negatively affect welfare. An effective management strategy should therefore identify operating conditions that simultaneously maintain acceptable welfare levels and improve resource efficiency [5]. Continuous data collection provides a basis for evaluating these relationships quantitatively. Environmental measurements can be combined with behavioral, physiological, health, and productivity indicators to generate a more comprehensive representation of the animal environment. This integrated perspective enables management decisions to be evaluated not only according to production outcomes but also according to their potential effects on animal welfare and sustainability.

Advances in IoT, artificial intelligence (AI), machine learning (ML), and data analytics have created new possibilities for intelligent animal management. Sensor networks can continuously measure environmental parameters, while wearable devices, cameras, activity sensors, and farm information systems can provide complementary information regarding animal behavior and health. However, collecting large quantities of data alone does not guarantee effective management [6]. The primary requirement is to convert these data into meaningful indicators, predictions, risk assessments, and recommendations. A data-driven Decision Support System (DSS) can integrate information obtained from multiple sources and analyze complex relationships among environmental and welfare variables. Machine learning models can identify patterns that may be difficult to recognize through conventional monitoring and can estimate the probability of environmental stress or welfare deterioration. For example, combinations of

elevated temperature, high humidity, inadequate ventilation, and abnormal activity may indicate an increasing risk of thermal stress even before severe clinical symptoms become apparent [7]. The decision-support layer can subsequently translate predictive outputs into understandable management information. Depending on the detected condition, the system may recommend adjustments to ventilation, cooling, water availability, feeding schedules, stocking conditions, or environmental control strategies. Such an approach shifts animal management from predominantly reactive intervention toward preventive and predictive decision-making [8].

Despite substantial developments in precision livestock farming and intelligent monitoring, several challenges limit the effective use of data-driven technologies for sustainable animal environment management [9]. Many existing systems concentrate on isolated applications such as disease detection, activity recognition, thermal stress assessment, or environmental monitoring. Environmental sustainability and animal welfare are often evaluated separately, despite their strong interdependence. Another challenge is the heterogeneous nature of animal-management data [10]. Environmental sensors generate continuous numerical measurements, whereas animal-centered monitoring may produce behavioral observations, physiological measurements, images, activity records, and categorical health information. Differences in sampling frequency, missing observations, sensor errors, and changing operating conditions complicate the integration of these data sources [11]. Furthermore, predictive accuracy alone is insufficient for practical decision support. Farm managers and animal-care professionals require outputs that can be interpreted and translated into specific actions. Therefore, there is a need for an integrated framework capable of combining environmental and welfare information, predicting emerging risks, evaluating sustainability-related conditions, and generating understandable management recommendations.

2. Data Acquisition and Animal Environment Assessment

The effectiveness of a data-driven decision support system largely depends on the quality and diversity of the information used to represent the animal environment. Environmental conditions, animal behavior, physiological responses, and management practices collectively influence animal welfare and sustainability. Therefore, the proposed study adopts an integrated data acquisition and assessment approach in which environmental and animal-centered variables are continuously collected, processed, and transformed into meaningful

indicators. The resulting dataset provides the foundation for predictive modeling and decision support.

2.1 Animal and Environmental Monitoring Parameters

Animal environments are characterized by several interacting physical and operational factors. The proposed framework considers temperature, relative humidity, air quality, ventilation, light intensity, water availability, feed conditions, and stocking conditions as major environmental variables. Among these, temperature and relative humidity are particularly important because their combined effect determines the thermal conditions experienced by animals. Prolonged exposure to high temperature and humidity may result in thermal stress, altered feeding behavior, increased water consumption, reduced activity, and deterioration in overall welfare [12].

Air-quality parameters provide additional information about housing conditions. Concentrations of ammonia, carbon dioxide, particulate matter, and other gaseous contaminants may increase because of inadequate ventilation, waste accumulation, or high animal density. Continuous monitoring of these variables enables early detection of potentially harmful environmental conditions [13]. Ventilation and airflow measurements are therefore considered together with air-quality observations to obtain a more representative assessment of the housing environment.

Animal-centered variables complement environmental measurements. Depending on the animal production system and available sensing infrastructure, these variables may include body temperature, activity level, movement frequency, resting duration, feeding frequency, water intake, respiratory rate, and other observable behavioral indicators [14]. Integrating environmental and animal-centered variables makes it possible to evaluate not only whether an environmental condition exceeds a predefined threshold but also whether animals demonstrate measurable responses to that condition.

2.2 IoT Sensors and Data Acquisition

The proposed monitoring environment employs an IoT-based data acquisition architecture to enable continuous collection of environmental and animal-related information. Distributed sensors installed at appropriate locations within the animal housing environment record temperature, humidity, air-quality parameters, light intensity, and other relevant

measurements. Animal-centered information can additionally be acquired through wearable sensors, activity trackers, smart feeding systems, cameras, or existing farm-management records.

Sensor observations are collected at predefined sampling intervals and transmitted through a communication network to a local gateway or centralized data repository. The gateway provides an intermediate layer between sensing devices and analytical components and can perform preliminary validation, aggregation, and filtering before forwarding data for subsequent processing. This arrangement reduces unnecessary transmission while enabling continuous monitoring.

Each observation is associated with temporal information and, where applicable, animal or location identifiers. A generalized monitoring record can be represented as

$$X_t = T_t, H_t, AQ_t, L_t, V_t, F_t, W_t, B_t, P_t$$

where (T_t) represents temperature, (H_t) represents relative humidity, (AQ_t) represents air-quality measurements, (L_t) denotes light intensity, (V_t) represents ventilation-related information, (F_t) and (W_t) represent feed and water-related variables, and (B_t) and (P_t) represent behavioral and physiological indicators at time (t), respectively.

The continuous acquisition of these variables produces a multidimensional time-series dataset capable of describing both environmental dynamics and corresponding animal responses.

2.3 Animal Welfare Indicators

Animal welfare assessment in the proposed framework combines environment-based and animal-based indicators. Environmental indicators describe external conditions that may affect welfare, whereas animal-based indicators provide evidence of how animals respond to these conditions. The combined use of both categories reduces dependence on isolated measurements and provides a broader representation of welfare status.

Environmental welfare indicators include thermal conditions, air quality, ventilation adequacy, resource availability, and housing conditions. Animal-centered indicators may include changes in activity, feeding behavior, drinking behavior, resting patterns, body temperature, respiratory activity, and other measurable behavioral or physiological responses. Significant deviations from expected patterns can indicate environmental discomfort or potential welfare deterioration.

Thermal stress can additionally be represented using a Temperature-Humidity Index (THI), expressed in a generalized form as

$$THI = f(T, RH)$$

where (T) denotes ambient temperature and (RH) represents relative humidity. The specific THI formulation and associated threshold ranges can be selected according to the animal species considered in the experimental study.

Instead of relying exclusively on a single indicator, the proposed assessment considers multiple variables simultaneously. Welfare conditions are subsequently categorized into interpretable levels such as normal, moderate risk, and high risk, enabling the analytical output to be directly incorporated into the decision-support process.

2.4 Data Preprocessing and Feature Engineering

Raw sensor and animal-monitoring data may contain missing observations, noise, outliers, inconsistent sampling frequencies, and differences in measurement scales. Data preprocessing is therefore performed before predictive analysis. The preprocessing pipeline includes data validation, missing-value treatment, noise reduction, outlier analysis, temporal synchronization, and normalization.

Missing observations arising from temporary sensor or communication failures are identified and treated according to their duration and the characteristics of the corresponding variable. Abnormal values outside physically meaningful ranges are examined before being retained or removed. Measurements obtained from different sensors are synchronized according to timestamps to create integrated observation records.

Numerical attributes with substantially different ranges are normalized or standardized when required by the predictive model. A commonly adopted min-max transformation is represented as

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where (x) represents the original measurement and (x') represents the normalized value.

Feature engineering is subsequently performed to derive informative variables from the processed observations. In addition to individual sensor measurements, features may include moving averages, minimum and maximum values, rate of environmental change, duration above critical thresholds, THI, activity variation, feeding-pattern

changes, and interactions between environmental and animal-centered variables. Temporal attributes such as hour of the day, season, or monitoring period can also be incorporated where appropriate.

These derived features enable the predictive models to capture both instantaneous environmental conditions and their temporal effects on animal welfare.

2.5 Sustainability and Welfare Assessment Criteria

The processed dataset is finally transformed into sustainability and welfare assessment indicators that support subsequent decision-making. The assessment considers three interconnected dimensions: environmental suitability, animal welfare condition, and resource efficiency.

Environmental suitability evaluates whether temperature, humidity, air quality, ventilation, and other housing parameters remain within desirable operating ranges. Welfare assessment evaluates corresponding behavioral and physiological responses of animals. Resource-efficiency indicators consider factors such as water utilization, feed utilization, ventilation operation, cooling requirements, and energy consumption when such information is available.

For an observation (i), an integrated assessment score can be conceptually represented as

$$S_i = w_E E_i + w_W W_i + w_R R_i$$

where (E_i) represents environmental suitability, (W_i) represents animal welfare status, (R_i) represents resource-efficiency performance, and (w_E), (w_W), and (w_R) are their respective weighting coefficients.

Based on the resulting indicators, the operating condition can be assigned to different management levels. A normal condition indicates that environmental and welfare parameters remain within acceptable ranges. A moderate-risk condition identifies emerging deviations requiring closer monitoring or preventive intervention, while a high-risk condition indicates a combination of environmental or animal-centered indicators requiring immediate management attention. The complete data acquisition and assessment stage therefore converts heterogeneous sensor and animal-monitoring observations into a structured analytical dataset containing environmental, behavioral, physiological, temporal, and sustainability-related features.

3. Proposed Data-Driven Decision Support Framework

The proposed Data-Driven Decision Support Framework integrates environmental monitoring, animal welfare indicators, predictive analytics, and sustainability assessment within a unified computational architecture. The primary objective of the framework is to transform continuously collected heterogeneous data into actionable management information. Rather than depending exclusively on fixed environmental thresholds, the proposed approach analyzes interactions among environmental conditions, animal responses, and resource-utilization parameters to identify emerging welfare risks and recommend appropriate management actions. The overall processing sequence of the proposed framework is represented as:

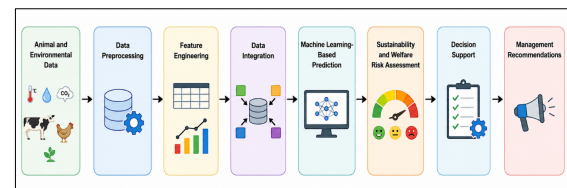


Figure 1. Proposed Data-Driven Decision support framework

3.1 Overall System Architecture

The proposed framework is organized into interconnected data acquisition, processing, analytics, assessment, and decision-support components. Environmental and animal-centered observations collected through IoT sensors, wearable devices, monitoring systems, and management records constitute the primary inputs. These observations are initially subjected to preprocessing operations to remove inconsistencies and establish a reliable analytical dataset. preprocessing, feature engineering generates additional attributes representing thermal conditions, environmental variation, animal activity, behavioral changes, resource utilization, and temporal patterns. These features are supplied to machine learning models for identifying relationships between environmental conditions and animal welfare outcomes. The prediction results are subsequently passed to the risk-assessment component, which evaluates the predicted condition together with sustainability and welfare indicators. The resulting risk level is interpreted by the decision-support layer to generate management recommendations. The proposed architecture therefore establishes a continuous information flow from monitoring to prediction and finally to management intervention.

3.2 Environmental and Welfare Data Integration

Environmental and animal welfare data originate from heterogeneous sources and may differ considerably in their measurement frequency, scale, and interpretation. The proposed framework integrates these observations according to common timestamps and monitoring identifiers to construct unified feature vectors.

For each observation period (t), the integrated feature representation can be expressed as

$$F_t = [E_t, A_t, P_t, R_t, T_t]$$

where (E_t) represents environmental features, (A_t) represents animal behavioral features, (P_t) denotes physiological indicators, (R_t) represents resource-utilization information, and (T_t) represents temporal features.

Environmental features may include temperature, humidity, air quality, ventilation, and light intensity. Behavioral features represent activity, resting, feeding, and drinking patterns, whereas physiological features may contain body temperature, respiratory indicators, or other available health-related measurements. Resource-related attributes provide information regarding water, feed, cooling, ventilation, or energy utilization. This integrated representation enables the analytical model to identify relationships that may not be observable when variables are analyzed independently. For example, increased temperature may not necessarily indicate severe welfare risk when ventilation and water availability remain adequate. However, elevated temperature combined with high humidity, reduced activity, and increased water consumption may provide stronger evidence of thermal stress. The proposed integration strategy therefore emphasizes multivariable assessment rather than isolated threshold evaluation.

3.3 Machine Learning-Based Prediction and Assessment

Machine learning forms the analytical core of the proposed decision support framework. Multiple supervised learning algorithms can be evaluated to determine their effectiveness in predicting animal environmental and welfare conditions. The study considers models such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Gradient Boosting, depending on the characteristics of the available dataset.

The processed feature vector (F_t) is supplied to a predictive model (M), producing the estimated welfare or environmental condition:

$$\hat{Y}_t = M(F_t)$$

where ($\hat{Y}_t$) represents the predicted condition at time (t).

For classification-based assessment, the output may be categorized into three operational classes:

$$\hat{Y}_t \in \{\text{Normal, Moderate Risk, High Risk}\}$$

The Normal class represents environmental and animal conditions within acceptable operational ranges. Moderate Risk indicates emerging deviations that may require preventive management, whereas High Risk represents conditions requiring immediate attention. The performance of alternative machine learning models is evaluated using appropriate classification metrics, including accuracy, precision, recall, F1-score, and area under the ROC curve where applicable. Cross-validation is employed to reduce dependence on a single train-test partition. The best-performing model is subsequently incorporated into the decision-support component.

3.4 Sustainability and Welfare Risk Evaluation

Prediction alone does not provide sufficient information for sustainable animal management. The predicted condition is therefore combined with environmental suitability, animal welfare, and resource-efficiency indicators to obtain an integrated risk assessment.

A generalized risk score can be represented as

$$R_t = \alpha E_r + \beta W_r + \gamma S_r$$

where (E_r) represents environmental risk, (W_r) denotes animal welfare risk, (S_r) represents sustainability or resource-utilization risk, and (α), (β), and (γ) represent their respective weighting coefficients.

Environmental risk increases when monitored parameters deviate substantially from acceptable operating conditions. Welfare risk is determined from changes in behavioral and physiological indicators, while sustainability risk represents inefficient utilization of resources such as water, feed, cooling, ventilation, or energy. The calculated score is mapped into interpretable management levels. Lower scores indicate acceptable environmental and welfare conditions, intermediate scores represent conditions requiring preventive action, and higher scores indicate potentially critical situations requiring immediate intervention. This integrated assessment prevents management decisions from being based exclusively on predictive probabilities and provides a broader representation of the actual operating condition.

3.5 Decision Support and Management Recommendations

The final component of the proposed framework converts analytical outputs into practical recommendations. The decision-support mechanism evaluates the predicted class, integrated risk score, and individual environmental and welfare indicators to determine the most appropriate management response.

For example, detection of elevated temperature and humidity combined with abnormal animal activity may result in recommendations to increase ventilation, activate cooling systems, improve drinking-water availability, or modify animal exposure conditions. Poor air-quality measurements may trigger recommendations related to ventilation adjustment, waste removal, or stocking-condition inspection. Changes in feeding or activity behavior without substantial environmental variation may instead indicate the need for closer animal-level health observation.

The decision mechanism can be represented as

$$D_t = g(\hat{Y}_t, R_t, F_t)$$

where (D_t) represents the management decision, ($\hat{Y}_t$) is the predicted welfare condition, (R_t) represents the integrated risk score, and (F_t) contains the contributing environmental and animal features.

The recommendations are prioritized according to the estimated severity of the condition. Under normal conditions, routine monitoring is continued. Moderate-risk conditions generate preventive recommendations and increased monitoring frequency, while high-risk conditions generate immediate alerts and corrective actions. Importantly, recommendations are designed to consider both animal welfare and resource efficiency. For instance, environmental control systems should be activated according to actual predicted requirements rather than continuously operating at maximum capacity, thereby reducing unnecessary energy consumption. Through this integrated mechanism, the proposed framework establishes a transition from conventional reactive animal management toward predictive and evidence-based decision support. Continuous monitoring identifies changing environmental conditions, machine learning predicts potential welfare risks, integrated assessment evaluates their severity, and the decision-support component translates the results into actionable recommendations. The framework consequently provides a systematic foundation for improving

animal welfare while supporting sustainable and resource-efficient management practices.

4. Comparative Analysis and Discussion

The comparative performance of the machine learning models was evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. Table 4 presents the performance of Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB) for animal welfare and environmental risk classification.

Table 4. Comparative Performance of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Logistic Regression (LR)	84.6	83.8	82.9	83.3	0.87
Decision Tree (DT)	87.2	86.5	85.8	86.1	0.89
Support Vector Machine (SVM)	89.4	88.9	88.2	88.5	0.92
Random Forest (RF)	93.1	92.6	92.2	92.4	0.95
Gradient Boosting (GB)	94.3	93.8	93.5	93.6	0.96

As observed from Table 4, all evaluated models demonstrated satisfactory capability for classifying animal environmental and welfare risk conditions. However, noticeable differences were observed in their overall predictive performance. Logistic Regression achieved an accuracy of 84.6%, indicating that a linear decision boundary can capture the general relationships within the dataset but may be insufficient for representing complex interactions among environmental, behavioral, and physiological variables. Decision Tree improved the accuracy to 87.2%, demonstrating its ability to model nonlinear relationships, although its performance remained below that of the ensemble approaches. The SVM provided further improvement, achieving 89.4% accuracy, 88.5% F1-score, and a ROC-AUC of 0.92. This indicates its

effectiveness in separating different welfare-risk categories using multidimensional environmental and animal-centered features. However, the ensemble models produced the strongest overall performance. Random Forest achieved an accuracy of 93.1%, with precision, recall, and F1-score values of 92.6%, 92.2%, and 92.4%, respectively. Its strong performance can be attributed to the aggregation of multiple decision trees, which enables effective representation of nonlinear interactions while reducing the sensitivity associated with individual decision trees. Among all evaluated approaches, Gradient Boosting achieved the highest overall performance, with an accuracy of 94.3%, precision of 93.8%, recall of 93.5%, F1-score of 93.6%, and ROC-AUC of 0.96. The high recall is particularly relevant for animal welfare monitoring because it indicates a stronger capability to identify actual risk conditions and consequently reduces the possibility of potentially harmful conditions remaining undetected.

The comparative results demonstrate that ensemble learning methods are more suitable for the proposed decision-support framework than simpler linear or individual tree-based approaches. Environmental stress and animal welfare are influenced by interacting factors such as temperature, humidity, air quality, ventilation, activity, and resource availability. Gradient Boosting can progressively learn these complex relationships and correct classification errors across successive learners, resulting in improved predictive performance. Based on the comparative evaluation, Gradient Boosting is selected as the predictive component of the proposed Data-Driven Decision Support Framework. Its output is subsequently integrated with environmental suitability, animal welfare, and resource-efficiency indicators to determine the overall risk level and generate appropriate management recommendations.

5. Conclusion and Future Research

This study presented a Data-Driven Decision Support Framework for Sustainable Animal Environment and Welfare Management by integrating environmental monitoring, animal-centered indicators, machine learning-based prediction, sustainability assessment, and management recommendations. The proposed approach addresses the limitations of conventional threshold-based monitoring by considering the combined influence of temperature, humidity, air quality, ventilation, resource availability, behavioral patterns, and physiological indicators. The integration of these heterogeneous variables enables a more comprehensive assessment of animal environmental conditions and associated welfare risks. The comparative evaluation of Logistic

Regression, Decision Tree, Support Vector Machine, Random Forest, and Gradient Boosting demonstrated the effectiveness of machine learning for welfare-risk prediction. Among the evaluated models, Gradient Boosting provided the best overall performance, achieving 94.3% accuracy, 93.8% precision, 93.5% recall, 93.6% F1-score, and a ROC-AUC of 0.96. These results indicate its capability to capture complex relationships among environmental and animal-centered variables and identify emerging welfare-risk conditions. An important contribution of the proposed framework is its transition from simple prediction toward actionable decision support. Predicted welfare conditions are combined with environmental suitability and resource-efficiency indicators to classify operating conditions into normal, moderate-risk, and high-risk levels. This enables timely recommendations related to ventilation, cooling, water availability, feeding conditions, environmental control, and animal monitoring. Such predictive intervention can potentially reduce prolonged environmental stress while avoiding unnecessary resource consumption. The proposed framework therefore provides a foundation for proactive, welfare-oriented, and sustainable animal management. Future research can extend the framework through real-time IoT deployment, larger and species-specific datasets, deep learning and time-series prediction, explainable AI techniques, and automated environmental control. Integration with edge computing and digital-twin technologies could further enable real-time adaptive management while improving scalability, interpretability, and resource efficiency in practical animal production environments.

References

- [1] Pretty, J.N. Agricultural sustainability: Concepts, principles, and evidence. *Philos. Trans. R. Soc.* **2008**, *363*, 447–465.
- [2] Godfray, C.; Beddington, J.R.; Crute, I.R.; Haddad, L.; Lawrence, D.; Muir, J.F.; Pretty, J.; Robinson, S.; Thomas, S.M.; Toulmin, C. Food security: The challenge of feeding 9 billion people. *J. Sci.* **2010**, *327*, 812–818.
- [3] Mazonde, I.N. Social transformation and food security in the household: The experience of rural Botswana. In *Alltagswelten Im Umbruch: Facets of a Changing Society*; Lit Verlag: Hamburg, Germany, 2000; pp. 53–73.
- [4] Myers, J.H.; Savoie, A.; Randen, E.V. Eradication and pest management. *Annu. Rev. Entomol.* **1998**, *43*, 471–491.
- [5] Chavan, D. P. A Network-Centric Web Application for Dynamic Crop and Fertilizer Decision Support. International

- Journal on Advanced Electrical and Computer Engineering, 2025, 14(2), 9–15.
- [6] Muriu, P. *Mobile Based Expert System Model for Animal Health Monitoring: Cow's Disease Monitoring in Kenya*. Ph.D. Thesis, Strathmore University, Nairobi, Kenya, 2016.
 - [7] N. M. Pawar, R. M. Sairise, P. Karemore, A. Jadhav, D. Turaev, and S. N. Ajani, "ML-based verification systems using discrete mathematical models," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 29, no. 2-B, pp. 971–978, 2026, doi: 10.47974/JDMSC-2548.
 - [8] Ortigosa, G.R.; De Leo, G.A.; Gatto, M. VVF: Integrating modelling and GIS in a software tool for habitat suitability assessment. *Environ. Model. Softw.* **2000**, *15*, 1–12.
 - [9] Hendrickx, G.; Biesemans, J.; Deken, R.D. The use of GIS in veterinary parasitology. In *GIS and Spatial Analysis in Veterinary Science*; CABI Publishing: Wallingford, UK, 2004; pp. 145–176.
 - [10] Ronchi, B.; Nardone, A. Contribution of organic farming to increase sustainability of Mediterranean small ruminant livestock systems. *Livest. Prod. Sci.* **2003**, *80*, 17–31.
 - [11] Tabo, R.; Tarawali, S.A.; Singh, B.B.; Bationo, A.; Traore, B.; Traore, M.D.; Don-Gomma, A.; Odion, E.C.; Nokoe, S.; Harris, F.; et al. Enhancing the productivity and sustainability of integrated crop-livestock systems in the dry savannahs of West Africa. In *Sustainable Agriculture Systems for the Drylands*; CGSpace: Niamey, Niger, 2005.
 - [12] Rivington, M.; Matthews, K.B.; Bellocchi, G.; Buchan, K.; Stöckle, C.O.; Donatelli, M. An integrated assessment approach to conduct analyses of climate change impacts on whole-farm systems. *Environ. Model. Softw.* **2007**, *22*, 202–210.
 - [13] Perry, B.D.; Randolph, T.F.; McDermott, J.J.; Sones, K.R.; Thornton, P.K. *Investing in Animal Health Research to Alleviate Poverty*; International Livestock Research Institute: Nairobi, Kenya, 2002; p. 140.
 - [14] Veglia, F. *Anatomy and Life-History of the Haemonchus contortus (Rud.)*; UPSpace: West Chester, PA, USA, 1915.