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International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

Automated Animal Welfare Assessment Under Climate Change Using Deep Learning

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Abstract
Climate change is increasingly affecting livestock health and welfare through rising temperatures, humidity variations, heat waves, and extreme environmental conditions. Continuous assessment of animal welfare is therefore essential for sustainable and climate-resilient livestock management. This study presents a deep learning-based framework for automated animal welfare assessment by integrating visual, behavioural, and environmental information. Animal images and video sequences are analysed to identify welfare-related behaviours such as feeding, drinking, walking, standing, lying, resting, and abnormal inactivity. Environmental parameters, including temperature, relative humidity, seasonal conditions, and Temperature-Humidity Index, are integrated with the extracted behavioural features to provide climate-aware welfare assessment. Deep learning models are employed for automated feature extraction, behaviour recognition, temporal pattern analysis, climate-stress detection, and welfare-risk classification. The framework categorizes welfare conditions into normal, moderate concern, and high-risk levels and can generate early warnings when climate-induced behavioural abnormalities are detected. The resulting information can support management interventions related to ventilation, cooling, water availability, shade provision, and feeding schedules. The proposed approach reduces dependence on subjective manual observation while enabling continuous and scalable livestock monitoring. Overall, integrating deep learning with environmental intelligence provides a promising foundation for automated welfare assessment, early climate-stress detection, and sustainable livestock management.

Keywords: Animal Welfare, Climate Change, Deep Learning, Computer Vision, Climate Stress, Livestock Monitoring, Environmental Intelligence, Sustainable Livestock Farming.

1. Introduction
Animal welfare has become an important component of sustainable livestock production due to increasing concerns regarding animal health, productivity, environmental sustainability, and ethical farming practices. Livestock are continuously exposed to environmental conditions such as temperature, humidity, solar radiation, air quality, and seasonal variations. Climate change is intensifying these environmental pressures through rising temperatures, irregular rainfall, prolonged heat waves, and increasing frequency of extreme weather events. Such changes can significantly influence animal behaviour, physiological condition, disease susceptibility, feed intake, reproduction, and overall welfare. Therefore, continuous and reliable assessment of animal welfare under changing climatic conditions has become essential for modern livestock management.

1.1 Background and Motivation

Conventional animal welfare assessment generally depends on manual observation, periodic veterinary examination, behavioural scoring, and physiological measurements. Although these approaches provide useful information, they are often time-consuming, labour-intensive, subjective, and difficult to implement continuously in large livestock populations. Periodic assessment may also fail to identify subtle behavioural or physiological changes occurring during the early stages of environmental stress.

Recent developments in Artificial Intelligence (AI), computer vision, Internet of Things (IoT), and smart sensing technologies provide opportunities to automate animal welfare monitoring. In particular, deep learning models can automatically learn complex patterns from images, videos, sensor measurements, and environmental observations. Convolutional Neural Networks (CNNs), recurrent neural architectures, and vision-based deep learning models can be employed to identify posture, movement, activity, feeding behaviour, resting patterns, social interactions, and other welfare-related indicators [1]. Integration of these observations with climatic variables can support more comprehensive assessment of animal welfare.

1.2 Climate Change and Animal Welfare

Climate change introduces several direct and indirect risks to livestock welfare. Increasing ambient temperature and humidity can produce heat stress, while variations in rainfall and water availability can affect feed quality, drinking-water availability, and surrounding environmental conditions. Extreme climatic events may further increase the risk of disease, nutritional stress, reduced mobility, and abnormal behaviour. Animals experiencing climate-related stress can exhibit changes such as reduced feeding activity, increased water consumption, altered resting duration, changes in movement, abnormal posture, crowding around shaded areas, and reduced social activity. These behavioural responses can serve as observable indicators of declining welfare [2]. Consequently, combining animal-level observations with environmental variables such as temperature, relative humidity, heat index, and seasonal conditions can provide an effective basis for climate-aware welfare assessment.

1.3 Need for Automated Welfare Assessment

Large-scale livestock farms generate substantial amounts of visual, behavioural, physiological, and environmental data. Manual interpretation of these heterogeneous data is difficult and may prevent timely identification of welfare problems. An automated assessment framework can continuously analyse animal behaviour and environmental conditions to identify abnormal patterns and estimate welfare risks. Deep learning provides an effective mechanism for extracting meaningful information from complex livestock data. Vision-based models can analyse animal images and video streams, while temporal models can identify behavioural changes over time. Environmental information can additionally be integrated with animal observations to distinguish normal behavioural variations from climate-induced stress responses [3]. Such automated assessment can enable early intervention, reduce dependence on continuous human observation, and support evidence-based welfare management.

1.4 Research Objectives and Contributions

This study focuses on developing a deep learning-based approach for automated assessment of animal welfare under climate change conditions. The framework integrates animal behavioural information with environmental and climatic variables to identify welfare-related patterns and climate-induced stress conditions. Deep learning models are employed to analyse animal observations, detect relevant welfare indicators, and classify different levels of welfare risk.

The major contribution of the study is the development of a climate-aware automated welfare assessment framework capable of transforming heterogeneous animal and environmental data into meaningful welfare information. The proposed approach supports continuous monitoring, early identification of abnormal behaviour, recognition of climate-related stress, and data-driven welfare risk assessment. The resulting information can assist farmers and livestock managers in implementing timely interventions and improving animal health, welfare, productivity, and sustainability under changing climatic conditions.

2. Literature Review

Animal welfare monitoring has evolved from conventional observation-based assessment toward automated approaches supported by sensors, computer vision, machine learning, and deep learning. At the same time, climate change has increased the importance of continuously evaluating environmental stress and its influence on livestock behaviour and health. Existing studies demonstrate considerable progress in automated animal monitoring; however, integrating climate information with deep learning-based welfare assessment remains an important research challenge.

2.1 Animal Welfare Assessment Methods

Traditional animal welfare assessment is generally based on behavioural observation, physiological measurements, veterinary examination, and farm-level indicators. Common indicators include body condition, feeding and drinking behaviour, mobility, posture, social interaction, resting patterns, injury, disease occurrence, and reproductive performance. Physiological parameters such as body temperature, heart rate, respiration rate, and stress-related biomarkers can provide additional evidence regarding animal health and welfare [4]. Although these approaches are widely used, they depend considerably on trained personnel and periodic observations. Manual assessment can also be affected by observer variability and may become difficult when monitoring large herds. Furthermore, intermittent examination provides only limited information about short-term behavioural changes or rapidly developing environmental stress [5]. These limitations have encouraged the adoption of automated and continuous welfare-monitoring technologies.

2.2 Climate-Induced Stress and Welfare Indicators

Environmental conditions strongly influence livestock health and behaviour. Temperature, humidity, solar radiation, rainfall, air movement, and seasonal variation can affect thermal comfort and physiological regulation. Among these factors, heat stress has received significant attention because increasing temperatures can reduce feed intake, alter drinking behaviour, increase respiration, affect reproduction, and decrease animal productivity [6]. Behavioural changes can provide early indications of climate-induced stress. Animals may reduce movement and feeding activity, increase standing duration or water consumption, seek shaded areas, modify resting behaviour, or demonstrate abnormal social interactions during periods of environmental discomfort. Physiological responses such as increased body temperature and respiration rate may accompany these behavioural changes [7]. Therefore, simultaneous analysis of environmental and animal-level indicators can provide a more reliable representation of welfare conditions than either source alone.

2.3 AI and Deep Learning in Animal Monitoring

Artificial Intelligence has increasingly been applied to livestock monitoring for disease identification, behaviour recognition, productivity prediction, and welfare assessment. Machine learning techniques can analyse structured information collected from environmental sensors, wearable devices, feeding systems, and farm records. However, conventional machine learning approaches generally require manual feature selection and may have difficulty representing complex patterns within high-dimensional visual and temporal data. Deep learning provides greater capability for automatically learning discriminative representations from large datasets. Convolutional Neural Networks (CNNs) have been extensively applied to image-based animal detection, identification, posture recognition, and behavioural classification. Temporal architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks can analyse sequential behavioural and sensor observations [8][9]. More recent attention-based and transformer architectures further enable modelling of long-range dependencies within complex temporal data [10]. These developments provide a foundation for intelligent welfare monitoring in which behavioural, physiological, and environmental patterns can be automatically learned rather than being completely dependent on manually defined welfare rules.

2.4 Vision-Based Animal Behaviour Analysis

Computer vision offers a non-invasive mechanism for continuous monitoring of livestock. Cameras installed within animal housing or farm environments can generate image and video streams without requiring physical contact with individual animals. Deep learning-based object detection and tracking methods can locate individual animals and monitor their movement across consecutive video frames. Vision-based systems can identify welfare-related behaviours including feeding, drinking, standing, lying, walking, social interaction, inactivity, and abnormal posture [11]. Changes in the frequency or duration of these activities can provide valuable information regarding discomfort, disease, injury, or environmental stress. Automated tracking can additionally support the analysis of movement trajectories, activity levels, spatial distribution, and group behaviour [12]. When combined with climatic observations, vision-based behaviour analysis can provide additional contextual information. For example, prolonged inactivity during high-temperature conditions may represent heat-related discomfort, while clustering near drinking or shaded areas may indicate thermal stress [13][14]. Therefore, contextual interpretation is important for transforming behavioural recognition into meaningful welfare assessment.

2.5 Research Gaps and Challenges

Despite significant developments in AI-enabled livestock monitoring, several limitations remain. Many existing systems focus primarily on a single task such as animal detection, behaviour recognition, disease identification, or productivity prediction. Environmental conditions are frequently treated as supplementary variables rather than being systematically integrated into welfare assessment. Another important challenge is the heterogeneity of livestock data. Visual observations, environmental measurements, behavioural sequences, and physiological information have different structures, sampling frequencies, and levels of uncertainty. Developing effective mechanisms for integrating these heterogeneous sources remains necessary. Model performance can also be affected by variations in animal breed, age, farm configuration, camera position, illumination, weather conditions, and geographical location. Furthermore, limited labelled datasets, class imbalance, model interpretability, computational requirements, and cross-farm generalizability continue to restrict practical deployment. Climate change introduces an additional challenge because welfare models developed under historical environmental conditions may not adequately represent emerging or extreme climatic patterns.

These gaps indicate the need for a unified climate-aware deep learning framework that combines animal observations with environmental information for automated welfare assessment. Such a framework should support behavioural recognition, climate-stress identification, welfare-risk classification, and continuous decision support while maintaining sufficient robustness for deployment under diverse livestock and environmental conditions.

3. Proposed Deep Learning Framework

The proposed framework is designed to automatically assess animal welfare by integrating animal-level observations with environmental and climatic information. The framework uses deep learning to identify behavioural patterns associated with normal conditions, discomfort, and climate-induced stress. It follows a structured processing sequence from data acquisition and preprocessing to feature extraction, multimodal integration, welfare classification, and risk assessment. The overall objective is to provide continuous and data-driven welfare monitoring that can support timely management decisions under changing climatic conditions.

3.1 Overall System Architecture

The proposed architecture combines visual animal monitoring with environmental sensing and deep learning-based analysis. Cameras capture animal images and video streams, while environmental sensors record climatic parameters such as temperature, relative humidity, solar radiation, air quality, and other farm-level conditions. Where available, physiological or wearable-sensor measurements can also be incorporated.

The overall processing sequence of the proposed framework can be represented as:

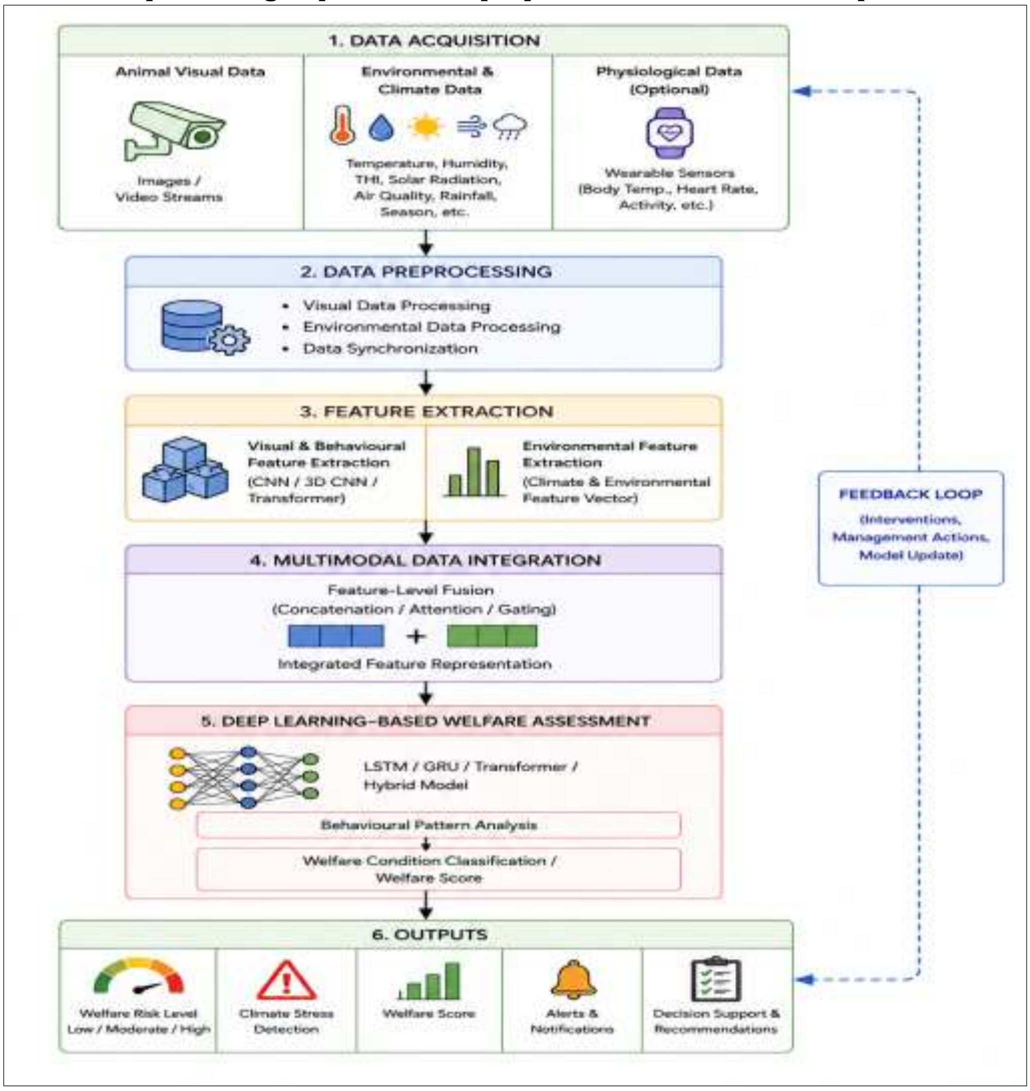

Figure 1. Proposed Climate-Aware Deep Learning Framework for Automated Animal Welfare Assessment. The architecture enables behavioural observations to be interpreted within their corresponding environmental context. This is important because a behavioural change may have different welfare implications depending on climatic conditions.

3.2 Animal and Environmental Data Acquisition

Data acquisition represents the first stage of the proposed framework. Animal-level information is primarily collected through cameras installed at appropriate locations within livestock facilities. The captured images and video sequences provide information related to animal posture, movement, feeding, drinking, resting, social interaction, and spatial distribution. Environmental sensors simultaneously collect parameters such as temperature, relative humidity, air quality, solar radiation, and ventilation conditions. Derived indicators such as the Temperature-Humidity Index (THI) can also be calculated to represent thermal stress conditions. Seasonal and weather information may additionally be incorporated to capture longer-term climate variability. Each animal observation is associated with the corresponding environmental measurements and timestamp. This synchronization creates a combined dataset capable of representing both animal behaviour and the climatic conditions under which the behaviour occurs.

3.3 Data Preprocessing and Feature Extraction

The collected data are preprocessed before being supplied to the deep learning model. Visual preprocessing includes image resizing, normalization, frame extraction, noise reduction, and data augmentation. Augmentation operations can improve model robustness against variations in illumination, orientation, camera position, and environmental conditions. Environmental sensor data are processed by removing erroneous measurements, handling missing values, normalizing variables, and synchronizing measurements with the visual observations. Temporal segmentation can further organize observations into appropriate time windows for identifying behavioural changes. Deep learning models are subsequently employed for automatic feature extraction. CNN-based architectures can learn spatial characteristics associated with posture, body orientation, movement, and activity. Temporal networks can extract sequential patterns representing changes in behaviour over time. Environmental features representing temperature, humidity, THI, season, and related conditions are retained for subsequent integration with the learned animal features.

3.4 Deep Learning-Based Welfare Assessment

The central component of the proposed framework is the deep learning-based welfare assessment model. The model receives the extracted behavioural and visual features and learns patterns associated with different animal welfare conditions. CNN-based architectures can be employed for image-level analysis, while temporal models such as LSTM or GRU networks can capture behavioural evolution across consecutive observations. The model can identify welfare-related activities such as feeding, drinking, walking, standing, lying, resting, and abnormal inactivity. Detected behaviours are analysed in terms of their frequency, duration, and temporal variation. Significant deviations from normal behavioural patterns can indicate discomfort or potential welfare deterioration. The welfare assessment can be formulated as a classification problem in which observations are categorized into levels such as normal welfare, moderate welfare concern, and high welfare risk. A probability or welfare score can additionally be generated to support continuous monitoring rather than relying exclusively on discrete classifications.

3.5 Climate-Aware Data Integration

Climate-aware integration distinguishes the proposed framework from conventional behaviour-only welfare monitoring approaches. Deep visual and behavioural features are combined with environmental parameters to establish the relationship between animal responses and climatic stress. For example, reduced feeding, increased drinking, prolonged standing, reduced movement, or clustering near shaded areas may become particularly important when observed simultaneously with elevated temperature and humidity. The integrated representation therefore enables the model to distinguish ordinary behavioural variation from patterns potentially associated with environmental stress.

Feature-level fusion can be employed to combine learned visual representations with normalized environmental variables before welfare classification. Temporal information can further capture how behavioural responses develop as environmental conditions change. This integrated analysis produces a climate-aware welfare risk estimate representing both the observed animal condition and the associated environmental exposure. The proposed framework therefore transforms heterogeneous animal and environmental observations into an automated welfare assessment mechanism. By combining deep learning-based behavioural analysis with climate-aware contextual information, the framework supports early detection of climate-induced stress and provides a foundation for intelligent and sustainable animal welfare management.

4. Experimental Analysis and Performance Evaluation

The experimental analysis evaluates the ability of the proposed deep learning framework to identify animal welfare indicators and assess climate-related stress from integrated animal and environmental data. The evaluation focuses on behavioural classification, climate-stress recognition, welfare-risk assessment, and overall predictive performance. Comparative analysis is also considered to determine the benefit of integrating environmental information with deep learning-based animal monitoring.

4.1 Experimental Setup and Dataset

The experimental dataset consists of animal images and video sequences combined with corresponding environmental observations. Visual data represent different animal activities and welfare conditions, including feeding, drinking, standing, lying, walking, resting, and abnormal inactivity. Environmental attributes include temperature, relative humidity, solar radiation, air-quality indicators, seasonal information, and the Temperature-Humidity Index (THI). The collected data are divided into training, validation, and testing subsets to support unbiased performance evaluation. Image frames are resized and normalized before model training, while augmentation techniques such as rotation, scaling, cropping, and horizontal transformation are applied to improve model generalization. Environmental attributes are normalized and synchronized with the corresponding visual observations using timestamps. The deep learning model is trained to extract relevant visual and behavioural features and associate them with environmental conditions. Training parameters such as learning rate, batch size, number of epochs, optimizer, and loss function are selected according to validation performance.

4.2 Welfare Indicator Detection and Classification

The deep learning-based welfare assessment framework identifies major behavioural indicators from animal images and video sequences and relates them to possible welfare conditions. The major indicators considered for automated assessment are summarized in Table 1.

Table 1. Animal Welfare Indicators and Their Classification

Welfare Indicator	Normal Behaviour	Possible Abnormal Behaviour	Associated Welfare Condition	Risk Level
Feeding	Regular feed intake	Reduced feeding frequency	Heat stress, discomfort	Moderate
Drinking	Normal water intake	Excessive drinking	Thermal stress, dehydration	Moderate–High
Walking/Movement	Regular movement	Reduced movement	Fatigue, heat stress	Moderate
Standing	Normal standing duration	Prolonged standing	Thermal discomfort	Moderate
Lying/Resting	Balanced resting pattern	Excessive or reduced resting	Stress, discomfort, illness	Moderate–High
Social Interaction	Normal group interaction	Isolation or reduced interaction	Stress or health problems	High
Shade Seeking	Occasional use of shade	Frequent clustering in shaded areas	Heat stress	High
Inactivity	Short inactive periods	Prolonged inactivity	Severe stress or illness	High

The welfare indicators in Table 1 provide the behavioural basis for automated classification. Under normal environmental conditions, animals generally demonstrate balanced patterns of feeding, drinking, movement, standing, resting, and social interaction. Significant deviations from these patterns can indicate declining welfare. For example, reduced feeding combined with increased drinking may indicate thermal stress, particularly during periods of high temperature and humidity. Similarly, prolonged standing, reduced movement, and frequent shade-seeking can indicate discomfort associated with excessive heat exposure.

The deep learning model analyses these behaviours from visual observations and assigns the detected patterns to corresponding welfare categories. Rather than considering an individual behaviour as sufficient evidence of poor welfare, the proposed framework evaluates multiple behavioural indicators together with their frequency, duration, and environmental context. The resulting observations are classified into normal, moderate concern, or high-risk welfare conditions. This combined assessment reduces the possibility of incorrectly interpreting temporary behavioural changes and provides a more reliable mechanism for identifying animals requiring management attention.

4.3 Climate Stress and Behavioural Pattern Analysis

Climate conditions are analysed together with animal behaviour to determine whether changes in activity are associated with environmental stress. Temperature, humidity, THI, and seasonal information provide contextual variables for interpreting behavioural responses. During thermally comfortable conditions, animals are expected to maintain relatively stable feeding, movement, resting, and social activity. Increasing thermal stress may result in reduced feed intake and movement together with increased drinking, standing, and shade-seeking behaviour. Persistent deviations under high-temperature and high-humidity conditions can indicate elevated welfare risk. Temporal analysis is also important because individual observations may not provide sufficient evidence of stress. Behavioural patterns observed continuously across multiple time intervals provide stronger indications of welfare deterioration. Therefore, the proposed framework evaluates both immediate behavioural responses and longer-term behavioural changes associated with environmental conditions.

4.4 Comparative Analysis

Comparative evaluation is conducted to examine the contribution of climate-aware data integration. A visual-only deep learning model can be compared with a model incorporating both animal behaviour and environmental information. The comparison helps determine whether climatic context improves the identification of welfare-related conditions.

Table 2. Comparative analysis of proposed model with benchmark models

Model Configuration	Input Information	Behaviour Recognition	Climate Context	Welfare Assessment
Conventional ML	Handcrafted features	Moderate	Limited	Moderate
Visual Deep Learning	Images/Video	High	No	High
Temporal Deep Learning	Behaviour sequences	High	Limited	High
Proposed Climate-Aware Model	Visual + Behavioural + Environmental Data	High	High	Comprehensive

The comparison demonstrates the conceptual advantage of integrating environmental information with animal-level observations. Visual deep learning can effectively recognize behaviour but may not always explain why behavioural changes occur. The climate-aware framework provides additional context by associating behavioural deviations with temperature, humidity, THI, and seasonal conditions. Overall, the experimental evaluation is designed to determine whether multimodal integration improves the reliability of automated welfare assessment. The combined analysis of animal behaviour and climatic conditions provides a more comprehensive basis for detecting welfare deterioration and identifying animals potentially exposed to climate-induced stress.

5. Climate-Aware Animal Welfare Management

Climate-aware animal welfare management extends automated monitoring beyond simple behaviour recognition by converting deep learning predictions into actionable information for livestock management. The proposed framework continuously evaluates animal behaviour together with environmental conditions and generates welfare-risk information that can support timely interventions. This approach is particularly important under climate change, where increasing temperatures, heat waves, humidity variations, and extreme weather conditions may expose livestock to prolonged environmental stress.

5.1 Automated Welfare Risk Assessment

The proposed framework estimates animal welfare risk using the behavioural patterns identified by the deep learning model and the corresponding environmental conditions. Indicators such as reduced feeding, increased drinking, prolonged standing, abnormal inactivity, changes in resting patterns, and reduced movement are evaluated together with temperature, humidity, THI, and seasonal conditions. Based on the combined analysis, welfare conditions can be categorized into levels such as normal, moderate concern, and high risk. A continuous welfare-risk score can also be generated to represent the severity of the detected condition. Such automated assessment reduces dependence on periodic manual inspection and enables livestock managers to identify animals or groups requiring attention.

5.2 Early Detection of Climate-Induced Stress

Early identification of environmental stress is essential because prolonged exposure can negatively affect animal health, productivity, reproduction, and overall welfare. The proposed framework evaluates temporal changes in behaviour to identify early deviations from established normal patterns. For example, increasing drinking frequency combined with reduced feeding and movement during elevated THI conditions can indicate developing heat stress. Similarly, persistent inactivity or changes in resting behaviour during extreme climatic conditions may indicate increasing discomfort. Continuous monitoring enables these patterns to be detected before severe welfare deterioration becomes apparent. The system can therefore generate early warnings when the predicted welfare risk exceeds a predefined threshold. These alerts provide an opportunity for preventive intervention rather than relying primarily on corrective action after significant stress has occurred.

5.3 Decision Support for Welfare Management

The outputs generated by the deep learning framework can be incorporated into a decision-support system for farm management. Welfare-risk scores, behavioural trends, environmental conditions, and detected abnormalities can be presented through dashboards or automated alert mechanisms. Depending on the detected condition, management recommendations may include improving ventilation, activating cooling systems, providing additional drinking water, increasing shaded areas, modifying feeding schedules, reducing animal density, or initiating closer veterinary observation. The decision-support mechanism can prioritize interventions according to the severity and persistence of the detected welfare risk.

5.4 Sustainable Livestock Management Implications

Automated climate-aware welfare assessment can contribute to sustainable livestock production by improving the efficiency and timeliness of farm management. Continuous monitoring enables environmental resources and welfare interventions to be applied according to actual animal requirements rather than through fixed management schedules. For example, cooling and ventilation systems can be activated when climatic conditions and animal responses indicate increasing thermal stress. Such targeted intervention may reduce unnecessary energy consumption while maintaining appropriate welfare conditions. Similarly, monitoring drinking and feeding behaviour can assist in optimizing resource availability during periods of environmental stress. The framework can also provide historical welfare and climate records that support long-term farm planning. Analysis of repeated stress events can identify vulnerable periods, locations, animal groups, or management practices and assist farmers in adapting livestock facilities to changing climatic conditions. Therefore, the proposed climate-aware management approach establishes a connection between automated animal monitoring, deep learning-based welfare assessment, climate-stress detection, and sustainable management decisions. This integration can support more responsive livestock production systems capable of maintaining animal welfare while adapting to increasingly variable and challenging climatic conditions.

6. Conclusion and Future Work

This study presented a deep learning-based framework for automated animal welfare assessment under changing climatic conditions. The framework addresses the limitations of conventional welfare assessment methods by integrating animal images, video-based behavioural observations, and environmental parameters within a unified intelligent monitoring system. Deep learning enables automatic identification of important welfare indicators such as feeding, drinking, standing, lying, movement, resting behaviour, and abnormal inactivity, while environmental variables including temperature, humidity, seasonal conditions, and Temperature-Humidity Index provide the climatic context required for reliable interpretation. A major advantage of the proposed approach is its ability to associate behavioural changes with environmental stress rather than assessing animal activities independently. The integration of behavioural and climatic information supports early detection of heat stress and other climate-induced welfare risks. The resulting welfare classifications and risk scores can be incorporated into decision-support systems to generate alerts and recommend interventions such as improved ventilation, cooling, water availability, shade management, and modified feeding schedules. Consequently, the framework provides a foundation for continuous, objective, and data-driven animal welfare management.

Despite its potential, practical implementation may be affected by variations in animal breeds, farm environments, camera conditions, sensor reliability, data availability, and climatic regions. Future research should therefore focus on larger and more diverse datasets, multimodal sensor fusion, explainable deep learning, lightweight edge-based models, and cross-farm validation. Integration with IoT-enabled monitoring and real-time environmental forecasting could further strengthen early-warning capabilities. Overall, climate-aware deep learning offers a promising approach for improving animal welfare, supporting timely management interventions, and promoting resilient and sustainable livestock production under increasingly challenging climate conditions.

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