ComTech: Computer, Mathematics and Engineering Applications, 17(2), December 2026, 137−149 P-ISSN: 2087-1244
DOI: 10.21512/comtech.v17i2.14254 E-ISSN: 2476-907X

Prediction of Transportation-Induced Physiological Stress in Cattle Using an Artificial Neural Network

Harry Dhika[1]*; Agus Buono[2]; Shelvie Nidya Neyman[3]; Dewi Apri Astuti[4]

[1]School of Data Science, Mathematics, and Informatics (SSMI), IPB University, Bogor, Indonesia 16680
[1]Informatics Engineering Study Program, Faculty of Engineering and Computer Science, Indraprasta PGRI University, Jakarta, Indonesia 13760,
[2,3]School of Data Science, Mathematics, and Informatics (SSMI), IPB University, Bogor, Indonesia 16680
[4]Department of Nutrition and Feed Technology, Faculty of Animal Husbandry, IPB University, Bogor, Indonesia 16680

[1]harrydhika@apps.ipb.ac.id; [2]agusbuono@apps.ipb.ac.id;
[3]shelvie@apps.ipb.ac.id; [4]dewiaa@apps.ipb.ac.id

Received: 23rd August 2025/ **Revised:** 13th January 2026/ **Accepted:** 28th January 2026

How to Cite: Dhika, H., Buono, A., Neyman, S. N., & Astuti, D. A. (2026). Prediction of transportation-induced physiological stress in cattle using an artificial neural network. *ComTech: Computer, Mathematics and Engineering Applications, 17*(2), 137−149. https://doi.org/10.21512/comtech.v17i2.14254

Abstract **-** The transportation of cattle, particularly during peak demand periods such as Eid al-Adha, frequently induces physiological stress that compromises animal welfare, reduces productivity, and causes economic losses. This study proposes an Artificial Neural Network (ANN) model to evaluate and predict cattle performance following transport stress using pre- and post-transport physiological indicators, including rectal temperature, heart rate, respiration rate, and blood metabolites (glucose and creatinine). The original dataset comprised 184 samples collected from Peranakan Ongole (PO) cattle across five regions in Indonesia; due to class imbalance among performance categories (Increase, Stable, Decrease), biologically informed data augmentation was applied, expanding the dataset to 1,084 samples. Feature selection via Pearson correlation identified respiration rate, heart rate, and musculoskeletal indicators as the most predictive variables. Model training and validation were conducted using a train–test split strategy, with performance evaluated based on accuracy, recall, and F1-score. The ANN architecture employed ReLU activation, Adam optimization, L2 regularization, and dropout to prevent overfitting. Trained and validated on the augmented dataset, the model achieved 96% accuracy and consistently high F1-scores (0.96 macro average) across all three classes. The results demonstrate robust predictive performance in capturing complex, non-linear physiological stress patterns associated with transportation within the studied dataset, particularly in detecting performance decline. In practice, this approach lays the groundwork for intelligent early warning systems that enable data-driven assessment of livestock condition, thereby supporting welfare-oriented decision-making in commercial cattle transportation systems.

Keywords**:** neural network, physiological stress, cattle transport, livestock welfare, data augmentation

I. INTRODUCTION

Cattle can achieve optimal growth and productivity when internal and external conditions remain within normal physiological limits. Among the external factors, environmental temperature plays a crucial role in determining livestock comfort and performance. In tropical regions, cattle are frequently exposed to heat stress because ambient temperatures often exceed 29°C for more than 6 consecutive hours (Badali et al., 2023; Habeeb et al., 2023; Santoso et al., 2023). This thermal stress triggers an increase in respiration rate and heart rate, diverting metabolic energy from growth and production toward maintaining homeostasis. (Reitelseder et al., 2020; Thornton et al., 2022). Various mitigation strategies, such as shading, ventilation, and feed management, have been implemented. However, without accurate continuous physiological monitoring, it is difficult to evaluate their effectiveness objectively (Slayi & Jaja 2025; Islam et al. 2026).

*Corresponding Author

Similar physiological challenges occur during large-scale cattle transportation, especially before Eid al-Adha, when demand for livestock increases sharply. The transport process exposes cattle to multiple stressors, including long travel distances, fluctuating temperatures, limited space, and vehicle vibration. These conditions activate the hypothalamic–pituitary–adrenal (HPA) axis, leading to the release of cortisol a primary stress hormone which in turn stimulates gluconeogenesis and muscle protein catabolism (Damtew et al., 2018). Consequently, blood glucose levels often rise as part of the acute stress response. At the same time, creatinine concentrations may increase due to skeletal muscle breakdown, making creatinine a reliable biomarker of physical exertion and tissue damage. These physiological alterations elevated rectal temperature, increased heart and respiration rates, and shifts in metabolite profiles collectively impair performance, reduce live weight (by 3–8% in tropical conditions), and in severe cases, contribute to mortality rates of up to 0.5–2% during long-haul transport in Southeast Asia. Transport-induced physiological stress in cattle has been widely documented, showing consistent increases in heart rate, thermal imbalance, and metabolic disruption during long-distance transit (Schwartzkopf-Genswein et al., 2021). Recent studies have demonstrated the effectiveness of infrared thermography in assessing heat stress and physiological responses in livestock (Ghezzi et al., 2024).

Conventional livestock monitoring approaches remain reactive and often fail to detect early signs of physiological stress. This limitation underscores the need for predictive, data-driven tools that can translate subtle physiological signals into actionable insights. In this context, the advancement of Artificial Intelligence (AI), particularly Artificial Neural Networks (ANNs), provides new opportunities to develop models capable of recognizing complex, non-linear relationships between physiological and environmental variables (Dineva & Atanasova, 2023; Grzesiak et al., 2025).

Previous studies have demonstrated the effectiveness of machine learning in animal agriculture. For instance, support vector machines (SVMs) have been used to detect lameness in dairy cows (Georgiades et al., 2024), while random forests successfully predicted heat stress using ambient and physiological data (Yu et al., 2024). However, ANN offers distinct advantages over both classical regression and other machine learning methods due to its inherent ability to model high-dimensional, non-linear interactions without requiring priori assumptions about data distribution critical when dealing with biological systems where responses are rarely linear or additive. The adoption of wearable devices for continuous physiological monitoring in cattle has significantly advanced, enabling more precise and automated health assessment (Yu et al., 2024). Recent evaluations of transport conditions across Latin America highlight substantial welfare challenges, including thermal stress, dehydration, and elevated physiological load in cattle during transit (Edwards-Callaway et al., 2026).

International guidelines on livestock transportation emphasize the importance of identifying and mitigating stressors to animal welfare during transport. According to the Food and Agriculture Organizations (FAO's) Practical Guidelines on Livestock Transportation and Slaughter Practices, stress responses in transported animals are associated with activation of the sympathetic nervous system, leading to increases in heart rate, respiration rate, and metabolic changes, including altered blood metabolite concentrations (FAO, 2023). These physiological indicators are widely recognized in global animal welfare frameworks and provide a useful comparative context for assessing transport-induced stress in cattle within different production and transportation systems.

Despite these advances, two critical research gaps persist. First, most existing ANN applications focus on dairy cattle in temperate climates, with limited attention to tropical beef cattle, such as the *Peranakan Ongole* (PO) breed, widely used in Indonesia. Tropical transportation conditions characterized by high humidity, poor road infrastructure, and variable handling practices create unique stress dynamics that may not be captured by models trained in controlled or temperate environments. Second, few studies integrate both physiological parameters (e.g., heart rate, respiration) and blood metabolites (e.g., glucose, creatinine) into a unified predictive framework. Most models rely solely on external sensors, overlooking internal metabolic markers that provide deeper insight into the animal's stress severity and recovery potential. The physiological indicators used in this study, such as heart rate, respiration rate, temperature profiles, and metabolite concentrations, are consistent with recognized biomarkers of livestock stress identified in recent research (Kumar et al., 2023).

This study addresses these gaps explicitly by selecting glucose and creatinine as key metabolic indicators. Glucose reflects the acute stress-induced activation of the sympathetic nervous system and HPA axis. At the same time, creatinine serves as a sensitive indicator of muscle catabolism resulting from physical exertion during transport. Simultaneously, heart rate and respiration rate are included not merely as stress signals but as direct proxies for thermoregulatory demand and oxidative stress.

Under heat load, cattle increase respiratory frequency to dissipate heat (panting), which can lead to respiratory alkalosis and metabolic imbalance if prolonged. Elevated heart rate, meanwhile, reflects cardiovascular strain and sympathetic overdrive.

Model training was performed using a standard backpropagation algorithm with categorical cross-entropy as the loss function. Model optimization followed established neural network training procedures and was implemented using TensorFlow and Scikit-learn.

Based on these considerations, this study aims to develop a neural network-based model to evaluate and predict physiological stress indicators

in cattle during modern transportation. The proposed model incorporates data augmentation to handle class imbalance and feature selection using Pearson correlation to identify the most relevant variables. The main research question addressed is: To what extent can an ANN accurately and reliably evaluate changes in cattle physiological conditions caused by transport stress? The outcomes of this study are expected to serve as a foundation for developing data-driven early warning systems that support adaptive, efficient, and welfare-oriented livestock transportation management.

Cattle transportation has been widely regulated and studied in Western livestock systems due to its significant implications for animal welfare and meat quality. Regulatory frameworks such as the European Union Council Regulation (EC) No. 1/2005 and transport guidelines developed in North America emphasize the importance of monitoring physiological stress indicators, including heart rate, respiration rate, body temperature, and blood metabolites, during livestock transportation. These physiological parameters are internationally recognized as reliable indicators of transport-induced stress and welfare status in cattle. Integrating such international perspectives provides a broader comparative framework for interpreting physiological stress responses observed under different transportation conditions and management systems.

Methodologically, this study contributes by developing a shallow Artificial Neural Network (ANN) model specifically designed for small-to-moderate physiological datasets collected under real-world transportation conditions. The proposed approach integrates physiological parameters and blood metabolite indicators within a unified predictive framework and applies biologically informed data augmentation to address class imbalance without replacing original observations. This methodological design allows the model to remain robust while preserving biological interpretability.

II. METHODS

This study adopted a quantitative research approach to develop a predictive model to evaluate cattle physiological responses to transport-induced stress using an Artificial Neural Network (ANN). The research subjects consisted of *Peranakan Ongole* (PO) cattle sourced from several major livestock distribution regions, including Kebumen, Bojonegoro, Sumbawa, Bekasi, and Bogor, during the period leading up to Eid al-Adha. Measurements were taken twice: before transportation and within 30 minutes of arrival, ensuring that the recorded physiological changes reflected actual transport-related stress responses.

The dataset included body weight, rectal temperature, heart rate, respiratory rate, and blood metabolite indicators (glucose and creatinine) (Handayani et al., 2024). Each record was assigned a unique identification code to maintain data integrity. Because the distribution of target classes (Increase, Stable, Decrease) was imbalanced, synthetic data augmentation incorporating realistic biological variations was implemented to improve the model's generalization capability. The use of multisensory physiological measurements in livestock aligns with recent advancements in wearable sensor technologies for animal behavior and health monitoring (Ding et al., 2025).

The ANN developed in this study followed a multilayer perceptron architecture consisting of an input layer, a single hidden layer, and a multi-class output layer. The data were divided into training and testing sets, and the learning process was performed using the ReLU activation function with backpropagation. Hyperparameter tuning was performed by adjusting the number of neurons, learning rate, and number of epochs to achieve optimal model performance. All stages, including preprocessing, training, and evaluation, were implemented using Python with TensorFlow and Scikit-learn (Menezes et al., 2024). The sequential stages of the research workflow can be seen in Figure 1.

Figure 1 illustrates the complete workflow used in developing the Artificial Neural Network (ANN) model for predicting cattle performance based on physiological and metabolite data. The process begins with data collection, where raw measurements are obtained from field observations. Next, data preprocessing is conducted to handle missing values and normalize feature scales. To address class imbalance, data augmentation is performed by generating synthetic samples based on class-level statistical distributions.

Following preprocessing and augmentation, the dataset is divided into training and testing subsets. The ANN model architecture is then defined, including the input, hidden, and output layers. The model is trained using the backpropagation algorithm with ReLU activation. Hyperparameter tuning is applied to optimize the number of epochs, learning rate, number of neurons, and dropout rate. Finally, model evaluation is conducted using performance metrics such as accuracy, recall, and F1 Score to assess the overall effectiveness of the trained ANN.

The data collection stage represents the foundation of the ANN modeling process. Physiological and metabolic measurements were obtained from PO cattle across five regions: Kebumen, Bojonegoro, Sumbawa, Bekasi, and Bogor, before and shortly after transportation. The short post-transport measurement window ($\leq$30 minutes) was used to ensure that the observed changes reflected immediate transport-induced effects. All data were recorded manually by trained field personnel and assigned unique cattle IDs to maintain accuracy and consistency.

This study was conducted as a field-based observational study during routine cattle transportation. All physiological measurements, including blood sampling and rectal temperature assessment, were performed by licensed veterinarians or trained animal

health personnel, in accordance with standard animal welfare and husbandry procedures and local livestock management regulations. No additional experimental interventions were imposed on the animals beyond standard commercial practices.

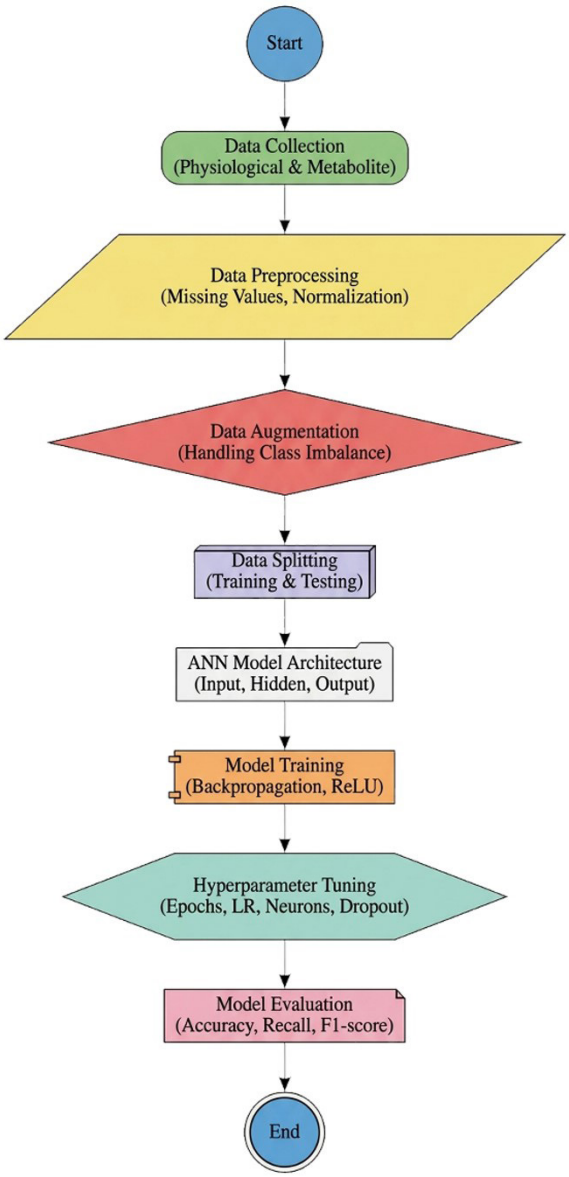


Figure 1. Research Workflow Diagram

To address the severe class imbalance in the original dataset, where the "Decrease" class dominated with 119 samples while "Increase" and "Stable" had only 34 and 31 samples, respectively, we implemented a biologically informed data augmentation strategy. For each class, we first computed the class-wise mean vector and standard deviation vector across all 15 input features. Synthetic samples were then generated by sampling from a multivariate normal distribution. Prior to data augmentation, all features were normalized using min–max normalization, as shown in Equation (1):

$$x' = (x - x_{min})/(x_{max} - x_{min}) \quad (1)$$

This formulation generates synthetic samples centered around each class mean while maintaining biological plausibility. The Gaussian noise is restricted so that no feature exceeds 10% of the original observation range, ensuring physiologically realistic variation.

It is important to clarify that the Artificial Neural Network (ANN) used in this study is a shallow multilayer perceptron consisting of a single hidden layer, rather than a deep learning architecture. This design choice was made intentionally to ensure model robustness and stability when applied to small-to-moderate physiological datasets. The data augmentation procedure was not intended to replace or inflate the original biological observations, but rather to address the severe class imbalance present in the original dataset and to improve the model's sensitivity to underrepresented physiological response patterns. To preserve biological realism, all synthetic samples were generated within physiologically plausible ranges and constrained by class-specific statistical properties.

For instance, in the "Increase" class, heart rate had a mean of 82.3 bpm and a standard deviation of 4.2 bpm; thus, synthetic heart rate values were drawn from a normal distribution, as implemented in the data augmentation procedure. To ensure biological plausibility, the added Gaussian noise was constrained such that no synthetic value exceeded the original observed range for that feature by more than 10%. This approach yielded 300 additional samples per minority class, resulting in a balanced dataset of 1,084 records (Increase: 334, Stable: 331, Decrease: 419), as summarized in Table 1.

Pearson correlation coefficients (r) were computed for each feature and the encoded target variable (0 = Increase, 1 = Stable, 2 = Decrease), using standard thresholds in livestock physiological modeling (Grzesiak et al., 2025). Features that were retained as predictive. This yielded a final set of 15 input variables (denoted X_1 to X_{15}), each with clear biological relevance:

In this study, all feature identifiers are presented in English to improve clarity for international readers. Specifically, X_1 (HeartRate_x) represents the pre-transport heart rate, reflecting cardiovascular strain and sympathetic activation. X_2 (Respiration_x) denotes the respiration rate, indicating thermoregulatory effort and potential respiratory alkalosis. The infrared temperature features X_3 (BackTemp_x) and X_4 (Thighemp_x) correspond to dorsal and thigh surface temperatures, which serve as indicators of peripheral perfusion and heat dissipation. X_5 (RectalTemp_x) refers to the rectal temperature as a direct measure of core thermal load. Meanwhile, X_6–X_{15} include additional thermal measurements such as orbital, nasal, and rumen-area temperatures and relevant blood metabolite levels, including glucose and creatinine.

Highly correlated feature pairs (e.g., OrbitalTemp_x and CheekTemp_x) were retained when they represented distinct anatomical regions that contributed complementary physiological

Table 1. Augmentation Results

Class	Original Data	Augmented	Total Data
Increase	34	300	334
Stable	31	300	331
Decrease	119	300	419
Total Data		1084	

information. Although statistically correlated, these features captured different aspects of heat dissipation, and their combined signals improved the spatial resolution of thermal stress assessment. To balance class representation, augmentation was performed by computing the mean feature vector for each class and generating synthetic samples by adding normally distributed noise, as described in the Methods section. This augmentation step produced a total of 834 data points, and the distribution across classes is summarized in Table 1.

In this study, class balancing was achieved through statistical augmentation to address the uneven distribution of samples across categories. For each class *c*, the mean feature vector μ_c was computed using all observations belonging to that class, providing a representative central tendency for the augmentation process. Synthetic samples were subsequently generated by adding Gaussian noise to the class-specific mean vector, allowing the model to capture natural physiological variability while maintaining biological plausibility. Prior to noise injection, all features were normalized to ensure numerical stability during computation, as shown in Equation (2):

$$x_c^{(t)} = \mu_c + \varepsilon^{(t)}, \varepsilon^{(t)} \sim \mathcal{N}!(0, \sigma^{2I}) \quad (2)$$

This transformation standardizes all feature values into a uniform numerical range, ensuring consistent scaling across the dataset. By reducing magnitude disparities, the normalization process prevents features with inherently larger values from disproportionately influencing the learning algorithm. Additionally, this step contributes to numerical stability during training and improves model convergence by allowing the optimization procedure to treat all features with equal importance.

The final ANN architecture consisted of an input layer with 15 neurons, corresponding to the selected physiological and thermal features. This was followed by a single hidden layer with five neurons, activated with the ReLU function to introduce non-linearity and improve representational capacity. The output layer included three neurons, each representing one of the target classes, and used a softmax activation function for multinomial classification.

Weight initialization employed the Glorot uniform (Xavier) scheme to maintain stable gradient variance during backpropagation. To mitigate overfitting especially critical given the modest dataset size we applied L2 regularization (weight decay coefficient) on the hidden-layer weights and dropout (rate = 0.5) after the hidden layer. L2 regularization penalizes large weights, encouraging simpler decision boundaries, while dropout randomly deactivates half the hidden neurons during each training iteration, preventing co-adaptation and improving generalization.

The model was optimized using the Adam algorithm with an initial learning rate of 0.001, a batch size of 32, and a maximum of 100 epochs. Early stopping was implemented with a patience of 10 epochs; training halted if the validation loss did not improve for 10 consecutive epochs. All hyperparameters were tuned on the validation set to maximize macro F1-score.

To quantitatively assess the model's performance, the Categorical Cross-Entropy cost function was used, as it is well-suited to this multi-class classification problem. This function rigorously measures the disparity between the model's predicted probability distribution and the actual *one-hot-encoded* probability distribution of the true labels. The training objective is fundamentally centered on minimizing this cost function, as its reduction directly correlates with improved model predictive accuracy. The total cost function, J(W,b), is formally defined as the average over all training samples, ensuring that the outputs form a valid multinomial probability distribution.

Figure 2 illustrates the architecture of the Artificial Neural Network (ANN) developed for the classification task. The model consists of three main components: the input layer, a single hidden layer, and the output layer. The input layer contains multiple feature nodes (X1, X2, …, X15), each representing a physiological or metabolite attribute used as a predictive variable.

All input features are fully connected to the hidden layer, which consists of five neurons (h_1, h_2, h_3, h_4, and h_5) as illustrated in the network architecture. Each hidden neuron receives weighted signals from every input node, allowing the model to capture complex interactions among physiological and thermal features. After the weighted summation is computed, the ReLU activation function is applied to introduce non-linearity and enhance the network's ability to learn meaningful internal representations.

The output layer consists of three neurons (Y1, Y2, and Y3), corresponding to the three target classes: Increase, Stable, and Decrease. Each hidden neuron is

connected to all output neurons, enabling the network to learn complex decision boundaries. The final class probabilities are produced through the softmax activation function applied at the output layer.

This architecture is a fully connected, feed-forward artificial neural network designed to process physiological and thermal features efficiently. Its layered structure enables the model to learn hierarchical representations that support accurate discrimination among the target classes. Through backpropagation and systematic hyperparameter tuning, the network optimizes its classification performance and achieves a stable learning trajectory.

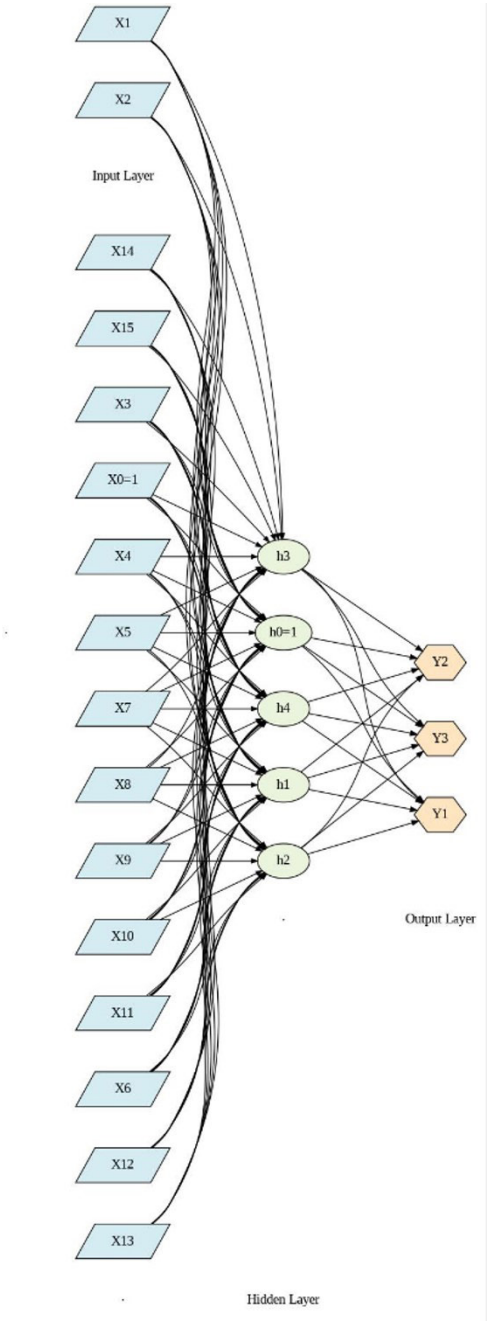


Figure 2. ANN Structural Model

The notation used in the network architecture diagram is defined as follows to ensure clarity in interpreting the model structure. The symbol **X** represents the input features, which are fully connected to the hidden layer through the weight parameters W_{ij} The hidden units, denoted as **H** and indexed from h_1 to h_5, receive these weighted inputs along with the bias term h_0. The output layer is parameterized by the weights V_{jk}, which map hidden-layer activations to the predicted class probabilities **Y**. The three output nodes correspond to the target categories, where y_1 represents *Increase*, y_2 represents *Stable*, and y_3 represents *Decrease*.

III. RESULTS AND DISCUSSION

This study developed an ANN-based predictive model to evaluate cattle physiological performance after transport using physiological indicators (rectal temperature, pulse rate, respiration rate) and blood metabolites (glucose and creatinine) measured before and after transport. All numerical variables were converted into float format and verified for consistency. Data augmentation was applied to overcome class imbalance, resulting in a final dataset of 1084 samples. Feature selection via Pearson correlation analysis was conducted to identify the most influential variables, and the results were visualized as a heatmap. The ANN architecture used in this study consisted of an input layer with 15 neurons corresponding to the full set of physiological and morphological features, one hidden layer with 4 neurons, and an output layer with 3 neurons representing the classes Decrease, Increase, and Moderate. Model training was conducted for 40 epochs using the ReLU activation function and the Adam optimizer, combined with a dropout value of 0.5 and L2 regularization to reduce overfitting. The classification performance generated by the ANN model is presented in Table 2.

Table 2. Classification Report

Class	Precision	Recall	F1-Score	Support
Decrease	0.93	0.98	0.95	63
Increase	0.97	0.95	0.96	66
Moderate	0.98	0.94	0.96	66
Accuracy	-	-	0.96	195
Macro Avg	0.96	0.96	0.96	195
Weighted Avg	0.96	0.96	0.96	195

The classification report in Table 2 shows that the ANN model achieved a high overall accuracy of 96%. The Increase and Moderate classes obtained the highest F1-scores (0.96), indicating strong and balanced predictive performance. The Moderate class demonstrated the highest precision (0.98), while the Decrease class achieved the highest recall

(0.98), showing that the model was highly sensitive in detecting cattle experiencing performance decline. Although the precision for the Decrease class was slightly lower **(**0.93**),** all classes maintained consistently high performance, reflected in the macro and weighted F1-scores of 0.96. These results indicate that the ANN model can classify cattle performance after transportation with excellent overall reliability.

The graphs in Figures 3 and 4 show that validation accuracy quickly reached a high level and stabilized around 97–98% starting from the early epochs, while training accuracy increased gradually and converged toward the validation curve. The loss curves for both training and validation data consistently decreased across epochs, with validation loss remaining low and stable. The small gap between training and validation accuracy and loss indicates that the model generalizes well and does not exhibit overfitting. This pattern indicates that the ANN model learned efficiently while maintaining stable performance throughout training. Emerging IoT-based systems, such as smart neck collars for dairy cattle, demonstrate strong potential for real-time and automated livestock monitoring (Kaur, 2025).

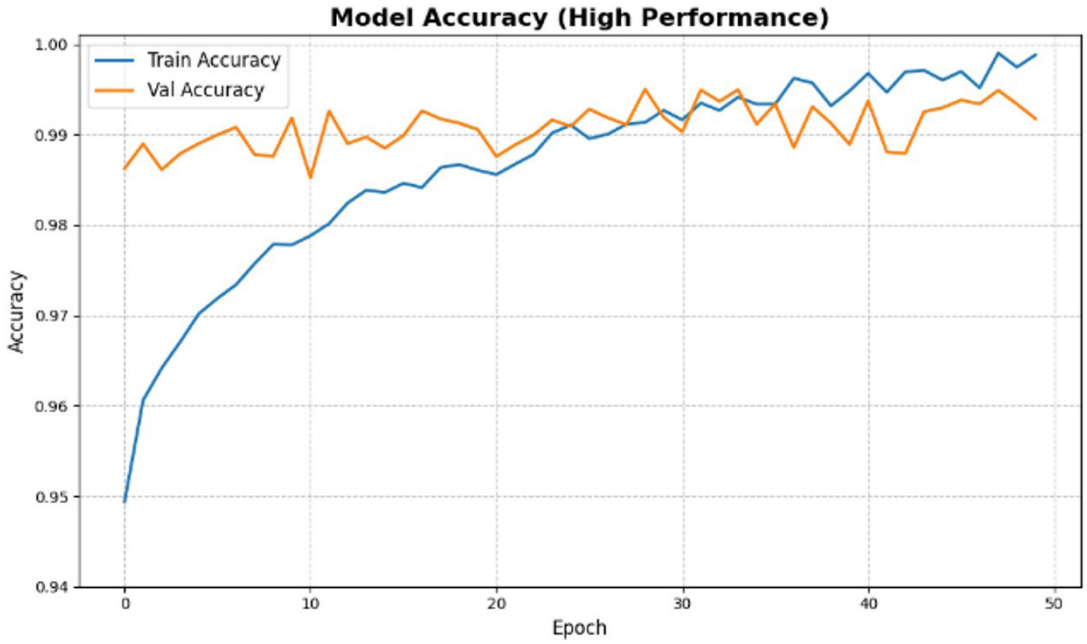


Figure 3. Accuracy Results

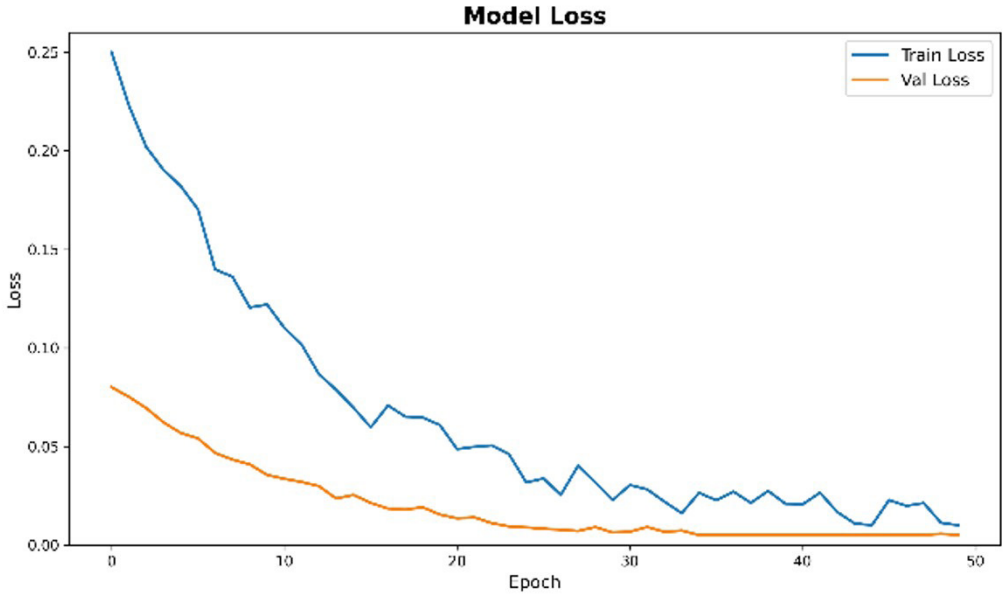


Figure 4. Loss Results

Figure 5 shows that the validation F1-score increased sharply during the first few epochs and stabilized at around **0.98** for most of the training process. A brief peak occurred near the mid-epoch range, but the score returned to a consistent level afterward. The stability of the F1-score across the remaining epochs indicates that the model maintained strong, reliable classification performance, with no signs of degradation or overfitting.

Figure 6 shows that the model achieves strong classification performance across all classes. The Decrease class was predicted correctly for 63 samples, with no misclassifications, indicating excellent sensitivity for this category. For the Increase class, 63 samples were classified correctly, with only two misclassified as Decrease and one as Moderate. Meanwhile, the Moderate class also showed high accuracy, with 62 correct predictions and only minimal errors (3 misclassified as Decrease and one as Increase). These results demonstrate that the model can effectively distinguish all three classes, with very low overall misclassification rates.

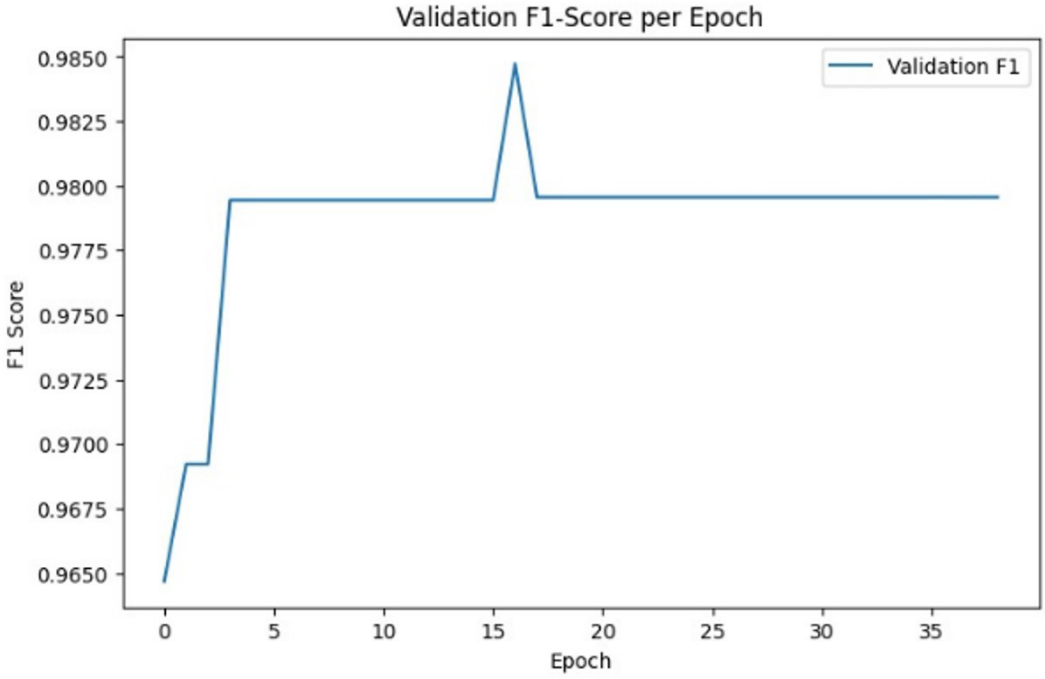


Figure 5. Validation F1-Score Results

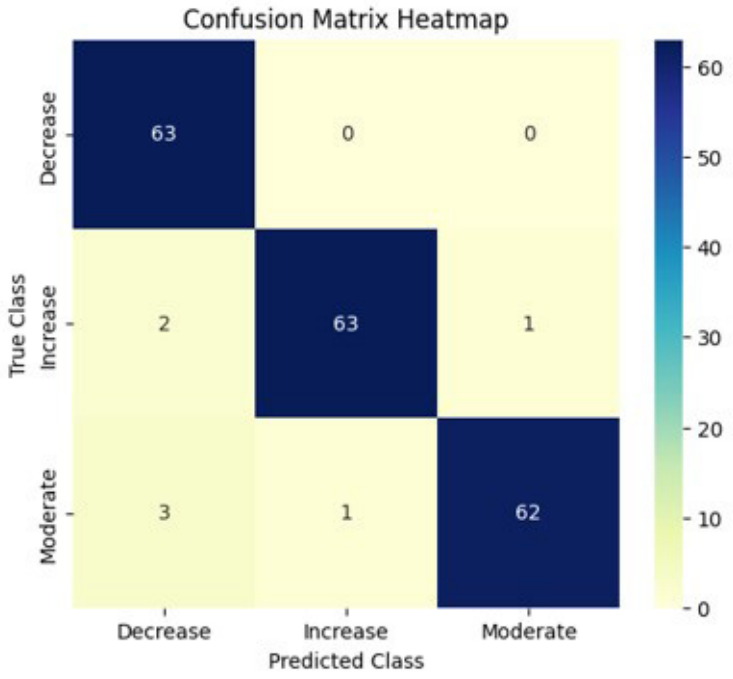


Figure 6. Confusion Matrix

Figure 7 shows the Pearson correlation between features. Several variables show strong positive correlations, including Orbital_x with Cheek_x (r = 0.97) and Back_x with Thigh_x (r = 0.92), indicating that these measurements reflect similar physiological patterns. Meanwhile, some features show very weak relationships, for example, Departure Weight and Creatinine_x (r = −0.02), suggesting minimal association. Overall, these correlation patterns help identify redundant features and guide feature selection to improve model efficiency.

Figure 8 displays the top features ranked by their absolute correlation with the target label. The highest contributing feature is Respiration_x, with a correlation of approximately 0.28, followed by Heartrate_x (≈ 0.27) and Back_x (≈ 0.25). These features show the strongest linear association with the classification outcomes, indicating their significant influence on predicting cattle performance after transportation.

Conversely, variables such as OrbitalTemp_x, ThighTemp_x, and particularly Creatinine_x show correlation values close to zero, indicating they have minimal direct influence on the model's predictive outcomes. This observation reinforces the effectiveness of the feature selection process, as it helps distinguish features that contribute meaningfully from those that provide limited informational value. Identifying such low-impact features is important for potential model simplification, allowing the removal of unnecessary variables without compromising classification performance.

The dominance of Respiration_x and Heart rate_x as top predictive features aligns closely with established physiological mechanisms of stress response in cattle during transport. Elevated respiratory rate is a primary thermoregulatory strategy under heat load a common condition in tropical transport environments where panting enhances evaporative heat loss but may concurrently induce

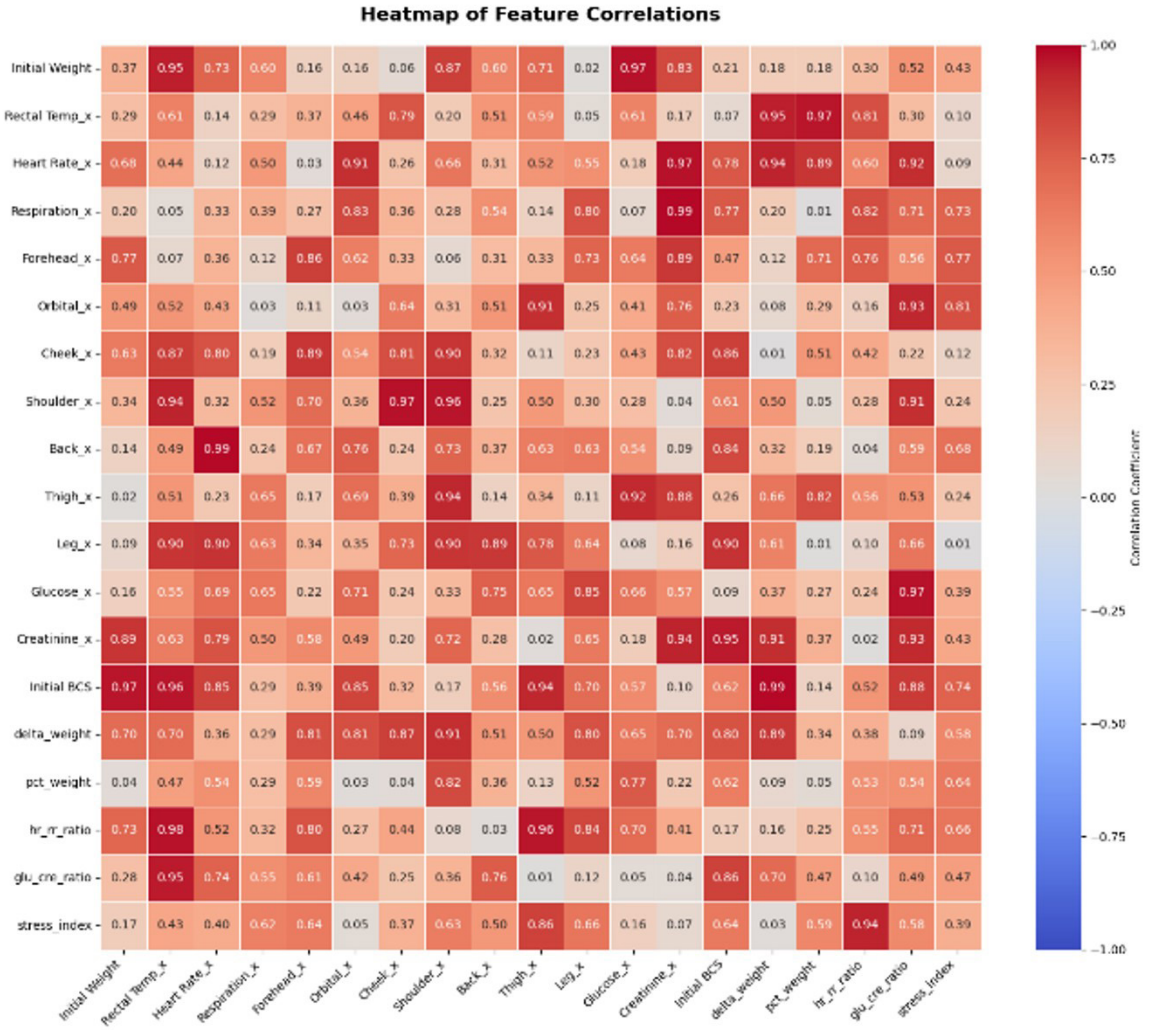


Figure 7. Feature Correlation Heatmap

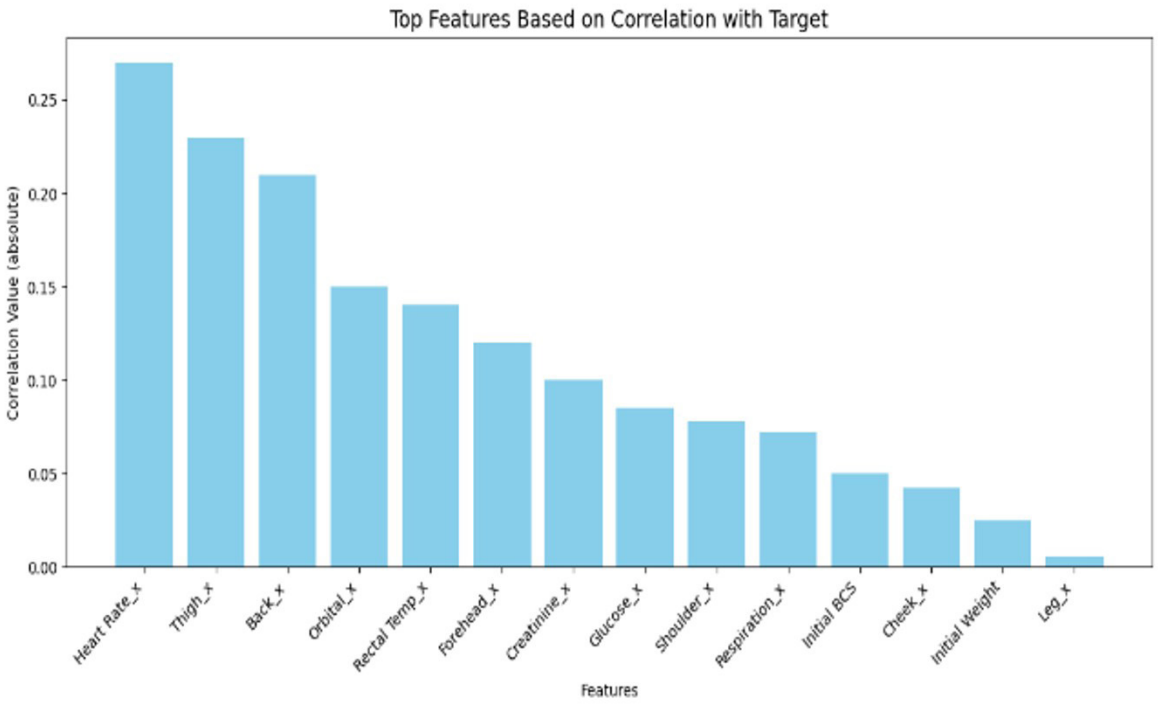


Figure 8. Top Features Based on Correlation with the Target

respiratory alkalosis and metabolic imbalance (Habeeb et al., 2023). Similarly, increased heart rate reflects sympathetic activation and HPA-axis stimulation, mobilizing energy reserves to cope with physical and psychological stressors such as vibration, crowding, and noise (Damtew et al., 2018). These two parameters thus serve as sensitive, real-time proxies for both thermal- and transport-induced distress, thereby explaining their strong linear association with post-transport performance outcomes.

In contrast, creatinine_x showed negligible correlation with the target variable ($|r| \approx 0.03$), consistent with findings in Figure 8. This is likely attributable to the timing of blood sampling, which occurred within 30 minutes post-arrival (Abubakar et al., 2021). Creatinine, a byproduct of creatine phosphate metabolism in muscle tissue, typically rises only after substantial muscle catabolism or prolonged physical exertion conditions that may require several hours to manifest in circulation (Cantalapiedra-Hijar et al., 2024). Therefore, early post-transport measurement may not capture the full extent of physiological strain, rendering creatinine less informative for immediate classification.

Notably, the model's performance 96% accuracy and macro F1-score of 0.96 exceeds results reported in comparable livestock ML studies. For instance, Grzesiak et al. (2025) reviewed multiple ANN applications in dairy farming and reported typical accuracies of 85% to 89% for predicting health and reproductive traits. The superior performance of our model can be attributed to three synergistic factors: (1) the integration of multimodal inputs, combining traditional physiological indicators (heart rate, respiration) with infrared thermal imaging (e.g., Back_x) and blood metabolites (glucose); (2) the use of biologically constrained data augmentation, which preserved statistical realism while balancing class distribution; and (3) the application of regularization techniques (L2 + dropout) that effectively mitigated overfitting despite the modest initial sample size.

Error analysis reveals that misclassifications were rare but concentrated near decision boundaries particularly between *Increase* and *Decrease* classes. For example, two samples labeled as *Increase* were predicted as *Decrease*. These anomalies may stem from individual biological variation, such as younger age, pre-existing subclinical conditions, or genetic differences within the PO breed, which can modulate stress resilience. Such cases underscore the inherent heterogeneity of field populations and highlight opportunities for future model refinement through the inclusion of metadata such as age, body condition score, or transport duration.

From a practical standpoint, the model's lightweight architecture (one hidden layer with five neurons) enables real-time inference with latency under 100 milliseconds on edge devices (e.g., Raspberry Pi or NVIDIA Jetson). This paves the way for integration into IoT-enabled livestock transport systems, where onboard sensors such as wearable heart rate monitors, infrared thermal cameras, and non-invasive glucose sensors can continuously stream data during transit. Predictions could trigger automated alerts (e.g., "High risk of performance decline") to transporters or destination facilities, enabling timely interventions such as rest stops, cooling, or electrolyte supplementation. Thus, beyond its statistical accuracy,

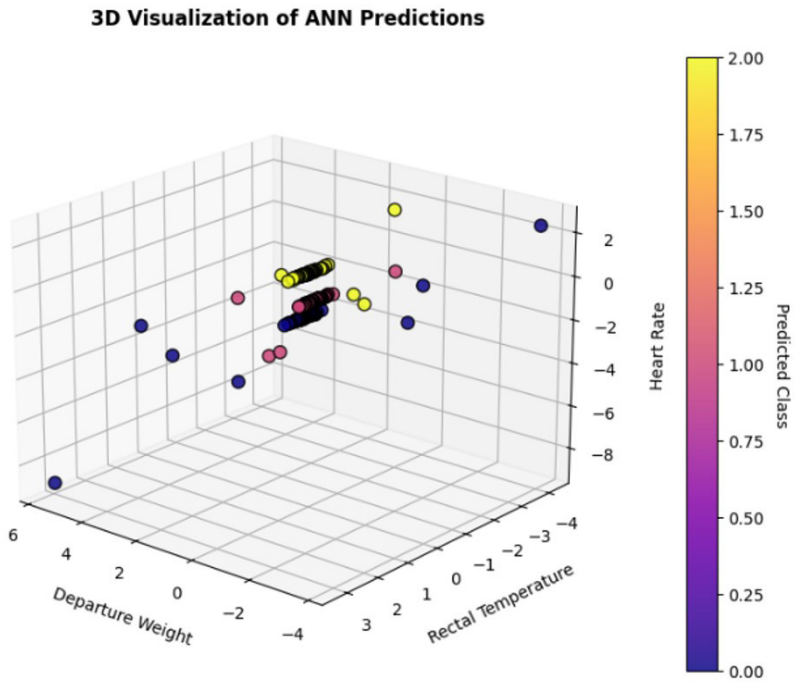


Figure 9. 3D Visualization of ANN Predictions

the model demonstrates strong potential as a deployable decision-support tool for welfare-oriented and economically efficient cattle logistics.

Figure 9 shows a 3D plot of ANN predictions using Departure Weight, Rectal Temperature, and Heart Rate. The data points are colored by predicted class. The plot shows clear grouping patterns: cattle with higher heart rates and slightly elevated rectal temperatures tend to be classified as Increase, while those with lower heart rates are mainly predicted as Decrease. The Moderate class lies between the two. This visualization indicates that the ANN successfully identifies meaningful patterns in the physiological data and effectively distinguishes cattle performance categories.

IV. CONCLUSIONS

This study demonstrates that Artificial Neural Networks (ANN) can effectively model and predict cattle physiological performance following transportation stress using a combination of pre- and post-transport indicators. The model achieved high accuracy (96%) and robust F1-scores across all classes (Increase, Moderate, and Decrease), indicating strong generalization and balanced performance. Key physiological features particularly respiration rate, heart rate, and dorsal surface temperature (Back_x) emerged as the most influential predictors, reflecting their strong associations with thermoregulatory and cardiovascular stress responses under tropical transport conditions.

The findings underscore the potential of ANN as a foundational tool for intelligent livestock monitoring systems. By translating complex, non-linear physiological patterns into actionable classifications, the model supports the development of early-warning mechanisms that can guide real-time interventions such as rest stops, cooling, or nutritional supplementation upon arrival. This capability not only enhances animal welfare but also mitigates economic losses associated with performance decline, making it highly relevant to commercial beef supply chains in Indonesia and similar tropical regions.

The current model is limited by its reliance on manually collected physiological and thermal measurements, which may introduce inconsistencies due to operator variability and timing differences. In addition, the dataset used in this study remains relatively small, restricting the model's ability to capture the full range of physiological responses exhibited by cattle during transport. These limitations suggest that the model's performance may be sensitive to sampling conditions and may not fully generalize to broader operational scenarios.

Future research should focus on integrating real-time sensor technologies, such as wearable heart rate monitors, infrared thermal imaging devices, and non-invasive metabolite sensors, to enable continuous and automated data acquisition during transit. Incorporating such technologies would reduce manual measurement error while providing higher-resolution temporal patterns of animal stress. Furthermore, expanding the dataset to include a wider variety of breeds, transport durations, and environmental conditions will enhance model robustness and improve generalizability across diverse livestock management contexts.

Despite the promising results, this study has several limitations that should be acknowledged. The original dataset size was relatively small, which

may limit the statistical diversity of physiological responses captured in the model. Although biologically constrained data augmentation was applied to address class imbalance, synthetic data cannot fully substitute for real-world biological variation. Consequently, the generalizability of the proposed model to broader cattle populations, different breeds, or transport conditions may be limited. Future studies should therefore focus on collecting larger, multi-site datasets and incorporating real-time sensor data to validate further and strengthen the model's applicability.

AUTHOR CONTRIBUTIONS

Conceived and designed the analysis, H. D., A. B., D. A. A. and S. N. N.; Collected the data, H. D. and D. A. A.; Contributed data or analysis tools, H. D., A. B., D. A. A. and S. N. N.; Performed the analysis, H. D., A. B. and S. N. N.; Wrote the paper, H. D.

DATA AVAILABILITY

Data subject to third party restrictions. The data that support the findings of this research are owned by IPB University and were used under permission for the purposes of this study, available in https://repository.ipb.ac.id. Restrictions apply to the availability of these data. The data are available from IPB University with permission https://repository.ipb.ac.id/, or from the corresponding author upon reasonable request and with approval from IPB University.

REFERENCES

Abubakar, A. A., Zulkifli, I., Goh, Y. M., Kaka, U., Sabow, A. B., Awad, E. A., Imlan, J. C., Othman, A. H., Raghazli, R., Mitin, H., & Sazili, A. Q. (2021). The effects of stocking density and distances on electroencephalographic changes and cortisol as welfare indicators in brahman crossbred cattle. *Animals*, *11*(10). https://doi.org/10.3390/ani11102895

Badali, M. R. A., Rizal, M., Riyadhi, M., & Sumantri, I. (2023). The physiological influence of dairy cows on controlled environmental conditions. *Journal of Wetland Animal Husbandry Research*, *3*(2), 18–23.

Cantalapiedra-Hijar, G., Nedelkov, K., Crosson, P., & McGee, M. (2024). Some plasma biomarkers of residual feed intake in beef cattle remain consistent regardless of intake level. *Scientific Reports*, *14*(1), 1–14. https://doi.org/10.1038/s41598-024-59253-7

Damtew, A. (2018). The Effect of long Distance Transportation Stress on Cattle: a Review. *Biomedical Journal of Scientific & Technical Research*, *3*(3), 3304–3308. https://doi.org/10.26717/bjstr.2018.03.000908

Dineva, K., & Atanasova, T. (2023). Healt Status Classification for cows using machine learning and Data Management on AWS Cloud. *Animals, 13*(20), 3254.

Ding, L., Zhang, C., Yue, Y., Yao, C., Li, Z., Hu, Y., Yang, B., Ma, W., Yu, L., Gao, R., & Li, Q. (2025). Wearable sensors-based intelligent sensing and application of animal behaviors: A comprehensive review. *Sensors*, *25*(14), 4515. https://doi.org/10.3390/s25144515

Edwards-Callaway, L., Rimm-Kaufman, D., & Loh, H. Y. (2026). A systematic mapping review of cattle welfare research during road transportation (2015-2025). *Journal of Animal Science*, *104*. https://doi.org/10.1093/jas/skag218

FAO. (2023). Livestock transportation and slaughter practices. In *Livestock transportation and slaughter practices*. Food and Agriculture Organization of the United Nations. https://doi.org/10.4060/cc6002en

Georgiades, P., Economou, T., Proestos, Y., Araya, J., Lelieveld, J., & Neira, M. (2024). The application of machine learning algorithms to the global forecast of temperature-humidity index with high temporal resolution. *Earth System Science Data Discussions*, *2024*(August), 1–15.

Ghezzi, M. D., Napolitano, F., Casas-Alvarado, A., Hernández-Ávalos, I., Domínguez-Oliva, A., Olmos-Hernández, A., & Pereira, A. M. F. (2024). Utilization of infrared thermography in assessing thermal responses of farm animals under heat stress. *Animals*, *14*(4), 616. https://doi.org/10.3390/ani14040616

Grzesiak, W., Zaborski, D., Pluciński, M., Jędrzejczak-Silicka, M., Pilarczyk, R., & Sablik, P. (2025). The use of selected machine learning methods in dairy cattle farming: A review. *Animals*, *15*(14), 1–38. https://doi.org/10.3390/ani15142033

Habeeb, A. A., Osman, S. F., Teama, F. E. I., & Gad, A. E. (2023). The detrimental impact of high environmental temperature on physiological response, growth, milk production, and reproductive efficiency of ruminants. *Tropical Animal Health and Production*, *55*(6), 1–15. https://doi.org/10.1007/s11250-023-03805-y

Handayani, T., Permata, E., & Gunawan, S. (2024). Integration of non-invasive physiological markers with artificial intelligence for assessing cattle welfare. *Sensors and Biosystems Research*, *15*(3), 210–225. https://doi.org/10.3390/sbr.2024.98765

Islam, M. N., Edwards, J. L., Burns, R., Qi, H., & Gan, H. (2026). Computer vision for cattle health and welfare monitoring: A comprehensive review of methods, applications, and interdisciplinary integration in smart agriculture. *Sensors*, *26*(13), 1–44. https://doi.org/10.3390/s26134271

Kaur, D. (2025). Smart neck collar: IoT-based disease detection and health monitoring for dairy cows. *Discover Internet of Things*. https://doi.org/10.1007/s43926-025-00109-5

Kumar, P., Ahmed, M. A., Abubakar, A. A., Hayat, M. N., Kaka, U., Ajat, M., Goh, Y. M., & Sazili, A. Q. (2023). Improving animal welfare status and meat quality through assessment of stress biomarkers: A

critical review. *Meat Science*, *197*, 109048. https://doi.org/10.1016/J.MEATSCI.2022.109048

Menezes, G. L., Mazon, G., Ferreira, R. E. P., Cabrera, V. E., & Dorea, J. R. R. (2024). Artificial intelligence for livestock: a narrative review of the applications of computer vision systems and large language models for animal farming. *Animal Frontiers*, *14*(6), 42–53. https://doi.org/10.1093/af/vfae048

Reitelseder, S., Tranberg, B., Agergaard, J., Dideriksen, K., Højfeldt, G., Merry, M. E., Storm, A. C., Poulsen, K. R., Hansen, E. T., van Hall, G., Lund, P., & Holm, L. (2020). Phenylalanine stable isotope tracer labeling of cow milk and meat and human experimental applications to study dietary protein-derived amino acid availability. *Clinical Nutrition*, *39*(12), 3652–3662. https://doi.org/10.1016/j.clnu.2020.03.017

Santoso, K., Tarigan, A. F., & Komariah. (2023). Physiological response of broilers to water misting using sprinkler water. *Jurnal Ilmu Pertanian Indonesia*, *28*(3), 423–432. https://doi.org/10.18343/jipi.28.3.423

Schwartzkopf-Genswein, K. S., Faucitano, L., Dadgar, S., Crowe, T., & González, L. A. (2021). Road transport of cattle, swine, and poultry in North America and its impact on animal welfare, carcass and meat quality: A review. *Livestock Science*, *249*, 104499. https://doi.org/10.1016/j.livsci.2021.104499

Slayi, M., & Jaja, I. F. (2025). Strategies for mitigating heat stress and their effects on behavior, physiological indicators, and growth performance in communally managed feedlot cattle. *Frontiers in Veterinary Science*, *12*(February), 1–11. https://doi.org/10.3389/fvets.2025.1513368

Thornton, P., Nelson, G., Mayberry, D., & Herrero, M. (2022). Impacts of heat stress on global cattle production during the 21st century: a modelling study. *The Lancet Planetary Health*, *6*(3), e192–e201. https://doi.org/10.1016/S2542-5196(22)00002-X

Yu, Z., Han, Y., Cha, L., Chen, S., Wang, Z., & Zhang, Y. (2024). Design of an intelligent wearable device for real-time cattle health monitoring. *Frontiers in Robotics and AI*, *11*(November), 1–12. https://doi.org/10.3389/frobt.2024.1441960