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Machine learning algorithms to predict core, skin, and hair-coat temperatures of piglets

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ABSTRACT

Internal-body (core) and surface temperatures of livestock are important information that indicate heat stress status and comfort of animals. Previous studies focused on developing mechanistic and empirical models to predict these temperatures. Mechanistic models based on bioenergetics of animals often require parameters that may be difficult to obtain (e.g., thickness of internal tissues). Empirical models, on the other hand, are data-based and often assume linear relationships between predictor (e.g., air temperature) and response (e.g., internal-body temperature) variables although, from the theory of bioenergetics, the relationship between the predictor and the response variables is non-linear. One alternative to consider non-linearity is to use machine learning algorithms to predict physiological temperatures. Unlike mechanistic models, machine learning algorithms do not depend on biophysical parameters, and, unlike linear empirical models, machine learning algorithms automatically select the predictor variables and find non-linear functions between predictor and response variables. In this paper, we tested four different machine learning algorithms to predict rectal (T_r), skin-surface (T_s), and hair-coat surface (T_h) temperatures of piglets based on environmental data. From the four algorithms considered, *deep neural networks* provided the best prediction for T_r with an error of 0.36%, *gradient boosted machines* provided the best prediction for T_s with an error of 0.62%, and *random forests* provided the best predictions for T_h with an error of 1.35%. These three algorithms were robust for a wide range of inputs. The fourth algorithm, *generalized linear regression*, predicted at higher errors and was not robust for a wide range of inputs. This study supports the use of machine learning algorithms (specifically deep neural networks, gradient boosted machines, and random forests) to predict physiological temperature responses of piglets.

1. Introduction

One of the current challenges in agriculture is to increase food production to feed the world's growing population while considering environmental responsibilities and the comfort of the biological object (livestock; Hunter et al., 2017). In animal production, the challenge is in developing precision livestock farming techniques (Van Hertem et al., 2017; Wathes et al., 2008) to increase animal comfort and production. These techniques (Guarino et al., 2017) are focused on continuous monitoring of animal health, comfort, and production indicators, such as internal-body and skin-surface temperature. These temperatures indicate the health status and production levels of animals (Da Silva and Maia, 2013; Soerensen and Pedersen, 2015), as well as their heat stress level, estimated to cost the swine industry \$300 million each year (St-Pierre et al., 2003).

Heat stress is a major issue that decreases animal welfare (Silanikove, 2000), production (Nienaber et al., 1999), reproduction (Wolfenson et al., 2000), and growth potential (Collin et al., 2001). To cope with heat stress, pigs rely on behavioral (Vasdal et al., 2009) and physiological (Brown-Brandl et al., 2001, 2014; Robertshaw, 2006) responses. Because of the importance of monitoring heat stress of pigs (Shao and Xin, 2008), and the difficulty of measuring the necessary parameters that indicate heat stress (McCafferty et al., 2015), two classical approaches are used to estimate heat stress of animals: (1) mechanistic modelling, and (2) empirical modelling.

Mechanistic models are based on the biophysical understanding of conservation of energy, momentum, and mass in live animals (Collier and Gebremedhin, 2015; DeShazer, 2009). Using conservation equations, a governing equation for the problem is formulated and solved analytically or numerically. The limitations of analytical and numerical

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models are the assumption that internal and/or superficial temperatures are known, or a simple mathematical relationship exists between them, and/or some of the parameters are also difficult to obtain (e.g., thickness of internal tissues, etc.). Furthermore, mechanistic models reveal that the relationship between environmental and physiological responses are non-linear (Hensley et al., 2013; Milan and Gebremedhin, 2016a,b; McArthur, 1981).

Empirical models are data-based and usually assume a linear relationship between predictor variables (e.g., air temperature) and the response variable (e.g., internal-body temperature). These relationships are chosen by the researcher and has a considerable impact on the accuracy of the model (Mostaço et al., 2015; Pathak et al., 2009; Ramirez, 2017; Soerensen and Pedersen, 2015).

A third approach that is receiving increased attention from swine researchers are machine learning and computer vision algorithms (Kamilaris and Prenafeta-Boldú, 2018). Recent applications include monitoring animal behavior (Cross et al., in press; Lao et al., 2016; Nasirahmadi et al., 2017; Shao and Xin, 2008), and weight (Kashiha et al., 2014; Shi et al., 2016; Wongsriworaphon et al., 2015). In this paper, we propose the use of machine learning algorithms to predict internal-body temperature, skin-surface temperature, and hair-coat surface temperature of piglets from environmental variables. The advantage of this approach compared to mechanistic models is that it does not rely on biophysical parameters. The advantage of this approach compared to empirical models is that it automatically finds a non-linear function from the data, removing the subjectivity from the researcher choosing the relationship between predictor and response variables. To the best of our knowledge, this is the first study that applies machine learning algorithms to predict physiological temperatures of swine.

2. Materials and methods

2.1. Experimental measurements

Animal use and research protocol were approved by the Animal Care and Use Committee from São Paulo State University (FAPESP Proc. 17.519/14). The experiment was conducted in Jaboticabal, São Paulo, Brazil (21°15′40″ South Latitude and 595 m elevation) for five consecutive days. Ten 5-days-old piglets (weight = 3.76 ± 0.41 kg, mean ± SEM) from the commercial lineage "Large White" were randomly selected from the same farrowing. The farrowing was not provided with supplemental heat. The selected piglets were randomly separated into 5 groups (2 piglets in each group) and managed inside a brooder ($1.0 \times 1.0 \times 1.0\,m^3$) from 3 a.m. to 8 a.m. Physiological measurements were performed hourly and started one hour after the piglets were inside the brooder (i.e., from 4 a.m. to 8 a.m.) to allow for adaptation to the environment. Four of the five groups were provided with supplemental heat (lamps) with intensities of 60 W, 100 W, 160 W, or 200 W. The fifth group (control) was not provided with supplemental heat.

Skin-surface temperature (T_s, °C) at the upper leg of the animal was measured with a skin- temperature probe (MLT422/AL, ADInstruments, accuracy ± 0.2 °C) and rectal temperature (T_r, °C) was measured with a rectal temperature probe (MLT1403, ADInstruments, accuracy ± 0.2 °C). These probes were connected to thermistor pods (ML309, ADInstruments), and the pods were connected to a data acquisition system (PL3516/P, PowerLab 16/35 and LabChart Pro, ADInstruments) that recorded data every second for approximately 5 min. Hair-coat-surface temperature (T_h, °C) at the upper leg was measured with an infrared thermometer (Model 568, Fluke, accuracy ± 1 °C). Air temperature (T_a, °C) and relative humidity (RH, %) inside the brooder were measured every minute (HOBO U12 Temp/RH, Onset, accuracy ± 0.35 °C and ± 2.5%). Black globe temperature (T_g, °C) inside the brooder was measured using a 15-cm dia. black globe installed 10 cm above the ground (thermocouple TMC20-HD, datalogger U12-013, accuracy ± 0.35 °C, Onset).

2.2. Model development

2.2.1. Data processing

The experiment was designed to provide 200 data points. Each individual data point contained the time of measurement (in hours), intensity of the supplemental heat, T_a, RH, T_g, T_r, T_s, and T_h. Time of measurement, intensity of supplemental heat, T_a, and T_g were used as predictors of T_r, T_s, and T_h. RH was not used as a predictor variable because 22% of the data was lost due to sensor failure. Further technical problems led to a reduction in the number of collected datapoints from 200 to 173. Correlations of the variables, mean and standard error of the mean were calculated. The univariate number of the outliers in the dataset was calculated using the z-score method at 2.5 standard deviations above or below the mean (Cousineau and Chartier, 2010).

The dataset was divided into training and testing datasets (Hastie et al., 2003). The training dataset was used to develop the machine learning models and the testing dataset was used to evaluate the predictive performance of the models. The training dataset consisted of 130 data points (75% of the dataset) and the testing dataset consisted of 43 points (25% of the dataset). The testing dataset was first obtained using stratified random sampling for each combination of time of measurement/intensity of supplemental heat (strata). This approach ensured that the testing dataset contained at least two data points from each stratum. Mean values were calculated for each strata of the dataset (yielding 20 data points) to determine the mean percentage error of each model for every stratum.

2.2.2. Overview of machine learning models

The machine learning algorithms used in this study were generalized linear regression model with elastic net regularization (GLM; Zou and Hastie, 2005), random forests (RF; Breiman, 2001), gradient boosted machines (GBM; Natekin and Knoll, 2013), and deep neural networks (feedforward neural networks) with the ReLU activation function (DNN; Goodfellow et al., 2016). Each algorithm has hyperparameters that influence the model learned from the data.

GLM is ordinary linear regression with penalty terms in the L_1 (sum of magnitudes) and L_2 (sum of squares) norms of the linear regression coefficients. The penalties shrink irrelevant regression coefficients and limit the impact of collinearity between the predictor variables (Zou and Hastie, 2005). The objective function of the GLM model is described as

$$\min_{\beta,\beta_0} \frac{1}{2N} \sum_{i=1}^{N} (x_i^T\beta + \beta_0 - y_i)^2 + \lambda\left[\alpha\ \|\beta\|_1 + \frac{1}{2}(1-\alpha)\|\beta\|_2^2\right]$$

where β, β_0 are regression coefficients, the summation represents the squared residual errors, x_i is the predictor variable from the i^{th} row of data, y_i is the predicted variable from the i^{th} row of data, λ is the severity of penalty applied, and α distributes the penalty between $L_1(\|\beta\|_1)$ and squared $L_2(\|\beta\|_2^2)$ norms of the regression coefficients. The hyperparameters are λ and α.

The RF and GBM models rely on decision trees, which are simple predictive models that stratify the input data space into output areas. The output-area prediction of decision trees is the mean of the response variables from the training dataset that fall in that output area (Fig. 1). For RF, several decision trees are developed independently from different subsets of the training dataset as well as from the different predictor variables. The prediction of the RF is the average of the predictions from all decision trees. The hyperparameters for RF are number of decision trees, minimum number of observations in a leaf, number of variables used to develop each split in a decision tree, and the maximum depth of the decision trees. For the GBM model, decision trees are developed sequentially, where each new decision tree is designed to improve on the predictive performance of the previous decision trees. The hyperparameters of the GBM are nearly the same as the hyperparameters for the RF, except GBM uses all predictor variables in a