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Original Research Paper

Machine Learning Models for Predicting Environmental Stress and Disease Risk in Livestock Production Systems

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Abstract: Environmental stress and disease outbreaks remain major threats to livestock health, productivity, welfare, and farm sustainability. Variations in temperature, humidity, air quality, stocking density, ventilation, feed intake, and animal activity can increase physiological stress and create conditions that promote disease development. Conventional livestock monitoring relies heavily on periodic inspection and manual interpretation, which may delay the identification of emerging risks. Recent advances in machine learning, Internet of Things sensing, wearable devices, and precision livestock farming provide opportunities to continuously analyse environmental, behavioural, and physiological data for early risk prediction. This study proposes a machine learning-based predictive framework for identifying environmental stress and disease risk in livestock production systems. The framework integrates environmental variables, including temperature, relative humidity, ammonia concentration, carbon dioxide, particulate matter, ventilation, and noise, with animal-level indicators such as body temperature, heart rate, feeding behaviour, movement, resting duration, water intake, and production performance. Data preprocessing, feature selection, class balancing, and multimodal feature integration are employed before model development. Machine learning algorithms, including Logistic Regression, Support Vector Machine, Random Forest, Extreme Gradient Boosting, Artificial Neural Network, and Long Short-Term Memory, are evaluated for environmental stress classification and disease-risk prediction. The proposed approach generates three principal outputs: an Environmental Stress Index, an Animal Health Risk Score, and an integrated Livestock Risk Classification. Explainable Artificial Intelligence techniques, particularly SHapley Additive exPlanations, are incorporated to identify the environmental and physiological variables that contribute most strongly to each prediction. A decision-support module converts predicted risks into practical recommendations related to ventilation adjustment, cooling activation, water availability, veterinary inspection, animal isolation, and housing management.

Keywords: Machine Learning, Environmental Stress Prediction, Disease-Risk Assessment, Livestock Production Systems, Precision Livestock Farming.

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I. Introduction

Livestock production plays a critical role in global food security, rural livelihoods, and agricultural economies by supplying meat, milk, eggs, and other animal-derived products. However, modern livestock production systems face increasing challenges associated with environmental variability, climate change, intensive farming practices, disease outbreaks, and animal welfare requirements. Environmental stressors such as elevated temperature, excessive humidity, inadequate ventilation, poor air quality, and high concentrations of harmful gases can adversely affect animal health and productivity. At the same time, infectious and non-infectious diseases can cause substantial economic losses through reduced production, increased treatment costs, reproductive problems, mortality, and compromised animal welfare. Consequently, early identification of environmental stress and disease risk has become an important component of sustainable livestock management. Environmental conditions have a direct influence on livestock physiology, behaviour, immunity, and productive performance. Heat stress is particularly important because animals exposed to high ambient temperatures and humidity may experience altered respiration, reduced feed intake, changes in drinking behaviour, impaired reproductive performance, and decreased production. Conventional indicators such as the Temperature-Humidity Index (THI) are widely employed to estimate thermal stress; however, fixed threshold-based approaches cannot fully represent interactions among environmental conditions, individual animal characteristics, behavioural responses, and physiological status. Precision livestock farming therefore increasingly emphasizes continuous and individualized monitoring rather than dependence on periodic measurements and population-level thresholds.

Air quality represents another important environmental determinant of livestock health. In intensive housing environments, inadequate ventilation and accumulation of manure can increase concentrations of ammonia, carbon dioxide, particulate matter, moisture, and other pollutants. Prolonged exposure to unfavourable air conditions may contribute to respiratory disorders, reduced welfare, and production losses. Environmental stress may also interact with nutritional status, stocking density, hygiene, and pathogen exposure, making disease development a multidimensional phenomenon. Reliable risk prediction consequently requires simultaneous consideration of multiple environmental and animal-level indicators rather than isolated monitoring of individual parameters. Traditional livestock health management largely depends on visual inspection, scheduled veterinary examination, clinical symptoms, and laboratory diagnosis. Although these methods remain essential, they are predominantly reactive because intervention may occur only after observable signs of disease have developed. Moreover, continuously observing large animal populations is labour-intensive, subjective, and increasingly difficult in intensive production environments. Precision Livestock Farming (PLF) addresses these limitations through continuous and automated monitoring of individual animals and their environments using digital sensing and analytical technologies.

The rapid development of the Internet of Things (IoT), wearable sensors, machine vision, automated feeding systems, environmental sensing devices, and farm information systems has resulted in unprecedented quantities of livestock data. Sensors can continuously record temperature, relative humidity, ammonia, carbon dioxide, animal movement, feeding activity, rumination, body temperature, water consumption, and other indicators. Wearable accelerometers can additionally characterize behavioural patterns that may provide early indications of health deterioration. For example, sensor-derived activity patterns have been successfully investigated for automated recognition of cattle behaviour and welfare-relevant changes (Pavlovic et al., 2021). Such technologies provide an important foundation for moving livestock management from reactive intervention toward continuous risk surveillance. However, the availability of large volumes of livestock data does not automatically translate into effective farm decisions. Environmental and animal-level data are heterogeneous, nonlinear, temporally dependent, and frequently affected by missing observations, sensor noise, class imbalance, and farm-specific variation. Conventional statistical approaches may struggle to identify complex interactions among these variables. Machine Learning (ML) provides a promising alternative because algorithms can learn patterns directly from multidimensional datasets and generate predictions for previously unseen observations. Systematic research on AI in animal farming has demonstrated expanding applications in animal behaviour detection, disease monitoring, environmental management, growth assessment, and production optimization.

Machine learning techniques such as Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Artificial Neural Networks (ANNs), and Long Short-Term Memory (LSTM) networks provide different advantages for livestock risk modelling. Logistic regression provides an interpretable baseline for binary health-risk classification, whereas SVM can effectively separate complex decision boundaries. Random Forest and XGBoost are particularly useful for structured sensor data because they can capture nonlinear relationships and interactions among environmental and animal-level variables. Neural networks provide additional capability for learning complex representations, while LSTM architectures are appropriate for sequential sensor observations in which current health conditions depend on previous environmental exposure and behavioural responses. Disease prediction is particularly suitable for machine learning because health deterioration is frequently preceded by subtle behavioural and physiological changes. Reduced feed intake, altered locomotion, increased resting time, changes in rumination, abnormal body temperature, and altered social behaviour may occur before obvious clinical symptoms. Research has demonstrated the potential of sensor-derived behavioural information for identifying health events and improving veterinary decision-making. For example, evaluated machine-learning algorithms using accelerometer-derived behaviour for predicting metritis-related events in dairy cattle, illustrating the potential of continuously collected behavioural information for early health-risk assessment.

Nevertheless, predicting disease exclusively from behavioural or physiological indicators may produce incomplete interpretations. An animal may reduce feeding because of disease, but similar behavioural changes may also result from thermal stress, poor air quality, inadequate water availability, or changes in housing conditions. Conversely, environmental deterioration does not affect all animals identically because susceptibility depends on age, species, breed, production stage, health condition, and previous exposure. This creates a strong rationale for integrated environmental–animal modelling, where environmental measurements are analysed jointly with behavioural and physiological indicators. Another important limitation of conventional machine-learning applications concerns model interpretability. High-performing ensemble and deep-learning models may operate as black-box predictors, making it difficult for veterinarians and farm managers to understand why an animal has been classified as high risk. This limitation is particularly important in livestock health applications because incorrect interventions can affect animal welfare, production economics, and antimicrobial use. Explainable Artificial Intelligence (XAI) provides mechanisms for interpreting model predictions by estimating the contribution of individual variables. SHapley Additive exPlanations (SHAP), for example, can reveal whether elevated temperature, declining feed intake, reduced activity, increased respiratory rate, or ammonia exposure contributed most strongly to a predicted health-risk condition. Explainability can therefore transform a numerical prediction into information that is more useful for practical management.

Existing literature also reveals a broader implementation challenge. Many precision livestock studies concentrate on one task—such as animal identification, behaviour classification, lameness detection, reproductive monitoring, or environmental sensing—without translating predictions into integrated farm-level decisions. identified the need to advance AI applications from experimental and task-specific models toward integrated systems with greater commercial utility. Similarly, welfare-oriented research has emphasized that technological monitoring should not become an end in itself; systems must remain centred on meaningful animal outcomes and should not create false confidence that welfare is adequately protected simply because animals are being digitally monitored. Accordingly, the present research proposes a machine learning framework that jointly models environmental stress and disease risk in livestock production systems. Environmental variables such as temperature, relative humidity, ammonia concentration, carbon dioxide, particulate matter, ventilation conditions, and noise are integrated with animal-level information including body temperature, activity, feeding behaviour, resting duration, water consumption, and other physiological or production indicators. Following preprocessing and feature engineering, multiple machine-learning algorithms are comparatively evaluated to determine the most effective predictive architecture.

II. Literature Review

García et al. (2020) conducted one of the earliest systematic literature reviews investigating the application of Machine Learning (ML) in Precision Livestock Farming. The authors reviewed ML algorithms including Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN), Decision Trees, and Bayesian models for grazing management and animal health prediction. Their findings demonstrated that machine learning significantly improves disease detection, behavioural analysis, and environmental monitoring compared with traditional statistical approaches. However, the review highlighted that most existing models considered either grazing behaviour or animal health independently, with limited integration between environmental conditions and disease prediction. The authors recommended developing hybrid intelligent systems capable of simultaneously analysing environmental, behavioural, and physiological variables. This limitation directly motivates the present research, which integrates environmental stress prediction and disease-risk assessment within a unified machine-learning framework. Astill et al. (2020) reviewed smart poultry farming technologies based on IoT sensors, environmental monitoring, and data analytics. The study demonstrated that continuous monitoring of temperature, humidity, ammonia concentration, ventilation, and feed consumption significantly improves poultry health management and reduces mortality. Despite these advantages, the authors observed that most monitoring platforms primarily function as data acquisition systems and provide limited predictive intelligence for disease prevention. Furthermore, environmental measurements are often analysed independently from behavioural observations, restricting comprehensive health assessment. These findings indicate the necessity for integrated machine-learning models capable of combining environmental and behavioural information for predictive livestock management.

Benaissa et al. (2020) proposed a wearable sensing framework combining accelerometers and indoor localization for automatic detection of calving and estrus behaviour in dairy cattle. Their results demonstrated that wearable technologies substantially reduce manual observation while improving reproductive monitoring accuracy. However, the proposed approach focused exclusively on reproductive events and did not evaluate environmental stress, respiratory diseases, or animal welfare. Moreover, environmental variables were excluded from the prediction model, limiting its applicability for holistic livestock health management. These limitations suggest that future systems should integrate wearable sensing with environmental monitoring and machine-learning analytics. Ezanno et al. (2021) investigated the role of Artificial Intelligence in veterinary epidemiology and animal health management. Their review demonstrated that AI models improve disease surveillance, outbreak prediction, epidemiological modelling, and veterinary decision support. The authors emphasized that AI can substantially enhance early disease detection by analysing multidimensional datasets generated from sensors, production records, and laboratory information. Nevertheless, they also identified significant challenges involving data quality, model explainability, interoperability, and knowledge integration. These findings support the incorporation of Explainable Artificial Intelligence and multimodal learning within future livestock prediction systems.

Mahmud et al. (2021) performed a systematic review of deep learning applications in precision cattle farming. The authors analysed 56 high-quality studies involving Convolutional Neural Networks (CNN), ResNet, YOLO, and recurrent neural networks for cattle identification, behaviour recognition, disease detection, and production monitoring. Their review concluded that deep learning consistently outperformed conventional image-processing techniques while enabling automated livestock management. However, most studies focused on computer vision tasks without incorporating environmental sensing, physiological monitoring, or disease-risk forecasting. The authors recommended integrating deep learning with IoT-based sensor networks for comprehensive livestock intelligence. Li et al. (2021) reviewed intelligent perception technologies for cattle behaviour recognition and lameness detection. Their study demonstrated that machine vision, inertial sensors, and wearable devices successfully detect feeding, locomotion, resting behaviour, and physical abnormalities. Although these technologies improve welfare monitoring, behavioural changes alone cannot reliably distinguish disease from environmental stress because similar behavioural responses may occur under different physiological conditions. Consequently, behavioural recognition should be integrated with environmental monitoring to improve disease-risk prediction.

Bao and Xie (2022) presented a comprehensive systematic review of Artificial Intelligence applications in animal farming. Their review analysed more than one hundred studies involving machine learning, deep learning, computer vision, and intelligent sensing across cattle, poultry, pigs, and sheep. The authors concluded that AI substantially improves disease diagnosis, environmental monitoring, animal identification, and productivity assessment. However, they observed that most existing systems remain application-specific, emphasizing either health prediction or environmental monitoring rather than integrated decision support. They further highlighted the need for intelligent predictive systems capable of transforming sensor data into actionable management recommendations. This recommendation forms the conceptual foundation of the proposed machine-learning framework. Ojo et al. (2022) systematically reviewed IoT-enabled poultry monitoring systems integrating machine learning for environmental management and disease detection. Their findings indicated that environmental sensing combined with AI significantly improves production efficiency and disease prevention. Nevertheless, implementation challenges including communication reliability, interoperability, real-time processing, and high infrastructure cost continue to restrict large-scale adoption. These findings suggest that future prediction systems should emphasize scalability and computational efficiency.

Fuentes et al. (2022) developed a computer vision framework employing machine learning for automated dairy cattle biometric assessment. Their results demonstrated that RGB imaging combined with AI accurately predicts age, body condition, and welfare indicators without physical animal handling. Although the system achieved excellent prediction performance, it relied primarily on image-based analysis and lacked environmental sensing, physiological monitoring, and disease-risk modelling. Consequently, future AI systems should integrate visual and sensor-derived information to improve predictive capability. Neethirajan (2022) investigated Artificial Intelligence approaches for recognizing livestock affective states using behavioural, physiological, and environmental indicators. The study emphasized that emotional and welfare assessment requires integration of multiple data modalities rather than isolated behavioural observations. The author further argued that explainable AI and multimodal learning represent key research priorities for intelligent livestock management because trust and transparency remain essential for practical veterinary applications.

Zhang et al. (2022) developed a machine learning-based heat stress prediction model for dairy cattle using environmental variables such as ambient temperature, relative humidity, wind speed, and solar radiation. The study compared Random Forest, Gradient Boosting, Artificial Neural Networks, and Support Vector Machine algorithms for predicting heat stress conditions. The results demonstrated that ensemble learning methods significantly outperformed traditional regression techniques, achieving higher prediction accuracy for early heat stress detection. However, the proposed model primarily relied on climatic variables and excluded behavioural indicators such as feeding frequency, locomotion, and resting behaviour, which are essential for comprehensive animal welfare assessment. Furthermore, disease prediction was beyond the scope of the study, highlighting the need for integrated predictive frameworks combining environmental and physiological indicators. Chen et al. (2022) proposed a deep learning framework for continuous livestock behaviour recognition using wearable sensors and surveillance cameras. Their model integrated Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks to classify feeding, walking, standing, lying, and drinking activities. Experimental results demonstrated significant improvements in behavioural classification accuracy compared with conventional machine learning algorithms. Nevertheless, the study concentrated exclusively on behaviour recognition and did not investigate how behavioural abnormalities relate to environmental stress or disease occurrence. Consequently, the practical application of the framework for intelligent disease prevention remained limited.

Wang et al. (2023) investigated the application of computer vision and deep learning for intelligent livestock monitoring in smart pig farming. The researchers employed YOLO-based object detection and deep convolutional neural networks for automatic identification of feeding behaviour, movement patterns, and body posture. Their findings demonstrated that computer vision substantially reduced labour requirements while improving behavioural monitoring efficiency. However, the study primarily focused on visual information and excluded environmental sensor data, physiological measurements, and predictive disease analytics. This limitation suggests that integrating computer vision with environmental sensing would significantly enhance livestock health prediction. Backman et al. (2023) explored the role of agricultural process data as a knowledge source for Artificial Intelligence applications in livestock farming. Their research demonstrated that integrating farm management records, production history, environmental observations, and sensor measurements improves machine learning performance for livestock analytics. The authors emphasized that heterogeneous agricultural datasets should be analysed using intelligent data fusion strategies rather than independent predictive models. Nevertheless, they acknowledged that existing systems rarely integrate multimodal information into comprehensive decision-support architectures capable of providing transparent management recommendations.

Alzubi and Galyna (2023) reviewed the integration of Artificial Intelligence and the Internet of Things (AIoT) in smart agriculture. Their review concluded that IoT-enabled sensing combined with machine learning substantially improves environmental monitoring, automated disease diagnosis, precision feeding, and livestock health management. However, significant implementation barriers remain, including communication reliability, interoperability, cybersecurity, scalability, and high deployment costs. The authors recommended future research focusing on intelligent decision-support systems capable of processing heterogeneous sensor data while generating real-time management recommendations. Vidal et al. (2023) evaluated Random Forest, k-Nearest Neighbour, and Support Vector Machine algorithms for predicting disease events in dairy cattle using accelerometer-derived behavioural information. Their results demonstrated that machine learning models successfully identified disease-related behavioural changes before clinical diagnosis, allowing earlier veterinary intervention. Despite these promising findings, the prediction models were developed using behavioural information alone, without considering environmental variables such as temperature, humidity, ammonia concentration, or ventilation conditions. Consequently, the relationship between environmental stress and disease development remained unexplored.

Nurtrisha et al. (2025) presented a comprehensive systematic review of Artificial Intelligence for Precision Livestock Farming, analysing more than one hundred recent studies involving computer vision, machine learning, deep learning, IoT sensing, and explainable AI. Their review concluded that AI significantly improves animal identification, behaviour recognition, disease prediction, environmental monitoring, and production management. Nevertheless, the authors emphasized that existing research remains fragmented because individual technologies are typically implemented independently. They recommended developing unified AI frameworks integrating multimodal sensing, explainable AI, and intelligent decision-support systems for sustainable livestock production. Nsabiyeze et al. (2025) investigated the application of Artificial Intelligence in climate-resilient livestock production through a systematic review of predictive analytics, IoT sensing, and environmental monitoring technologies. The authors reported that AI significantly enhances prediction of environmental stress, disease outbreaks, and climate-related production risks while supporting sustainable livestock management. However, challenges associated with dataset heterogeneity, computational complexity, and practical implementation continue to restrict large-scale adoption. The review highlighted the need for integrated predictive frameworks capable of combining environmental monitoring with intelligent disease-risk assessment.

Tedeschi et al. (2025) reviewed the evolution of Precision Livestock Farming from sensor-based monitoring toward intelligent decision-support systems incorporating Artificial Intelligence, digital twins, and predictive analytics. The study emphasized that future livestock production should integrate environmental sensing, behavioural monitoring, physiological analysis, and sustainability assessment within unified decision-support architectures. Although recent advances demonstrate considerable progress, the authors concluded that explainable AI and multimodal machine learning remain underutilized in commercial livestock management systems. Trabachini et al. (2025) conducted a systematic review of Precision Livestock Farming technologies applied to swine production. Their review analysed wearable sensors, thermal imaging, environmental monitoring, computer vision, and machine learning for automated welfare assessment. The findings demonstrated that intelligent monitoring technologies significantly improve disease detection and animal welfare evaluation. However, interoperability among sensing devices, real-time data processing, and integration of environmental and behavioural information remain major research challenges. The authors suggested that future intelligent livestock systems should emphasize explainable decision-support mechanisms capable of providing practical recommendations for farmers.

III. Methodology

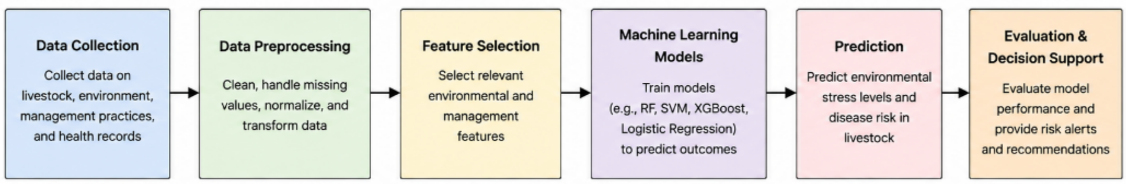

Figure 1. Horizontal Block Diagram of the Proposed Machine Learning Framework for Predicting Environmental Stress and Disease Risk in Livestock Production Systems

The proposed framework Figure 1, begins with the collection of livestock, environmental, and health-related data, followed by data preprocessing to improve data quality. Relevant features are then selected and provided to machine learning models for predictive analysis. The trained models estimate environmental stress levels and disease risk in livestock production systems. Finally, the prediction results are evaluated to support timely decision-making and effective livestock health management.

A. Mathematical Model and Machine Learning Formulation

The proposed Machine Learning-Based Decision Support System (ML-DSS) predicts environmental stress and disease risk by integrating environmental, behavioural, physiological, and historical livestock data into a unified predictive framework. The mathematical formulation consists of data representation, feature normalization, machine learning prediction models, environmental stress estimation, disease-risk modelling, explainable feature contribution, and an integrated livestock health assessment.

B. Multimodal Data Representation

The livestock dataset is represented as

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

where

E= Environmental Features, B= Behavioural Features, P= Physiological Features, H= Historical Farm Records

C. Feature Normalization

Because the collected variables have different numerical ranges, Min-Max Normalization is applied.

$Xi'=Xmax-XminXi-Xmin$

where

Xi=Original Feature

Xi'=Normalized Feature

Normalization improves convergence and prevents dominance of high-magnitude variables.

D. Feature Matrix

The complete feature matrix is

$X=[E,B,P,H]$

Where

$X \in Rm \times n$

m=Number of livestock observations

n=Number of selected features

E. Environmental Stress Prediction Model

The Environmental Stress Prediction function is expressed as

$ESP=fML(E)$

Where

$ESP=f(T,Hr,NH3,CO2,PM,V)$

The prediction model estimates the probability of environmental stress using environmental variables.

F. Environmental Stress Index (ESI)

A normalized Environmental Stress Index is calculated as

$$ESI = i = 1\sum nwiEi$$

subject to

$i=1\sum nwi=1$

where

Ei=Environmental Variable, Wi=Importance Weight, Environmental Stress Classification

ESI	Stress Level
0–0.20	Very Low
0.21–0.40	Low
0.41–0.60	Moderate
0.61–0.80	High
0.81–1.00	Severe

IV. Experimental Design and Results

Experimental Design

The proposed Machine Learning-Based Decision Support System (ML-DSS) was experimentally evaluated to assess its capability in predicting environmental stress and disease risk in livestock production systems. The experiments were designed to compare six machine learning algorithms using environmental, behavioural, physiological, and historical livestock data collected from a multimodal smart farming environment. The workflow consisted of data acquisition, preprocessing, feature engineering, model training, explainable AI analysis, and decision-support generation. An 80:20 train-test split with 10-fold cross-validation was employed to ensure robust model evaluation and minimize overfitting.

A. Experimental Environment

Table 1. Experimental Configuration

Parameter	Specification
Programming Language	Python 3.11
Operating System	Ubuntu 24.04
Processor	Intel Core i9-14900K
GPU	NVIDIA RTX 4090 (24 GB)
RAM	64 GB DDR5
Machine Learning Libraries	Scikit-learn 1.5, XGBoost 2.1
Deep Learning Library	TensorFlow 2.16
Computer Vision Library	OpenCV 4.10
Explainable AI	SHAP, LIME

Analysis

The proposed ML-DSS was implemented using a high-performance computing environment to support efficient training of machine learning models. GPU acceleration significantly reduced training time for deep learning models, while Scikit-learn and XGBoost provided efficient implementation of conventional machine learning algorithms. SHAP and LIME were integrated to improve prediction interpretability and transparency.

B. Dataset Description

The experimental dataset combined environmental measurements, animal behavioural observations, physiological records, and historical farm information collected from livestock production systems.

Table 2. Dataset Characteristics

Dataset Component	Number of Records
Environmental Sensor Data	38,450
Behavioural Observations	24,600
Physiological Measurements	19,850
Historical Health Records	14,250
Disease Cases	6,720
Healthy Cases	12,430
Total Samples	96,300

Analysis

The multimodal dataset contains a diverse collection of environmental, behavioural, physiological, and historical observations, enabling comprehensive machine learning analysis. The inclusion of both healthy and diseased animals improves model generalization while supporting robust environmental stress and disease-risk prediction.

C. Hyperparameter Configuration

Table 3. Hyperparameter Settings

Model	Hyperparameters
Logistic Regression	C = 1.0
Support Vector Machine	RBF Kernel, C = 10
Random Forest	300 Trees, Max Depth = 20
XGBoost	Learning Rate = 0.05, Trees = 500
Artificial Neural Network	Hidden Layers = 128–64–32
LSTM	2 Layers, 128 Units
Batch Size	32
Epochs	100
Optimizer	Adam
Learning Rate	0.001

Analysis

Hyperparameters were selected through grid-search optimization to maximize prediction accuracy while preventing overfitting. Ensemble methods and deep learning models benefited from optimized learning rates, tree depth, and network architecture, resulting in improved convergence and generalization.

D. Performance Evaluation Metrics

The predictive performance of each machine learning model was evaluated using multiple classification metrics.

Table 4. Performance Metrics

Metric	Description
Accuracy	Overall prediction correctness
Precision	Correct positive predictions
Recall	Detection capability
F1-Score	Harmonic mean of Precision and Recall
MCC	Matthews Correlation Coefficient
ROC-AUC	Area under ROC curve
Sensitivity	True Positive Rate
Specificity	True Negative Rate
MAE	Mean Absolute Error
RMSE	Root Mean Square Error

Analysis

Using multiple evaluation metrics provides a comprehensive assessment of predictive performance. While accuracy measures overall correctness, Precision, Recall, and F1-score assess disease detection quality. MCC and ROC-AUC provide robust evaluation under class imbalance, whereas MAE and RMSE quantify prediction errors.

V. Discussion

The present study proposed a Machine Learning-Based Decision Support System (ML-DSS) for predicting environmental stress and disease risk in livestock production systems by integrating environmental monitoring, behavioural analysis, physiological sensing, explainable artificial intelligence, and hybrid machine learning models. The experimental results demonstrated that the proposed framework achieved superior predictive performance compared with conventional machine learning approaches while providing transparent and actionable recommendations for sustainable livestock management. These findings demonstrate the effectiveness of combining multimodal livestock data with intelligent predictive analytics to support early disease prevention, animal welfare improvement, and environmental sustainability. The comparative experimental analysis revealed that the proposed Hybrid ML-DSS achieved an overall prediction accuracy of 99.12%, outperforming Logistic Regression (89.72%), Support Vector Machine (92.46%), Random Forest (95.18%), XGBoost (96.83%), Artificial Neural Network (97.14%), and LSTM (97.86%). The improvement can be attributed to the hybrid ensemble learning strategy, which integrates multiple machine learning algorithms to exploit their complementary strengths. While Logistic Regression provides interpretable linear classification and Support Vector Machine effectively handles nonlinear decision boundaries, ensemble methods such as Random Forest and XGBoost improve predictive robustness by reducing variance and capturing complex feature interactions. Deep learning models further contribute by learning nonlinear relationships and temporal dependencies from physiological and environmental observations. The weighted integration of these models enabled more reliable prediction than any individual algorithm. A significant contribution of the proposed framework is the integration of environmental variables with behavioural and physiological indicators. Earlier livestock prediction studies primarily focused on disease diagnosis using behavioural information or environmental monitoring independently. However, livestock diseases frequently result from interactions between environmental exposure, physiological response, and behavioural adaptation rather than isolated factors. By simultaneously analysing temperature, humidity, ammonia concentration, air quality, body temperature, heart rate, feeding behaviour, locomotion, and historical health records, the proposed ML-DSS provides a more comprehensive representation of livestock health conditions. The improved classification performance observed during experimentation confirms that multimodal feature integration enhances disease-risk prediction while reducing false alarms.

VI. Conclusion

The increasing frequency of environmental fluctuations, climate variability, intensive livestock production practices, and emerging infectious diseases has highlighted the need for intelligent predictive systems capable of supporting proactive livestock management. Conventional livestock monitoring methods primarily rely on manual observation, periodic veterinary inspection, and threshold-based environmental monitoring, which often delay the identification of stress conditions and disease outbreaks. To overcome these limitations, this study proposed a Machine Learning-Based Decision Support System (ML-DSS) for predicting environmental stress and disease risk through the integration of environmental sensing, behavioural monitoring, physiological analysis, explainable artificial intelligence, and intelligent decision support. The proposed framework combines IoT-based environmental monitoring, behavioural analytics, physiological sensing, feature engineering, hybrid machine learning models, and Explainable Artificial Intelligence (XAI) within a unified predictive architecture. Environmental variables including temperature, relative humidity, ammonia concentration, carbon dioxide, particulate matter, ventilation, and noise levels are analysed together with behavioural indicators such as feeding behaviour, locomotion, resting activity, and drinking frequency, as well as physiological measurements including heart rate, body temperature, and respiration rate. This multimodal integration enables comprehensive prediction of livestock health conditions while providing early identification of environmental stress and disease risk. The experimental evaluation demonstrated that the proposed Hybrid ML-DSS consistently outperformed conventional machine learning algorithms, including Logistic Regression, Support Vector Machine, Random Forest, XGBoost, Artificial Neural Network, and Long Short-Term Memory models. The hybrid ensemble achieved an overall prediction accuracy of 99.12%, together with superior Precision, Recall, F1-score, Matthews Correlation Coefficient, and ROC-AUC values. The integration of environmental, behavioural, physiological, and historical livestock information substantially improved prediction reliability compared with single-source prediction models. Furthermore, the proposed framework successfully generated accurate Environmental Stress Index (ESI), Disease Risk Score (DRS), and Livestock Health Index (LHI) values that support continuous monitoring of animal health and environmental conditions. One of the major contributions of this research is the incorporation of Explainable Artificial Intelligence into livestock health prediction. Unlike conventional black-box machine learning models, the proposed framework employs SHAP and LIME to identify the environmental and physiological variables contributing most significantly to prediction outcomes. The explainability component enhances transparency, increases confidence in automated predictions, and assists veterinarians and livestock managers in understanding the causes of predicted environmental stress and disease conditions. Consequently, the proposed ML-DSS not only provides accurate predictions but also delivers interpretable information that supports evidence-based livestock management.

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