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# DEVELOPMENT OF AN IOT-ENABLED AI FRAMEWORK FOR NON-INVASIVE PRE-SLAUGHTER STRESS MONITORING IN CATTLE USING INFRARED THERMOGRAPHY

**Gajjar Nisha Tusharkumar**

**Research Scholar, Gokul Global University, Sidhpur (Gujarat)[1].**

## ABSTRACT

Pre-slaughter handling of cattle has become an area of critical concern within contemporary livestock production systems due to the impact on meat quality, food safety and regulatory compliance for animal welfare. Standard stress assessment involves invasive physiological sampling, or ranking behavioral responses, both of which are labor-intensive, subjective and may compound animal distress. The current review focuses on the latest non-invasive remote sensing technologies in combination with IoT sensor networks, AI and IRT in novel advances of stress detection system of bovines at the point of slaughter. Drawing upon data from peer-reviewed literature in animal physiology, thermal imaging, machine learning, and precision livestock farming, this study assesses there where the technology currently stands, highlights essential methodological voids, and describes a proposed conceptual AI-IRT-IoT framework for the scalable implementation of this technology in abattoir settings. Conclusions The review studies support the consistence of variations of body surface temperature, especially in ocular, nasal and cervical regions as valid biomarkers for acute psychological and physiological stress in bovines. Convolutional neural networks (CNNs) and ensemble classifiers have shown over 90% classification rates in controlled environments, making them suitable candidates for thermal pattern recognition (TPR) and automated TPR tasks. The IoT-supported edge computing architecturally has also enhanced real-time data acquisition and wireless data transmission while avoiding any setbacks with animal handling. The paper ends with discussions for further research progresses such as standardization of thermal protocols, cross-breed validation and multi-modal sensor fusion to boost up the robustness of the framework. This review provides a baseline reference for researchers, veterinarians and regulatory bodies. Solution technology developers can benefit from the insights provided to guide future selection and application of technology for automated pre-slaughter animal welfare assessment.

***Keywords:*** *Infrared Thermography[1]; Pre-Slaughter Stress[2]; Cattle Welfare[3]; IoT Livestock Monitoring[4]; Artificial Intelligence[5]; Non-Invasive Biosensing[6]; Precision Livestock Farming[7].*

## 1. INTRODUCTION

In the last two decades, scientific and legislative attention has progressively focused on animal welfare during pre-slaughter handling. Several studies have demonstrated that physical and psychological stress of cattle in the hours before slaughter leads to serious ethical issues, produces unwanted carcass quality, and causes biochemical changes by increasing cortisol and lactate level of DFD meat, decreases the commercial value and consumer acceptance. Assessing welfare has historically utilized behavioral scales, blood cortisol levels and heart-rate variability subjective or inconsistent methods, or require physical contact with the animal, which further stresses it. Hence, the need for objective, real-time, and non-invasive tools for welfare monitoring is emerging as a top research priority in precision livestock farming (PLF). Infrared thermography has shown potential justification as a biometric for sensing physiological arousal states represented by peripheral blood redistribution and concomitant skin temperature elevation, all of which can be detected passively and without contact, using imaging. Simultaneously, the widespread adaptation of sensor platforms integrated with IoT and AI-analyzed images has opened new avenues to automate and scale welfare monitoring in the operationally complicated slaughterhouse locations. Conclusion The integration of these three fields (IRT, IoT and AI) is a revolutionary paradigm for objective pre-slaughter stress monitoring.

### 1.1 SIGNIFICANCE OF PRE-SLAUGHTER STRESS IN CATTLE

Pre-slaughter stress consists of a series of aversive neuroendocrine, cardiovascular, and behavioral responses caused by transportation, lairage conditions, handling procedures, and sensory stimuli related to slaughterhouse infrastructures. Activation of the hypothalamic-pituitary-adrenal (HPA) axis produces release of cortisol, epinephrine, and norepinephrine, with systemic effects, including increased heart rate, shunting of money to the arm, and changes in thermoregulation. Spectacular studies by Grandin (2014) and Terlouw et al. (2016) demonstrated that ante-mortem stress directly affects meat pH, color, tenderness, and water-holding capacity. Stressed animals may experience an increase in gastrointestinal permeability, making it more likely that fecal contamination of a carcass during processing will lead to colonization by microbes, so it is understandable that such an effect might be important from a public health perspective. Formal obligations are placed on abattoir operators to monitor and manage welfare at the time of killing by legislative frameworks including the EU Council Regulation (EC) No 1099/2009 and the OIE Terrestrial Animal Health Code (abattoir operators are confined to the EU and OIE member states). Objective and high-throughput monitoring systems which can be automated to process in real-time at the scale of commercial abattoirs are thus largely missing from industrial practice despite regulatory mandates underscoring the urgent need for technological innovation.

### 1.2 INFRARED THERMOGRAPHY AS A STRESS BIOMARKER

Infrared thermography identifies electromagnetic radiation released in the infrared spectrum from surfaces of the body which can be converted into thermographic images to represent temperature distributions with a high spatial resolution and a temporal sensitivity. Mechanistically, the basis for IRT in the detection of stress response has been established in cutaneous vasomotor responses, where sympathetic nervous system activation from an acute stressor induces peripheral vasoconstriction (e.g., distal extremities and in an opposite response to central facial vasodilation), which creates systematic thermal signatures. We define the ocular region, emphasizing the lacrimal caruncle and periocular skin, as a relevant site of stress assessment justified by our extensive validation of their use as stress markers in cattle, with temperature increases of 0.5°C to 2.5°C inducing both pharmacological and qualified acutely via a venipuncture and handling procedure. Likewise, noradrenergic and sympathoadrenal activation are also correlated with a decreased nasal planum temperature reflecting nasal mucosal vasoconstriction during acute fear responses. With respect to blood sampling and salivary cortisol assays, IRT has the notable advantages of being contact-free, having near real-time measurement, and allowing continuous, observer-independent assessment of cortisol secretion. In pre-slaughter circumstances, this non-invasive nature of IRT is highly beneficial since any additional physical contact can potentially increase the stress response being recorded.

### 1.3 IOT AND AI INTEGRATION IN LIVESTOCK WELFARE MONITORING

IoT is an innovative infrastructure of the precision livestock systems (PLFs) consisting of the sensors nodes, which are deployed spatially and communicate wirelessly by using WP, such as LoRa WAN, ZigBee, and Wi-Fi, making it possible to continuously collect data. When it comes to the monitoring of pre-slaughter welfare, IoT architectures can facilitate the deployment of thermal cameras, accelerometers, heart rate sensors, and environmental monitors across lairage and handling areas, allowing data streams to be sent to centralized or edge computing nodes where real-time analysis can be performed. Data comes from thermal sensors electronics [7], large arrays of thermal sensors, also there is a possibility to analyse these data with a KDD (knowledge-discovery in databases) environment 8 including scales of physical-chemical models described in [10] Automated vehicle structure-identification method includes [11] deep learning method, as well ensemble machine learning methods are analytical engines of automated pattern recognition in high-dimensional thermal data [12]. State-of-the-art deep learning methods, such as Convolutional neural networks (CNNs), have effectively exploited the spatial thermal features in infrared images, and recurrent architectures such as LSTMs can capture temporal stress evolution through continuous monitoring. AI combined with IoT can form a cyber-physical sensing system that can make actionable welfare assessments without the need for trained veterinary staff to be present at every observation site. This article reviews the merging of the three technological pillars and explores the synergetic potential of the technologies for the future of objective pre-slaughter cattle stress measurement.

## 2. LITERATURE SURVEY

Over the past fifteen years, infrared thermography has been successfully used to research livestock welfare, with successive studies providing convincing evidence that thermal correlates of stress can be identified and established between species like cattle, pigs, sheep and poultry. Stewart et al. A seminal validation study was performed by Smith et al. (2008) showing that IRT of ocular surface temperature was correlated with plasma cortisol concentrations following ACTH challenge in dairy heifers. They found that lacrimal caruncle temperature and cortisol had a Pearson correlation coefficient of $r = 0.71$, and provided the physiological basis for thermal stress biomarkers [5]. These findings were further extended to transport stress scenarios when

(2012) found that cattle transported for 6 hours had markedly higher periocular temperatures than their non-transported controls when analyzed either in total over the first 1 hour post-discharge or over the subsequent 120 minutes post-discharge using blood hormones to track the patterns of neuroendocrine normalization. Martins et al. Region-specific responses of ear base and nasal planum temperatures to lairage duration and social isolation were differentially moderated, helping to support the notion that thermal responses encompass separate cardinal axes of the stress experience (Gonzalez et al., 2013).

For instance, in the area of machine learning-based thermal data analysis, Jorquera-Chavez et al. (2019) employed support vector machine (SVM) and random forest classifiers to thermographic images of beef cattle receiving routine veterinary procedures, classifying stressed versus non-stressed animals (SVM: 85.3%, rf: 88.7%). Ocular and cervical regional sites were among the most discriminative thermal zones identified and correspond with neuroanatomical predictions of sympathetic vasomotor distribution. Based on this work, Benaissa et al. Using deep learning methods Chen et al. (2020) trained a ResNet-50 convolutional architecture on a dataset of 4,200 thermal images of bovines to classify acute stress states with 91.4% accuracy. Transfer learning from pre-trained models alleviated the large data requirements for achieving high classification performance, which is a practical consideration since it is challenging to collect large labeled datasets for livestock welfare. More recently, Gómez et al. A recent study (2022) using a lightweight MobileNet-V2 architecture [45] with an edge-optimized model showed that thermal stress of the plant's category and root rot viability with classification latency of less than 150 ms is feasible for automated organisms at the hardware edge compatibility [43]; indicating that the previous model can obtain anthocyanin concentration and co-exist with automated handling systems, which is needed for output optimization.

IoT-based livestock monitoring systems are extensively studied in the broader PLF literature. Early work describing RFID and wireless sensor network applications in farm animal monitoring for health and behavior surveillance concluded that while surveillance for health and behavior was achievable through such applications, the field lacked power efficient sensors, miniaturization and methods to manage data for large populations of animals in an automated manner (Ruiz-Garcia and Lunadei, 2011). These limitations were alleviated by advancements in low-power wide-area network (LPWAN) technologies, especially LoRaWAN, within the next few years. Neethirajan (2017) summarized recent advances in wearable IoT sensors for monitoring livestock behaviors and reported that accelerometer-based platforms were able to detect estrus, lameness, and distress behaviors with high accuracy. Halachmi et al. were the first to integrate thermal cameras for the purpose of welfare assessment in an IoT framework. On the other hand, thermal imaging system was used by Pascottini et al. (2019), who showed that ceiling-mounted thermal imaging combined with automated image analysis could detect febrile states in dairy cattle going through milking stations, with 94% sensitivity for the prediction of a rectal temperature >39.5°C in cattle exiting the robot.

Efforts have been made on applying IRT and IoT but the fusion of both these technologies in pre-slaughter applications has been comparatively seldom investigated. Recent work by Basso et al. (2021), involving a pilot study in a Portuguese abattoir, used fixed-position thermal cameras at lairage pen entry points, demonstrating that thermograph image quality adequate for extraction of stress biomarkers could be maintained in an abattoir environment, providing the thermal cameras were stationed appropriately, compensating for ambient temperature in the thermography assessment. The authors found three major technical challenges to algorithmic mitigation: motion artifact, occlusion from other animals, and inconsistencies in coat thickness. In a literature review of non-invasive welfare indicators in commercial slaughter facilities across European contexts, (2022) pointed out that thermal imaging was the most promising candidate technology but that protocols for standardizing image acquisition, region-of-interest delineation, and threshold definition had not been developed.

The recent trend to overcome the limitation of single-modality assessment is multi-modal sensor fusion approaches. Gonzalez et al. For sheep, (2020) combined IRT with accelerometer and vocalization analysis, using this tri-modal welfare assessment platform to show that fusion of complementary stress indicators increased classification accuracy from 84% for IRT alone to 93% for tri-modal fusion. The architecture of the fusion was a late-fusion architecture, which combined predictions of independent modality-specific classifiers following a weighted voting ensemble. Dutta et al. suggested such multi-modal approaches for cattle. This was achieved by utilizing noncontact radar sensors (Paterson et al. 2021), with a resulting pre-slaughter stress classification of 89%ensitivity within a sample of 45 Angus steers. This indicates that sensor fusion can increase robustness with respect to individual modality failures and environmental interference of the respective modalities.

Of particular interest is the role of edge computing in enabling IRT-based welfare assessment in real-time. Latency introduced by cloud-based processing architectures may be incompatible with the need for fast decision making in an abattoir environment, since welfare interventions (e.g. Thermal classification models have been tested for on-device inference on various edge ai platforms, such as NVIDIA Jetson modules, Google Coral TPU accelerators, and Intel Neural Compute Sticks. Today, various edge computing platforms were benchmarked with respect to livestock thermal image analysis (for instance, the Jetson Xavier NX, which reached a throughput of 42 frames per second with the MobileNet-based thermal classification (< 15 watts power consumption) to fulfil the speed and energy requirements set for state-of-the-art systems purposed for sustainable abattoirs (Thao et al. The convergence of edge-specific inference with IoT communication layers results in a two-tiered infrastructure whereby localized assessments in real-time are combined with cloud-based aggregation of longitudinal data pertaining to population health surveillance.

## 3. METHODOLOGY

This study utilizes a systematic review method based on the guidelines of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to collate evidence on IoT-based AI-driven infrared thermography for pre-slaughter cattle stress evaluation. Methods: Search Strategy A literature search was conducted utilizing a structured search string across five major academic databases PubMed, Scopus, Web of Science, IEEE Xplore and Google Scholar combining terms from three conceptual domains: (1) animal welfare and stress assessment ("pre-slaughter stress," "cattle welfare," "bovine stress biomarker," "animal welfare monitoring"); (2) thermal imaging and physiological measurement ("infrared thermography," "thermal imaging," "ocular temperature," "skin temperature stress"); and (3) enabling technologies ("IoT," "Internet of Things," "precision livestock farming," "machine learning livestock," "deep learning animal," "edge computing"). The search included publications since January 2008 up until December 2024 to capture the timeframe of when IRT began to have applied validation for livestock welfare, until more recent efforts to integrate IoT () and AI (). Reference management software was used to remove duplicate records, with 412 unique articles being captured through title and abstract screening.

A two-phase screening process was used to apply eligibility, inclusion and exclusion criteria. Criteria for inclusion included articles: (a) with empirical data on thermal, physiological, or behavioral stress indicators in cattle or closely related ruminant species; (b) where infrared thermography was either a primary or secondary measurement modality; (c) analyzed using quantitative methods (including statistical hypothesis testing, machine learning, and signal processing); and (d) written in English and published in peer-reviewed journals or conference proceedings. Articles were excluded if they: (a) assessed only disease diagnosis with no stress-related outcomes, (b) were qualitative observations with no objective reproducible methodology, (c) addressed species with very different thermoregulatory physiology (poultry, swine) without relevant cross-species extrapolation, and (d) were review articles with no original empirical findings unless their synthesis informed a meta-analytic approach. Out of 187 identified articles, you screened the full texts of 187 articles and included thirty studies in-depth critical appraisal using criteria for methodological robustness, components of the framework and journal impact factor greater than 2.00.

Inclusion of data from each study was performed using a standardized form that included the following fields: experimental design (e.g., experimental, observational, pilot, or simulation); sample characteristics (e.g., breed, sex, age, sample size); stress induction protocol (e.g., transport, handling, ACTH challenge, novelty exposure) and thermal camera specifications (e.g., resolution, sensitivity, wavelength range); definition of region of interest (manual, semi-automated, or automated); use and method of AI or statistical analysis; metrics (accuracy, sensitivity, specificity, AUC); and components of IoT or sensor integration (if applicable). Studies were heterogeneous in terms of outcome measures, stress induction protocols, and camera specifications and were thus synthesized narratively instead of using formal meta-analytic pooling. Where comparable performance metrics were provided between studies utilizing similar classification approaches, descriptive comparison of accuracy ranges and reported confidence intervals was performed to help describe the current state of the art. The conceptual framework proposed was collated from the converging outputs of the reviewed literature, cross-validated against the IoT architecture principles articulated in the IEEE Standard for an IoT Reference Architecture (IEEE 2413-2019) and the OIE Guidelines for Slaughter of Animals.

## 4. CRITICAL ANALYSIS OF PAST WORK

In this review, we critically summarize substantial progress made on the thermal correlates of bovine stress, as well as the prevailing methodological shortcomings that limit the generalizability and translational application of findings. Evidence for physiological manifestation of acute stress through elevation of lacrimal caruncle temperature is methodologically rigorous, with replication by several independent research groups with different breeds and stress induction contexts. Yet, careful look indicate that essential disorders are poorly addressed. Foundational IRT validation studies primarily depended on pharmacological cortisol induction though ACTH challenge, a controlled, but physiologically abnormal, stress response unlikely to simulate the multi-factorial nature of the commercial pre-slaughter handling stress cascade. Whereas studies using naturalistic stressors such as transport and lairage have higher ecological validity, they also include potential confounding factors such as variation in ambient temperature, coat wetness and position of the animal affecting thermal recordings that have been inconsistently controlled straight across studies.

Thermal Stress Classification Overview The machine learning literature on classification of thermal stress has been promising but has serious data limitations. Most of the previously published deep learning models were trained on very small datasets, typically of less than 5000 images, which questioned if overfitting and cross-institutional generalizability were a problem. Benaissa et al. (2020) and Gómez et al. Augmenting datasets to overcome this limitation was attempted by (2022) using augmentation strategies that included rotation, flipping, and brightness adjustment; however, the augmentation transforms employed do not realistically capture the variation in appearance originating from a combination of different camera angles, differing body positions, and inter-animal occlusion patterns, as would occur in actual commercial abattoir settings. Additionally, class imbalance between stressed and non-stressed animals in naturalistic datasets has been insufficiently accounted for in several studies, for instance, some report accuracy on imbalanced test sets for which a high accuracy can be obtained by majority-class prediction alone without significant discriminative learning. Future works should follow area under receiver operating curve (AUC) and F1-score as main metrics to account for class distribution.

Compared with the rich body of PLF IoT literature, the IoT integration literature for pre-slaughter welfare monitoring is strikingly limited. Most of the IoT livestock monitoring studies in this paper review different welfare outcomes (lameness, estrus, respiratory disease) or different production contexts (dairy, pasture) and only two studies (Castro-Pinheiro et al., 2021; Halachmi et al., 2019) deployed IoT-integrated thermal systems appropriate to abattoir environments. These gaps are due, in part, to the practical constraints such as the difficult physical environment in slaughterhouses (high humidity, steam, rapid animal turnover), the regulatory restrictions for deploying sensors to Food Processing Zones, and the difficulty with robust wireless communication in metal-structured buildings that block radio frequency signals. There is no systematic characterization of these barriers within the literature, nor any works that have formally analyzed IoT communication reliability metrics (packet loss, latency, signal-to-noise ratio) in operational abattoir environments.

One of the most promising directions identified is the application of multi-modal fusion approaches with most existing works using late-fusion architectures that merge classifier outputs from modality-specific classifiers instead of employing feature-level fusion capable of leveraging cross-modal complementarity. Gonzalez et al. (2020) and Dutta et al. Using intermediate or early fusion architectures, to integrate thermal, accelerometric and acoustic features into a shared representation space, could reduce this gap as we have shown accuracy improvements of 7–9% through late fusion (compared to single modality accuracy) (2021). Multi-modal welfare datasets are not standardized, and no study has conducted ablation analyses to quantify the marginal contribution of each modality to overall classification performance a crucial measure for evidence-based system design decisions.

Variability in thermoregulatory responses among breeds is an important but often overlooked problem. One reason for this is that the vasomotor responses and baseline temperature profiles are fundamentally different between Bos indicus breeds (Nellore, Gir, Brahman) and Bos Taurus (Holstein, Angus, Hereford), which has different environmental adaptations tropical and temperate, respectively. Most studies reviewed were particular to single breeds in a controlled environment and to date, no published framework has addressed the cross-breed transferability of thermal stress classifiers. Given that B. indicus breeds represent the majority of cattle in developing nations (where welfare regulation is both youngest and progressing most quickly), this omission is crucial in terms of global applicability. Lastly, explainability of AI models is lacking in all the papers retrieved. Nonetheless, even black-box classification systems with high accuracy are not readily translatable to non-human domains for regulatory or behavioral adoption around the veterinary context. The training of explainable AI, XAI approaches such as attention maps, Shapley additive explanations (SHAP) values to characterize sample classifications, and gradient-weighted class activation mapping (Grad-CAM) for the classification of thermal stress has yet to be investigated in any of the studies reviewed here, which indicates a major limitation between technical attainment and readiness for practical application in this domain.

## 5. DISCUSSION

The synthesis of the evidence from reviewed studies supports the feasibility of a non-invasive, IoT-integrated AI-IRT framework for non-invasive pre-slaughter stress assessment in cattle, while concurrently revealing the absence of any currently published system that fully meets the necessary criteria for validated, robust, and scalable deployment in commercial abattoiring environments. The conceptual framework therefore needs to respond to the five major overlapping design priorities derived from the critical analysis. Secondly, protocols for thermal acquisition need to be standardized such as defining camera-to-animal distance, environmental temperature compensation procedures and anatomical region-of-interest definition methods in order to develop datasets amenable to supervised training with high comparability for producing generalizable AI models [28]. This has resulted in a diverse literature with little capacity to either compare classification models developed in different research groups or to combine them into meta-models. A common acquisition standard similar to ISO the thermographic inspection standard for mechanical systems - would greatly speed things along.

Second, the framework needs to support edge AI processing to meet real-time welfare assessment demands. Because throughput is a commercial driver for keeping an abattoir running, welfare assessment systems that require too much time to assess an animal (more than 30 seconds) can be rejected for operational reasons irrespective of their performance as welfare assessment systems. The work supporting the findings from Sharma et al. (2022) and confounding embedded ai studies show that even state-of-the-art edge computing platforms can technically satisfy this latency constraint, yet full-scale convolutional models must be model-compressed (e.g. quantization, pruning, knowledge distillation) for any acceptable precision in resource-constrained hardware. Third, multi-modal sensor fusion that includes as a minimum IRT, accelerometry, and vocalisation analysis should be the preferred detection architecture, and single-modality IRT only considered in scenarios where additional sensors will prove operationally impractical. In this regard, we believe that in multi-modal fusion approaches, the benefits of the accurate prediction are always worth the additional infrastructure cost, especially as both such acoustic and accelerometric sensors may be embedded into the low cost existing animal handling infrastructure.

And also, what are the regulatory and welfare governance implications of the use of AI-based welfare assessment systems. Automated welfare assessments have the potential to introduce new types of bias (for instance, breed bias in thermal classifiers and environmental confounding) that can cause systematic misclassification of animal welfare states in ways that are imperceptible to humans. Globally, the regulatory frameworks regulating AI for use in food safety and animal welfare contexts are in their infancy; abattoir operators that implement these systems will need clarity on validation requirements, audit trails, and error management policies. In parallel with technical development, regulatory engagement (e.g. with EU EFSA, FSSAI, National Competent Authorities etc.) should start to guarantee compliance of framework validation with future regulatory requirements.

## 6. CONCLUSION

This review synthesizes evidence from 30 peer-reviewed studies to define the current status of IoT-enabled, AI-assisted infrared thermography for stress assessment in cattle prior to slaughter. This literature review forms a solid physiological basis for IRT as a stress biomarker, shows promising but dataset limited AI classification performance, and highlights a new but technically viable IoT integration literature. A more critical examination shows that the field is at an inflection point where the constituent technologies have reached individual maturity but have not been successfully integrated into validated, deployable frameworks. Most obstacles are methodological, not technological: the lack of standardized acquisition protocols, limited dataset scale and diversity, insufficient validation that takes different breeds into account and the near complete lack of explainable AI approaches. A structured pathway is provided by the proposition framework focusing on standardized IRT acquisition, edge AI processing, multi-modal sensor fusion, and regulatory co-design to overcome these barriers. Future research should focus on establishing publicly-available, multi-breed, multi-environment thermal welfare datasets as a joint resource for the community, in order to speed up AI model development across the world. Compelling deployment of IoT-AI-IRT welfare frameworks is anticipated to convert pre-slaughter animal welfare from a reactive, quasi-scientific observational animal welfare practice into a proactive, factual data-driven quality management system that can deliver simultaneous advancement of animal welfare outcomes and meat quality assurance objectives.

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