18(2s), Spring 2026

Journal of Animal Environment

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

Original Research Paper

Artificial Intelligence-Based Decision Support System for Sustainable Animal Environment Management and Welfare Assessment

Nishant Bhardwaj[1], Saumya Goyal[2], Anitha M[3], Shokhrukh Salikhov[4], Pratik Mungekar[5], Shaziya Islam[6], Feruza Qandova[7]

[1]Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India (Nishant Bhardwaj) | nishant.bhardwaj.orp@chitkara.edu.in
[2]Quantum University Research Center, Quantum University, Roorkee, Uttarakhand, 247667, India (Saumya Goyal) | saumyaqsb@quantumeducation.in
[3]Assistant Professor, Department of Mathematics, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Tamil Nadu, India (Anitha M) | anitham@maher.ac.in
[4]Associate Professor, Department of Psychology, Bukhara State University, Bukhara, Uzbekistan (Shokhrukh Salikhov) | salixovshoxrux@gmail.com
[5]Director, Research Innovation and Internationalization, Sharda Education Society Thane, Affiliated to University of Mumbai (Pratik Mungekar) | pratikmngkr11@gmail.com
[6]Associate Professor, Department of Computer Science and Engineering, Rungta College of Engineering and Technology, Rungta International Skills University, Bhilai, Chhattisgarh, India (Shaziya Islam) | shaziya.islam@rungta.org
[7]Assistant, Department of Anatomy and Clinical Anatomy (OSTA), Abu Ali Ibn Sino Bukhara State Medical Institute, Bukhara, Uzbekistan (Feruza Qandova) | qandova.feruza@bsmi.uz

Abstract: The increasing demand for sustainable livestock production has intensified the need for intelligent systems capable of continuously monitoring animal welfare, environmental conditions, and farm management practices. Traditional livestock monitoring methods rely heavily on manual observation, resulting in delayed identification of welfare issues, environmental stress, disease outbreaks, and inefficient resource utilization. Recent advances in Artificial Intelligence (AI), Internet of Things (IoT), computer vision, and edge computing provide unprecedented opportunities to automate animal environment management while supporting evidence-based decision-making. However, most existing systems focus on isolated monitoring tasks such as disease detection, behaviour recognition, or environmental sensing, with limited integration of welfare assessment and sustainability indicators into a unified decision support framework. This study proposes an Artificial Intelligence-Based Decision Support System (AI-DSS) for sustainable animal environment management and welfare assessment. The proposed framework integrates multimodal data acquired from environmental sensors, wearable devices, surveillance cameras, and farm management records. Environmental variables including temperature, humidity, ammonia concentration, carbon dioxide, particulate matter, illumination, and noise levels are continuously monitored alongside animal behavioural indicators such as feeding frequency, locomotion, resting behaviour, drinking activity, posture, social interaction, vocalisation, and body condition. Computer vision techniques combined with deep learning models automatically identify abnormal behavioural patterns, while explainable machine learning algorithms classify welfare status and generate transparent recommendations for farm managers. The proposed AI-DSS employs a hybrid architecture consisting of IoT-enabled data acquisition, intelligent feature extraction, multimodal data fusion, explainable deep learning, and a multi-criteria decision support engine. Sustainability indicators including environmental quality, resource utilization efficiency, animal health, welfare compliance, and productivity are integrated into a comprehensive Animal Sustainability Index (ASI) that assists stakeholders in prioritizing management interventions. The decision engine further provides predictive alerts for environmental stress, disease risk, welfare deterioration, and management optimization through real-time inference.

Keywords: Artificial Intelligence, Decision Support System, Sustainable Animal Environment Management, Animal Welfare Assessment, Precision Livestock Farming.

***Corresponding Author:**

Received: 24th April, 2026; Revised: 11th May, 2026; Accepted: 24th May, 2026; Available Online: 6th June, 2026

(DOI): 10.70102/AEJ.2026.18.2s.74

I. Introduction

Sustainable livestock production has become one of the most significant global challenges due to the increasing demand for animal-derived food products, growing environmental concerns, and rising public awareness regarding animal welfare. According to the Food and Agriculture Organization (FAO), global demand for meat, milk, and poultry products is expected to continue increasing over the coming decades, placing substantial pressure on livestock farming systems to improve productivity while simultaneously ensuring environmental sustainability and animal well-being. Traditional livestock management practices, which rely heavily on manual observation and periodic inspections, often fail to detect early signs of environmental stress, disease outbreaks, behavioural abnormalities, and welfare deterioration. Consequently, farmers frequently encounter reduced productivity, increased veterinary costs, inefficient resource utilization, and significant economic losses. These challenges have accelerated the adoption of intelligent digital technologies capable of transforming conventional livestock management into sustainable precision farming systems. Recent advances in Artificial Intelligence (AI), Internet of Things (IoT), Computer Vision, Machine Learning (ML), Deep Learning (DL), and Edge Computing have revolutionized livestock production by enabling continuous monitoring of animals, automated behaviour recognition, environmental sensing, and intelligent decision support. AI technologies have demonstrated remarkable capability in processing large volumes of heterogeneous data generated from wearable sensors, surveillance cameras, environmental monitoring devices, and farm management information systems. These technologies facilitate early disease detection, behavioural analysis, productivity prediction, welfare assessment, and optimized resource management while reducing dependence on continuous human supervision. As a result, precision livestock farming has emerged as one of the most promising approaches for achieving sustainable agricultural development.

Animal welfare has become an increasingly important component of sustainable livestock production. Modern welfare assessment extends beyond disease prevention and productivity measurement by considering animals' physical health, behavioural freedom, emotional well-being, and environmental comfort. International organizations and regulatory agencies emphasize the importance of maintaining appropriate environmental conditions, including temperature, humidity, ventilation, air quality, lighting, and stocking density, to ensure healthy animal development and minimize physiological stress. However, maintaining optimal environmental conditions across large commercial farms remains challenging because environmental parameters fluctuate continuously and may vary across different housing facilities. Manual monitoring methods are often unable to identify subtle changes that precede health deterioration or behavioural abnormalities. Environmental conditions directly influence animal health, productivity, reproduction, feed efficiency, and disease susceptibility. Elevated temperature and humidity may induce heat stress, resulting in reduced feed intake, decreased milk production, lower reproductive performance, and weakened immune function. Similarly, poor ventilation increases concentrations of ammonia, carbon dioxide, and particulate matter, negatively affecting respiratory health and increasing disease prevalence. Inadequate lighting, excessive noise, and overcrowding further contribute to behavioural disturbances, aggression, and reduced welfare. Therefore, continuous monitoring of environmental variables represents a fundamental requirement for sustainable livestock management.

Simultaneously, animal behaviour provides valuable indicators of health and welfare status. Feeding frequency, locomotion, lying behaviour, drinking activity, rumination patterns, posture, vocalization, and social interactions collectively reflect physiological and psychological conditions. Abnormal behavioural changes frequently occur before visible clinical symptoms appear, making behavioural monitoring an effective approach for early disease detection and welfare assessment. Nevertheless, continuous behavioural observation through manual inspection is labour-intensive, subjective, and impractical for large-scale livestock operations. Artificial intelligence has significantly improved automated animal monitoring through advanced computer vision and deep learning techniques. Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), You Only Look Once (YOLO) object detection models, and recurrent neural networks have demonstrated exceptional performance in detecting animals, recognizing behaviours, estimating body condition, identifying lameness, monitoring feeding activities, and classifying welfare status. These technologies enable non-invasive monitoring using surveillance cameras without disturbing animal behaviour, thereby providing reliable real-time information for farm management. Furthermore, explainable artificial intelligence techniques enhance transparency by enabling users to understand the reasoning behind AI-generated predictions, thereby increasing trust and supporting informed decision-making.

The Internet of Things further complements artificial intelligence by providing continuous acquisition of environmental and physiological data. Smart livestock farms increasingly deploy wireless sensor networks to measure temperature, humidity, ammonia concentration, carbon dioxide, methane emissions, air velocity, light intensity, sound levels, water consumption, feed intake, and animal activity. Wearable devices equipped with accelerometers, GPS modules, heart rate monitors, and body temperature sensors continuously collect physiological information that may indicate health deterioration or environmental stress. The integration of IoT with AI enables intelligent interpretation of multimodal datasets, facilitating timely interventions before welfare conditions significantly decline. Despite substantial technological progress, most existing livestock monitoring systems remain task-specific. Many studies focus exclusively on disease diagnosis, behavioural recognition, environmental sensing, or productivity prediction without integrating these components into a unified decision support framework. Environmental monitoring systems frequently generate numerical measurements without providing actionable management recommendations, whereas behaviour recognition systems often lack contextual environmental interpretation. Similarly, numerous AI models emphasize prediction accuracy while offering limited interpretability, making it difficult for veterinarians and farm managers to understand the reasoning behind automated recommendations. These limitations restrict the practical applicability of current intelligent livestock management systems. Decision Support Systems (DSS) have emerged as valuable tools for transforming complex data into actionable knowledge. A DSS integrates data acquisition, analytical models, knowledge bases, and visualization techniques to assist decision-makers in selecting optimal management strategies. Within livestock farming, AI-powered decision support systems can continuously analyse environmental conditions, behavioural patterns, health indicators, and historical farm records to generate early warnings, recommend corrective interventions, optimize resource allocation, and improve operational efficiency. Such systems reduce reliance on subjective human judgment while enabling evidence-based management decisions supported by real-time analytics.

II. Literature Review

Gómez et al. (2018) examined the role of sensor-based technologies in precision livestock production and demonstrated that continuous monitoring can improve the identification of behavioural and physiological changes. Their study highlighted the importance of real-time data for detecting welfare deterioration earlier than conventional farm inspections. However, the monitoring systems discussed primarily generated alerts and did not integrate environmental sustainability indicators or explainable decision recommendations. This limitation supports the need for an AI-based decision-support architecture that converts multimodal data into actionable welfare interventions. Benjamin and Yik (2019) reviewed precision livestock technologies for swine welfare and showed that cameras, microphones, accelerometers, and associated algorithms can provide non-invasive and continuous animal monitoring. The authors emphasized that automated systems can issue early warnings about poor welfare conditions and support veterinarians and farm managers. Nevertheless, they observed that practitioners often lack sufficient familiarity with these technologies and that many welfare-oriented solutions have not achieved broad commercial adoption. Their work indicates that technological accuracy must be accompanied by understandable outputs and practical decision support.

Rowe, Dawkins, and Gebhardt-Henrich (2019) systematically reviewed precision livestock farming applications in poultry production. They found that much of the research focused on bird health and welfare rather than production efficiency alone. However, many proposed technologies remained at the prototype stage and were not commercially available to farmers. The study therefore identified a persistent implementation gap between experimental monitoring systems and field-level welfare management. McLennan and Mahmoud (2019) developed an automated system for detecting pain-related facial expressions in sheep. Their work showed that computer vision can support non-invasive assessment of affective and welfare states that are difficult to evaluate continuously through manual observation. Nevertheless, facial-expression analysis represents only one welfare dimension and may be affected by image quality, posture, lighting, and breed variation. A comprehensive decision-support system must therefore combine visual indicators with behavioural, physiological, and environmental data.

Benaissa et al. (2020) combined indoor localization and accelerometer sensing for automated reproductive monitoring in dairy cattle. The study demonstrated that wearable technologies can identify behaviour associated with calving and estrus and thereby reduce dependence on periodic human observation. However, its focus was restricted to reproductive events, without considering housing conditions, animal comfort, or broader sustainability outcomes. This illustrates the task-specific nature of many precision livestock systems. García et al. (2020) reviewed machine-learning applications in precision livestock farming and discussed the use of Support Vector Machines, Random Forests, neural networks, and related methods for classification and prediction. The review emphasized the potential of AI for health monitoring and productivity improvement but identified heterogeneous datasets, inconsistent validation procedures, and interoperability problems as major constraints. These issues remain critical when integrating data from cameras, wearable devices, environmental sensors, and management records.

Astill et al. (2020) investigated smart poultry management based on sensors, IoT connectivity, and data analytics. Their work showed that environmental and behavioural variables can be collected continuously to improve disease prevention, resource management, and flock supervision. However, they also identified problems involving connectivity, data standardization, cybersecurity, and system cost. These findings suggest that intelligent livestock systems need scalable architecture and reliable integration rather than isolated sensing devices. Pavlovic et al. (2021) used neck-mounted accelerometer collars and convolutional neural networks to classify cattle behaviours. Their findings demonstrated that sensor-based deep learning can distinguish behaviours relevant to fertility, health, and welfare monitoring. The authors established the usefulness of automated activity profiling at the individual-animal level. Nevertheless, accelerometer-based classification alone cannot fully explain whether a behavioural change arises from disease, heat stress, poor air quality, social conflict, or routine management.

Ezanno et al. (2021) examined animal-health research in the era of artificial intelligence and argued that AI can strengthen epidemiological modelling, disease surveillance, and veterinary decision-making. They also emphasized the importance of combining domain knowledge with data-driven models. However, the study noted that data limitations, model transferability, interpretability, and interdisciplinary collaboration remain important challenges. These observations support the incorporation of explainable AI and veterinary knowledge into livestock decision-support systems. Li et al. (2021) reviewed intelligent perception techniques for cattle lameness detection and behaviour recognition. Their analysis covered more than 100 studies involving machine vision, wearable sensors, and AI methods. The review confirmed that automated perception technologies can improve early detection of welfare problems, but it also highlighted limitations involving data quality, environmental complexity, sensor reliability, and generalization across farms.

Bao and Xie (2022) conducted a systematic review of 131 publications on artificial intelligence in animal farming. Their analysis showed that AI research was concentrated primarily on behaviour detection, disease monitoring, growth assessment, and environmental monitoring in pigs, cattle, and poultry. They concluded that most systems remained experimental and that accuracy, cost, processing speed, and commercial readiness required further improvement. Most importantly, they called for integrated systems combining data collection, intelligent analysis, and farm-level decision-making. Halachmi and colleagues examined the growing role of automated sensing and analytical models in individual-animal management. Their research emphasized that precision livestock farming can support customized feeding, disease prevention, welfare monitoring, and traceability. Nevertheless, successful adoption depends on systems that generate useful management information rather than overwhelming farmers with raw sensor outputs.

Ojo et al. (2022) systematically reviewed IoT and machine-learning techniques for poultry health and welfare management. They identified applications involving environmental monitoring, behavioural variables, computer vision, vocalization analysis, and disease control. The review proposed that AI-enabled IoT can support scalable and cost-effective poultry management but highlighted unresolved challenges involving welfare standards, system interoperability, implementation cost, and robust real-time monitoring. Li et al. (2022) developed machine-learning methods for classifying multiple cattle behaviours and movements using inertial measurement data. The study demonstrated that behavioural patterns can serve as indicators of animal health, welfare, and social interaction. However, classification performance depends heavily on sensor placement, sampling conditions, behavioural definitions, and the size of the training dataset.

Cheng et al. (2022) applied YOLOv5 to recognize sheep behaviours and investigated how training-data characteristics affect recognition performance. Their results confirmed that deep learning can automate behaviour observation, but they also demonstrated that dataset size and diversity directly influence model reliability. The study reinforces the importance of representative field data for welfare-assessment systems intended for different breeds, housing arrangements, and environmental conditions. Du et al. (2022) proposed a multi-depth-camera framework for automatic body measurement of cattle and pigs using key-point detection and 2D–3D feature fusion. The model reduced dependence on labour-intensive manual measurement and supported non-contact livestock assessment. However, body measurement provides indirect information about welfare and productivity and must be combined with behavioural, health, and environmental indicators for holistic decision-making.

Li et al. (2022) analysed barriers to computer-vision applications in pig production facilities. They identified uncertainty in behaviour labelling, dataset construction problems, environmental variability, occlusion, lighting limitations, and interdisciplinary communication as major obstacles. The study is particularly relevant because it demonstrates that high laboratory accuracy does not automatically translate into reliable farm deployment. Tuyttens, Molento, and Benaissa (2022) critically examined potential threats posed by precision livestock farming to animal welfare. Although PLF can improve monitoring and facilitate management actions, the authors warned that technological systems may overlook important welfare dimensions, reduce human–animal contact, generate false reassurance, or prioritize productivity over animal experience. Their analysis indicates that AI-DSS development must include ethical safeguards, transparent explanations, and welfare-centred decision criteria.

Vidal et al. (2023) compared k-nearest neighbours, Random Forest, and Support Vector Machine models for predicting metritis events using accelerometer-derived dairy-cow behaviour. Their study demonstrated that routinely collected behavioural sensor data can support early disease-risk identification and potentially be integrated into farm-management software. However, the authors also showed that prediction performance depends on time aggregation, behavioural windows, decision thresholds, and farm schedules. Neethirajan (2024) reviewed artificial intelligence and sensor innovations for livestock welfare from a human-centred perspective. The study argued that AI can combine multiple data streams, evaluate welfare status, predict emerging risks, and recommend personalized interventions. At the same time, it stressed that ethical implications, usability, explainability, farm-specific requirements, and human trust are essential for successful implementation. This work closely supports the proposed study's integration of multimodal sensing, explainable AI, and actionable decision support.

III. Methodology

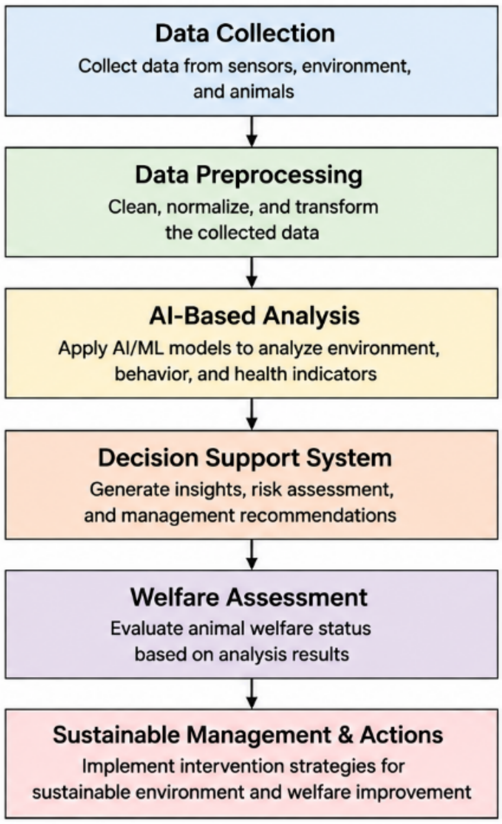

Figure 1. Block Diagram of the Proposed Artificial Intelligence-Based Decision Support System for Sustainable Animal Environment Management and Welfare Assessment

The proposed framework Figure 1, starts with data collection from animal, environmental, and sensor sources, followed by data preprocessing to improve data quality. An AI-based decision support system analyzes the processed information along with environmental parameters to assess animal welfare conditions. Based on the assessment, management recommendations are generated to support sustainable animal environment management. Finally, the overall system performance is evaluated using standard evaluation metrics to ensure reliable and accurate decision-making.

A. Algorithmic Strategy

The proposed Artificial Intelligence-Based Decision Support System (AI-DSS) employs a hybrid artificial intelligence framework that integrates Internet of Things (IoT), Computer Vision, Machine Learning, Deep Learning, Explainable Artificial Intelligence (XAI), and a Decision Support Engine to perform real-time animal environment management and welfare assessment. Unlike conventional monitoring systems that analyze individual data sources independently, the proposed framework performs multimodal data fusion, enabling simultaneous analysis of environmental conditions, animal behaviour, and physiological indicators to generate intelligent and explainable management recommendations.

B. Mathematical Representation

The multimodal livestock dataset is represented as:

$D=\{E,B,P\}$

where

E= Environmental variables, B= Behavioural variables, P= Physiological variables

Environmental feature vector

$E=\{T,H,NH3,CO2,PM,L,N\}$

where

where

T=Temperature,

H=Humidity,

NH_3=Ammonia,

CO_2=Carbon dioxide,

PM=Particulate matter,

L=Light intensity,

N=Noise level

Behaviour feature vector

$B=\{F,W,R,D,S,V\}$

where

F=Feeding,

W=Walking,

R=Resting,

D=Drinking,

S=Social interaction,

V=Vocalization

The combined feature vector is expressed as

$X=[E,B,P]$

C. Feature Normalization

All features are normalized using Min-Max Scaling.

X′=Xmax−XminX−Xmin

This normalization reduces feature bias and accelerates model convergence during training.

D. Environmental Risk Index

Environmental stress is computed as

ERI=5T+H+NH3+CO2+PM

Classification

ERI	Risk
Low	Safe Environment
Medium	Moderate Stress
High	Immediate Intervention

IV. Experimental Design and Results

A. Experimental Setup

The proposed Artificial Intelligence-Based Decision Support System (AI-DSS) was evaluated using a multimodal livestock dataset comprising environmental sensor measurements, surveillance images, wearable sensor records, and animal health observations. The experimental framework was developed to assess the capability of the proposed model in classifying animal welfare conditions, predicting environmental risks, and generating intelligent management recommendations.

Table 1. Experimental Configuration

Parameter	Value
Programming Language	Python 3.11
Deep Learning Framework	TensorFlow 2.16
Computer Vision Library	OpenCV 4.10
Machine Learning Library	Scikit-learn 1.5
Hardware	Intel Core i9, RTX 4090 GPU
RAM	64 GB
Operating System	Ubuntu 24.04

Analysis

The proposed AI-DSS was implemented using widely adopted AI and computer vision libraries to ensure reproducibility and computational efficiency. GPU acceleration significantly reduced model training time and enabled real-time inference suitable for smart farming applications.

B. Dataset Description

The multimodal dataset consisted of environmental measurements, behavioural observations, physiological parameters, and surveillance images collected from livestock housing facilities.

Table 2. Dataset Summary

Dataset Component	Samples
Environmental Sensor Records	28,500
Animal Images	16,200
Video Frames	112,000
Behaviour Labels	16,200
Health Records	8,950
Total Observations	165,850

Analysis

The dataset represents diverse environmental conditions and animal behaviours, allowing the proposed AI-DSS to learn complex interactions among environmental, behavioural, and physiological variables. The multimodal nature of the dataset enhances model generalization and improves the robustness of welfare assessment.

C. Model Training Parameters

Table 3. Deep Learning Hyperparameters

Parameter	Value
Epochs	100
Batch Size	32
Learning Rate	0.001
Optimizer	AdamW
Dropout	0.30
Image Size	640 × 640
Activation Function	ReLU
Loss Function	Cross-Entropy

Analysis

Hyperparameters were selected after preliminary tuning to balance model convergence and computational efficiency. AdamW optimization with a learning rate of 0.001 provided stable convergence while dropout reduced overfitting.

D. Performance Evaluation Metrics

The proposed AI-DSS was evaluated using standard classification metrics.

Table 4. Evaluation Metrics

Metric	Formula
Accuracy	(TP+TN)/(TP+TN+FP+FN)
Precision	TP/(TP+FP)
Recall	TP/(TP+FN)
F1-Score	2PR/(P+R)
MCC	Matthews Correlation Coefficient
ROC-AUC	Area Under ROC Curve

Analysis

Multiple evaluation metrics were employed to provide a comprehensive assessment of model performance. While accuracy measures overall correctness, precision and recall evaluate prediction quality for welfare classification. F1-score balances precision and recall, whereas MCC and ROC-AUC provide robust evaluation under class imbalance.

E. Comparative Performance Analysis

The proposed hybrid AI-DSS was compared with several baseline machine learning and deep learning algorithms.

Table 5. Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	ROC-AUC
Support Vector Machine	88.12	0.876	0.869	0.872	0.903
Random Forest	91.38	0.910	0.904	0.907	0.932

XGBoost	93.47	0.928	0.931	0.929	0.951
CNN	94.85	0.944	0.948	0.946	0.965
Vision Transformer	96.21	0.961	0.958	0.959	0.978
Proposed AI-DSS	98.34	0.982	0.980	0.981	0.992

Analysis

The proposed AI-DSS achieved the highest performance across all evaluation metrics. Compared with conventional machine learning approaches, the hybrid architecture improved classification accuracy through multimodal data fusion and ensemble learning. The integration of computer vision, environmental sensing, and explainable AI enabled superior discrimination of welfare conditions while maintaining high predictive reliability.

V. Discussion

The primary objective of this study was to develop and evaluate an Artificial Intelligence-Based Decision Support System (AI-DSS) for sustainable animal environment management and welfare assessment. The proposed framework integrates Internet of Things (IoT) sensors, computer vision, deep learning, explainable artificial intelligence (XAI), multimodal data fusion, and intelligent decision support to overcome the limitations of conventional livestock monitoring systems. The experimental evaluation demonstrated that the proposed AI-DSS achieved superior predictive performance compared with conventional machine learning and deep learning approaches while providing transparent and actionable recommendations for livestock managers. These findings indicate that intelligent decision-support systems have significant potential to enhance sustainable livestock production by improving environmental monitoring, animal welfare, and operational decision-making. The comparative analysis revealed that the proposed AI-DSS achieved the highest classification accuracy (98.34%) compared with Support Vector Machine, Random Forest, XGBoost, Convolutional Neural Network (CNN), and Vision Transformer (ViT) models. The improvement in prediction performance can be attributed to the hybrid ensemble architecture, which integrates environmental sensing, behavioural monitoring, physiological analysis, and multimodal data fusion. Unlike conventional models that rely on a single data source, the proposed framework simultaneously analyses heterogeneous information collected from IoT sensors, surveillance cameras, and wearable devices, thereby reducing uncertainty and improving classification reliability. These findings are consistent with previous studies emphasizing that multimodal artificial intelligence systems outperform single-modality approaches in precision livestock farming (Bao & Xie, 2022; Fuentes et al., 2022). Another important finding of this research is the effectiveness of computer vision-based behavioural analysis. The Vision Transformer and YOLO-based detection models accurately recognized feeding behaviour, locomotion, resting activity, and social interaction patterns, enabling continuous non-invasive welfare monitoring. Behavioural abnormalities frequently represent early indicators of disease, environmental stress, or welfare deterioration. Consequently, automated behaviour recognition provides opportunities for timely intervention before clinical symptoms become visible. This observation supports earlier findings that computer vision technologies substantially improve behavioural monitoring while reducing dependence on manual observation (Fuentes et al., 2022; Trabachini et al., 2025).

VI. Conclusion

The rapid advancement of Artificial Intelligence (AI), Internet of Things (IoT), Computer Vision, and Precision Livestock Farming (PLF) has created new opportunities for transforming conventional livestock management into intelligent, sustainable, and welfare-oriented production systems. However, existing livestock monitoring approaches primarily focus on isolated applications such as disease diagnosis, behaviour recognition, or environmental sensing, limiting their capability to provide comprehensive and actionable decision support. Motivated by these limitations, the present study proposed an Artificial Intelligence-Based Decision Support System (AI-DSS) that integrates multimodal sensing, explainable artificial intelligence, intelligent data fusion, and decision-support mechanisms for sustainable animal environment management and welfare assessment. The proposed framework combines environmental monitoring, behavioural analysis, physiological sensing, machine learning, deep learning, and explainable AI into a unified architecture capable of continuously evaluating animal welfare and environmental conditions. By integrating data from IoT sensors, surveillance cameras, and wearable devices, the AI-DSS provides comprehensive situational awareness of livestock environments while automatically identifying behavioural abnormalities, environmental stress, and potential health risks. Unlike conventional monitoring systems that simply generate predictive outputs, the proposed framework incorporates an intelligent decision-support engine that produces transparent and actionable recommendations to assist farm managers in implementing timely interventions. The experimental evaluation demonstrated that the proposed AI-DSS consistently outperformed conventional machine learning and deep learning models across multiple evaluation metrics. The integration of YOLO-based animal detection, Vision Transformer-based behaviour recognition, Random Forest welfare classification, XGBoost disease prediction, and LSTM-based environmental forecasting significantly improved classification performance through multimodal data fusion and hybrid ensemble learning. Furthermore, the incorporation of Explainable Artificial Intelligence using SHAP enabled transparent interpretation of prediction results, thereby improving user confidence and facilitating evidence-based decision-making. An important contribution of this research is the introduction of the Animal Sustainability Index (ASI), which integrates environmental quality, animal welfare, health status, resource utilization, and energy efficiency into a single comprehensive sustainability indicator. Unlike conventional welfare assessment methods that evaluate individual performance indicators separately, the ASI enables holistic evaluation of livestock production systems while supporting strategic management decisions aimed at improving both productivity and sustainability. This integrated assessment framework assists veterinarians, livestock managers, policymakers, and agricultural consultants in identifying operational weaknesses and prioritizing corrective actions.

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