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Research article

DEEP LEARNING-BASED FORECASTING OF HEAT STRESS EVENTS AND DAILY MILK YIELD DEPRECIATION IN DAIRY CATTLE USING METEOROLOGICAL DATA: AN *IN-SILICO* STUDY

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Climate change is a serious threat to food security as heat stress compronises animal welfare and production. Traditional statistical models struggle to capture these lagged and non-linear dynamics, limiting proactive herd management. Therefore, the aim of this study was to develop an early warning prediction system for milk yield losses due to heat stress in dairy cows by explicitly modeling physiological delay effects using Long Short-Term Memory (LSTM) based deep learning in a Digital Twin environment. For a *in silico* approch, a high-fidelity digital twin dataset was created to simulate a herd of 500 Holstein-Friesian cattle over a three-year period (1,095 days). The present study involved calculating the Temperature–Humidity Index (THI) by integrating biologically based response functions with time-series meteorological data, and simulated the associated physiological stress responses. A recurrent neural network model based on the LSTM architecture was trained on 80% of the time-series dataset to model the nonlinear temporal relationships between ambient conditions and milk yield. Model performance evaluation demonstrated strong predictive capability, with a root mean squared error (RMSE) of 1.48 kg/day and a coefficient of determination (R^2) of 0.81. Correlation analysis further revealed a strong negative association between THI and milk production (Pearson's $r = -0.76$, p-value < 0.001). The model also successfully detected the early onset of heat stress and captured the biological lag effect, as evidenced by its accurate prediction of seasonal declines in productivity. Overall, these findings, derived from a controlled simulation environment, support the potential applicability of LSTM-based frameworks as early warning systems to guide proactive mitigation strategies and reduce heat stress–related milk yield losses in dairy cattle. However, further validation under real farm conditions is necessary before practical implementation.

Keywords: Precision Livestock Farming; Heat Stress; LSTM; Digital Twin; Milk Yield Prediction; Dairy Cattle.

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INTRODUCTION

In recent years, global warming has become a major focus of scholarly research due to its far-reaching implications for the global food system, particularly regarding the sustainability of dairy production and food security. Empirical evidence has indicated that high-yielding dairy cattle breeds, such as Holstein–Friesian, exhibit low tolerance to elevated ambient temperatures owing to their high internal metabolic heat load [1]. Previous studies have demonstrated that when environmental thermal load exceeds an animal's capacity for heat dissipation, a state of heat stress develops, characterized by reduced feed intake, increased respiration rate, and a pronounced, non-linear decline in milk production [2].

It has been reported in many studies that climate change has economic impacts on many areas. As an example, heat stress in the United States leads to yearly losses of more than US$ 1.5 billion, which is mainly due to the decrease in milk production and reproductive functions [3]. At the global level, economic losses under severe climate scenarios are estimated to reach US$ 14.65 billion by 2045 [4]. Physiological researches have reported a "lag effect" where elevated temperature today leads to peak production losses 24 to 48 hours later [5,6]. This demonstates a non-instant response to heat stress in cattle.

Much research in recent years has focused on the immediate effects of environmental conditions on milk yield [7,8], analyzed daily observations independently, and consequently failed to represent the delayed and cumulative physiological responses of cattle to heat stress. However, the present study explicitly models the biological delay effects associated with heat stress, using a Long Short Term Memory (LSTM) architecture capable of capturing multi-day temporal dependencies and introducing a biologically constrained Digital Twin framework that enables systematic evaluation of model behavior under controlled but realistic environmental scenarios.

In fact, this temporal lag limits effective management because farmers generally respond only once a noticeable decline in milk yield becomes significant, by which time metabolic damage has already occurred.

To address this issue, Precision Livestock Farming (PLF) aims to use data-driven tools to predict adverse events before they occur [9]. Although traditional regression models have been used to relate temperature to yield, they treat data in isolation and lack the "memory" needed to model complex time-series data in which past events influence future outcomes [10].

Deep Learning, in particular Long Short Term Memory (LSTM) networks, offers a robust solution. Unlike standard neural networks, LSTMs have internal memory cells that can hold information over long sequences, making them ideal for modeling biological delay effects and temporal dependencies [11].

This study is aiming to develop an early warning prediction system for heat-stress related milk yield losses in dairy cows by explicitly modeling physiological delay effects using LSTM-based deep learning in a Digital Twin environment.

MATERIALS AND METHODS

Ethical Approval

This study was performed using computer-generated ("In-Silico") simulation and no live animal experiments were used. Therefore, formal ethical approval was not required.

The "Digital Twin" Data Strategy

In practical terms, obtaining detailed daily production data for large-size herds is often hindered by commercial confidentiality, data fragmentation and inconsistent recording standards. To achieve scientific rigor, reproducibility and ethical compliance (avoiding causing stress to livestock), an "In-Silico" experimental approach was used in this study. Accordingly, a Digital Twin was performed: a comprehensive synthetic dataset that mathematically replicates the biological and environmental dynamics of a real-world dairy farm [12].

The simulation parameters were defined as follows:

Herd Demographics: A commercial herd of 500 Holstein-Friesian cattle.

Time Horizon: A continuous 1,095-day period (3 years) to capture seasonal variability.

Meteorological Data: Daily Temperature (T) and Relative Humidity (RH) were simulated using sinusoidal functions with added stochastic noise to mimic realistic weather fluctuations (Mean T: 20°C, Range: 5–35°C).

Quantifying Heat Stress

Stress level can be determined by calculating the Temperature-Humidity Index (THI), according to the following formula [13]:

$$THI = (1.8 \times T + 32) - (0.55 - 0.0055 \times RH) \times (1.8 \times T - 26);$$

where **T** = ambient temperature (°C) and **RH** = relative humidity (%).

The upper limit of the thermal comfort zone was set at a THI of 72. For any THI unit exceeding this level, a biological penalty function was applied to the benchmark milk production. Yield losses were distributed using a weighted decay function, with 60% of the loss assigned to the first 24 hours and 40% to the subsequent 24 hours, consistent with reported physiological recovery dynamics [15].

Table 1. Descriptive statistics of simulated dataset of environmental parameters (N= 1095 days)

Variable	Mean	Std. Dev	Min	Max
Temperature (°C)	20.1	8.4	4.2	36.8
Humidity (%)	65.3	10.1	38.5	94.2
THI Index	66.8	9.2	45.1	84.5
Milk Yield (kg/cow/day)	35.4	3.8	26.1	41.2
Stress Events (Days > THI 72)	-	-	-	449 Days

Deep Learning Architecture: LSTM

A Recurrent Neural Network (RNN) using the Long Short-Term Memory (LSTM) architecture was used. The implemented model was developed by using the TensorFlow and Keras framework with the following characteristics:

Input Layer: An LSTM layer with 50 units and return_sequences=True, used to process the time series window (14-day lookback).

Regularization: Dropout layers (ratio = 0.2) were interspersed to prevent overfitting and enable the model to learn generalizable patterns instead of memorizing noise (16).

Hidden Layer: A second LSTM layer of 50 units to capture higher-order temporal dependencies.

Output Layer: A dense neuron to predict the scalar value of herd average milk yield for the target day.

In order to contextualize the relative benefits of sequence-aware architectures under identical simulated conditions, baseline models were included. Absolute performance values were interpreted as indicative rather than site-specific.

Performance Evaluation

To build reliable machine learning model, our dataset was divided into a training set (Years 1-2; 80%) and a test set (Year 3; 20%). The model performance was evaluated using the following three key metrics:

Root Mean Square Error (RMSE): Measures the average magnitude of the prediction error in kg/day.

Mean Absolute Error (MAE): Represents the average absolute difference between predicted and actual yield.

Coefficient of Determination (R^2): Indicates the proportion of variance in the dependent variable that can be estimated from the independent variable.

Statistical analysis

Pearson correlation analysis was performed to examine the linear relationships among environmental variables (THI, temperature, humidity) and milk yield. The Pearson correlation coefficient (r) was computed assuming linear relationships, continuous variables, and approximate normal distribution of the data. Statistical significance of correlations was assessed using two-tailed tests, with p-values < 0.05 considered statistically significant. A correlation matrix was generated and visualized using a heatmap to illustrate the strength and direction of associations among variables.

RESULTS

Environmental Dynamics and Correlation Analysis

The correlation heat map is shown in Figure 1. The simulated data successfully represent the seasonal variation expected in a temperate dairy production system. As can be seen, a strong negative Pearson correlation coefficient ($r = -0.76$, p-value < 0.001) was found between the Temperature–Humidity Index (THI) and daily milk yield. This statistically demonstrates a reduction in milk yield with increasing thermal load over the years.

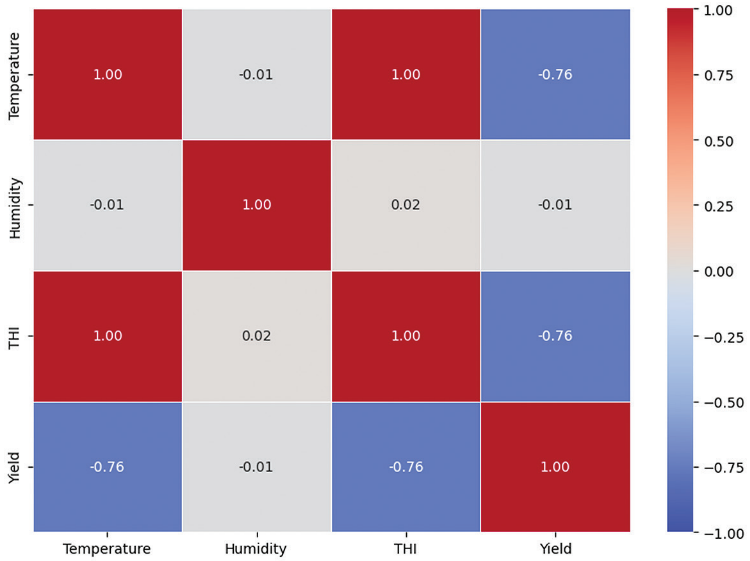

Figure 1. Pearson correlation matrix heatmap

Biological Validation of Stress Thresholds

The impact of thermal load on lactation yield over a time-series framework is presented in Figure 2. A strong inverse correlation was observed, with abrupt increases in the temperature–humidity index (THI; red dashed line) associated with corresponding declines in milk yield (green line). Over the 365-day period, the seasonal reduction in milk production during summer coincided with periods of peak thermal stress.

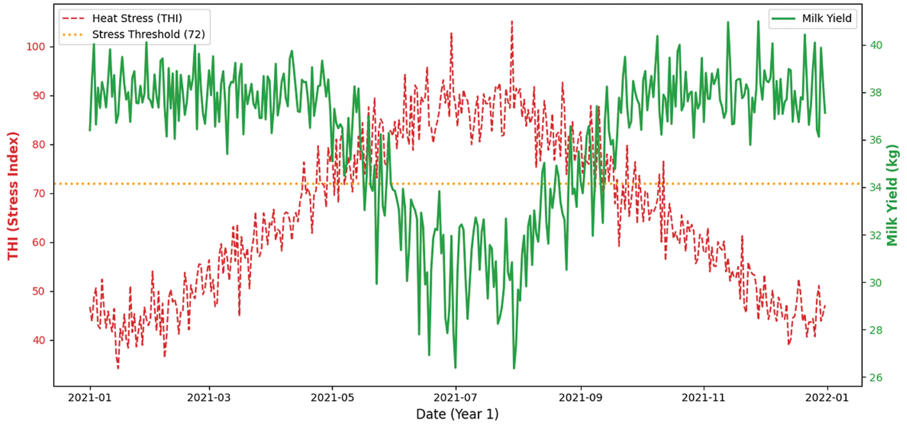

Figure 2. Temporal dynamics of heat stress and production

As expected, the scatterplot analysis presented in Figure 3, confirmed the breaking point theory.

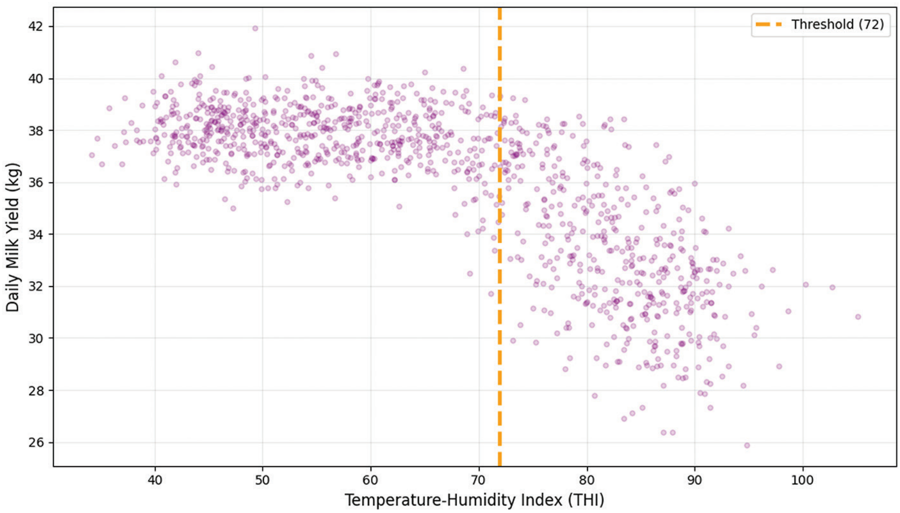

Figure 3. Biological response curve (the „elbow“ effect)

In the present study, a THI value of 72 was confirmed as the critical physiological threshold for the Holstein-Friesian cattle breed. This level is considered the onset of physiological stress and the associated loss of milk production. Below the identified threshold, milk yield remained relatively stable; however, increases in THI above this threshold were associated with a decline in milk yield of about 0.45 ± 0.1 kg per THI unit.

Model Training and Stability

This deep-learned model was shown to converge well. The training and validation loss values as depicted in Figure 4 were declining fast in the first ten epochs and then plateau as the values did not diverge. This finding shows that the LSTM network was able to absorb the biological regularities behind it without being overfit to the stochastic noise of the training data set.

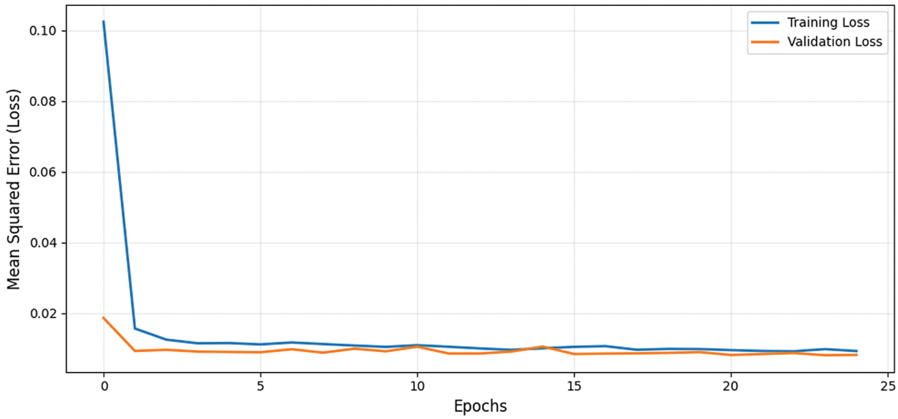

Figure 4. LSTM model learning curve

Forecasting Performance

The performance of the model is given in Table 2, and its predictive proficiency was evaluated using an independent test set in year 3. Coefficient of determination (R 2 = 0.81), a root-mean-square error of 1.48 – 1 kg day and a mean absolute error of 1.18 – 1 kg day were all achieved by the model. These results indicate a high predictive ability of the LSTM model in all the considered criteria.

Table 2. LSTM Model Performance Metrics (Test Set)

Metric	Value	Interpretation
RMSE	1.48 kg/day	Average prediction error < 1.5 kg
MAE	1.18 kg/day	High precision in daily estimates
R^2 Score	0.81	Explains 81% of production variance

Figure 5 shows a high-resolution illustration of the model predictions in the important summer months. The LSTM prediction (red) gave the best performance in the sense that it was able to predict the extent of production downturns, and the subsequent recovery after heat waves. This result testifies to the ability of the model to follow closely the biological variability that is evident in milk production (green).

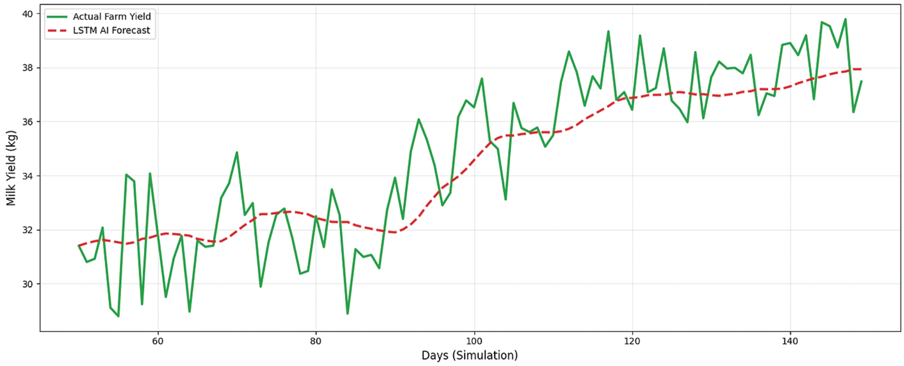

Figure 5. Forecast performance during summer stress (test set)

The analysis of the performance comparison between the candidate LSTM model and the reference models is presented in Table 3. Long-term memory-lacking models exhibited substantially poorer predictive performance, particularly during periods of rapid environmental change. By contrast, the LSTM architecture consistently captured the delayed and cumulative effects of heat stress on milk production. These findings stand out the need for sequence-aware learning approaches to accurately predict biologically delayed production responses.

Table 3. Performance comparison between baseline models and the proposed LSTM framework on the test dataset (Year 3).

Model	Temporal Memory	RMSE (kg/day)	MAE (kg/day)	R^2
Persistence Model ($y_t = y_{t-1}$)	None	2.41	1.98	0.52
Multiple Linear Regression	None	2.18	1.76	0.61
Random Forest Regression	Limited (lagged inputs)	1.89	1.49	0.71
Support Vector Regression (RBF)	None	1.94	1.53	0.69
LSTM (proposed)	Explicit	1.48	1.18	0.81

DISCUSSION

Prior studies have documented the immediate effects of environmental variables on milk yield, but have not fully captured the delayed and cumulative physiological responses of cattle to thermal stress [7,8]. In this study, we focused on developing an early warning prediction system for heat stress-induced milk yield losses in dairy cows by explicitly modeling physiological delay effects using LSTM-based deep learning within a Digital Twin environment.

The Power of Temporal Memory in Forecasting

A key finding of this study is that LSTM networks demonstrated good predictive performance for livestock production parameters under controlled simulation conditions ($R^2 = 0.81$). Traditional regression models treat each data point separately and assume that today's milk yield is only a result of today's weather conditions. However, bovine physiology is cumulative; a cow that was severely stressed yesterday is metabolically compromised today, even if the ambient temperature drops. Our LSTM model accounted for this physiological history by using a 14-day "look-back" window, resulting in a robust prediction that captures the biological system's inertia [17]. These results support the findings of Qi et al. [18] who used a bidirectional LSTM model to predict milk yield and reported better prediction accuracy compared to conventional regression models. However, other authors in a cattle weight gain prediction study have reported that Random Forest models outperformed LSTM models in terms of R^2 and error metrics [19], suggesting that simpler tree-based, non-temporal models can be competitive in certain scenarios when feature selection and data structure are appropriate.

Implications for Precision Livestock Farming

The practical application of this model is important for farm management. Currently, heat mitigation strategies (such as activating fans, or sprinklers) are usually reactive – triggered only when the barn temperature exceeds a set point. However, milk production loss is often determined by heat exposure occuring hours or even days in advance [20].

A forecasting tool with a margin of error <1.5 kg enables farmers to move from "Reactive" to "Proactive" management. If the model predicts a significant yield reduction 3 to 7 days in advance, the farmer can adjust ration energy level in advance, increase electrolyte availability, or modify the cooling program to reduce impending heat stress before it affects the bulk tank average [21].

Advantages of In-Silico Modeling

The use of the Digital Twin dataset offers clear ethical and scientific advantages. It adheres to the 3Rs principle (Replacement, Reduction, Refinement), avoiding the induction of heat stress in live animals for experimental purposes [22]. It also provides a controlled "clean" environment to validate the mathematical architecture of the Deep Learning model without the confounding variablescommonly present in raw data, such as feed mixing erros, infectious outbreaks, or genetic variability [23].

Limitations and Future Directions

Although the results are promising, this study is limited by its simulation-based nature. Real-world dairy farms are subject to variations such as fluctuations in feed quality and variable compliance with the management protocols controlled in the present simulation [24]. Future work should include validation of this LSTM architecture using anonymized data from commercial dairy farms to assess its robustness under real-word conditions field. Furthermore, integrating individual animal-level data, rather than herd averages, could enable precision livestock management approaches by identifying specific cows that are less tolerant to heat [25,26].

CONCLUSION

This study developed and evaluated a Deep Learning framework for predicting milk yield loss due to heat stress within a controlled simulation environment. Tools capable of translating weather forecasts into actionable biological insights may become increasingly important for dairy farm management under changing climatic conditions. The LSTM model was able to capture the complex, non-linear relationship between meteorological conditions and bovine physiology, achieving an RMSE of 1.48 kg/day and an R^2 of 0.81. These findings suggest the potential applicability of LSTM-based models as components of intelligent Early Warning Systems in dairy farming to support economic sustainability and animal welfare. However, since the present results are based on simulations, further validation using real dairy cow data under practical farm conditions is required before field implementation.

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Authors' contributions

IMA conceived and designed the study, collected and curated the meteorological and milk yield datasets, developed and implemented the deep learning models, performed the data analyses and forecasting procedures, interpreted the results, and drafted the manuscript. IMA read and approved the final manuscript.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability

The Digital Twin dataset created for this study is available from the author upon reasonable request.

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PROGNOZIRANJE TOPLOTNOG STRESA I SMANJENJA DNEVNOG PRINOSA MLEKA KOD MLEČNIH GOVEDA ZASNOVANO NA *DEEP LEARNING* PROGNOZI KORIŠĆENJEM METEOROLOŠKIH PODATAKA: *"IN SILICO"* STUDIJA

Ibrahima Mahamane ABDOURHAMANE

Klimatske promene predstavljaju ozbiljnu pretnju bezbednosti hrane, jer toplotni stres ugrožava dobrobit i proizvodnju životinja. Tradicionalni statistički modeli pokušavaju da obuhvate ovu nelinearnu dinamiku, ograničavajući proaktivno upravljanje stadom. Stoga je cilj ove studije bio da se razvije sistem ranog upozoravanja na gubitke prinosa mleka usled toplotnog stresa kod mlečnih krava eksplicitnim modeliranjem fizioloških efekata korišćenjem *"Deep Learning"* zasnovanog na dugoročnoj memoriji (LSTM) u okruženju digitalnih blizanaca. Za *in silico* pristup, kreiran je visokokvalitetni skup po-

dataka digitalnih blizanaca za simulaciju stada od 500 goveda rase Holštajn-Frizijske tokom perioda od tri godine (1.095 dana). Ova studija je obuhvatila izračunavanje indeksa temperature i vlažnosti (THI) integrisanjem biološki zasnovanih funkcija odgovora sa meteorološkim podacima vremenskih serija i simulaciju povezanih fizioloških odgovora na stres. Model rekurentne neuronske mreže zasnovan na LSTM arhitekturi je obučen na 80% podataka vremenskih serija kako bi modelirao nelinearne vremenske odnose između uslova okoline i prinosa mleka. Evaluacija performansi modela pokazala je snažnu prediktivnu sposobnost, sa srednjom kvadratnom greškom (RMSE) od 1,48 kg/dan i koeficijentom determinacije (R^2) od 0,81. Analiza korelacije je dodatno otkrila jaku negativnu vezu između toplotnog stresa i proizvodnje mleka (Pirson-ov $r = -0{,}76$, $p < 0{,}001$). Model je takođe uspešno detektovao rani početak toplotnog stresa i zabeležio efekat biološkog kašnjenja, što je dokazano njegovim tačnim predviđanjem sezonskog pada produktivnosti. Generalno, ovi nalazi, izvedeni iz kontrolisanog simulacionog okruženja, podržavaju potencijalnu primenljivost okvira zasnovanih na LSTM-u kao sistema ranog upozoravanja za vođenje proaktivnih strategija ublažavanja i smanjenje gubitaka prinosa mleka povezanih sa toplotnim stresom kod mlečnih goveda. Međutim, pre praktične primene neophodna je dalja validacija u realnim terenskim uslovima na farmi.