Using Classification Trees to Detect Lameness in Sows

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Summary and Implications

Developing an automatic lameness diagnosis algorithm will benefit scientists and producers in timely and effective identification of lame individuals before clinical signs are apparent as well as aid producers in their efforts to decrease herd lameness. Being able to predict the lameness in sows can aid in delivering maximum animal health benefits, improving sow lifetime productivity, and optimizing sow farm labor.

Introduction

The U.S. swine industry is experiencing increasing culling and mortality rates of sows in commercial pork production operations. More timely identification of lameness in breeding herd females will allow for better treatment decisions and outcomes by culling females while they still have salvage value rather than allowing lameness to progress where treatment delays marketing or where lameness results in mortality or necessitates euthanasia. The objective of this study was to determine if lameness could be detected using objective measurements of a sows' weight distribution on each foot.

Materials and Methods

Early in the lameness process sows will change the magnitude of the difference in weight distribution between legs from side to side, front to back, and contr-laterally. Twelve multiparous sows with mean weight 194 kg. The weights ranged from 162 kg to 241 kg. The 12 sows were randomly injected with 10mg amphotericin B in the distal interphalangeal joint of one of two injection sites (left rear claws (LR) and right rear claws (RR)). Following lameness (synovitis) induction, the sows' weight distribution on each foot was measured using a micro-computer based force plate for 6 days following lameness induction. Each sow was injected a second time in the opposite joint during the second round of measurements. This results in a total of 24 lameness events with weight distribution measurements.

The weight distribution was measured for 15 minutes each day. To determine if a shorter time period could be used for measurement, the data was analyzed in 1, 5, 10, and 15 minute collection periods. Since the rear legs were injected, the weight distribution on the two rear feet were analyzed with one foot being lame and the other being sound. The variables analyzed for each collection period were the minimum weight placed on each foot (min), the maximum (max), the mean, the range, the inter quartile range (qrange), the 5th percentile of weight measurements (p5), the 95th percentile of weight measurements (p95), the standard deviation (std), mode. The skewness (skew) and kurtosis (kurt) of the weight distribution during the collection period was also recorded. The sow's weight was also included as a variable in the analysis.

A classification tree analysis was performed using the rpart package in R. The randomForest package was used for a random forest analysis using 1,000 trees. The response variable in both analyses was foot status (lame or sound). The importance of each variable in the random forest analysis was evaluated to compare to the variables used in the classification tree.

Results and Discussion

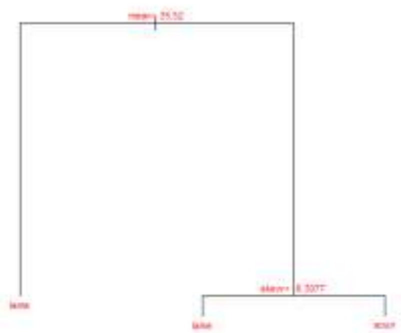
All data collection periods (1, 5, 10, and 15) were able to completely classify the lame and sound the first day following lameness induction. However, this is not as important as detecting lameness several days after lameness induction when clinical signs may not be as readily apparent.

The predictive ability of the classification tree was improved with increased time of data collection and worsened with increased days post lameness induction; however, the error rate was not significantly reduced with greater than 5 minutes of data collection. Based on this, it was determined 5 minutes is a sufficient amount of time to collect data from individual animals in order to accurately detect lameness using the micro-computer based force plate in sows.

Figure 1 shows the classification tree developed for the data collected 6 days post lameness induction and using 5 minutes of data. Mean and skewness were the variables used to classify each sows' foot as sound or lame. Figure 2 shows the variable importance in the random forest analysis. The variables that are important both classifications are similar. The two most important variables were mean and the 5th percentile. It is interesting to note that sow weight was not an important variable in classifying lameness. This could be a result of sow weight range in the present data being relatively small and not large enough to impact the lameness classification.

The random forest out of box estimates for the error rate was 31.35% while the classification tree had an error rate of 20.8%. Along with having a lower error rate, the classification tree is more interpretable. The tree developed from this project can be used to detect lameness in sows prior to sows clinical symptoms being detectable.

Figure 1: 6 Days Post Induction - Five Minute Data



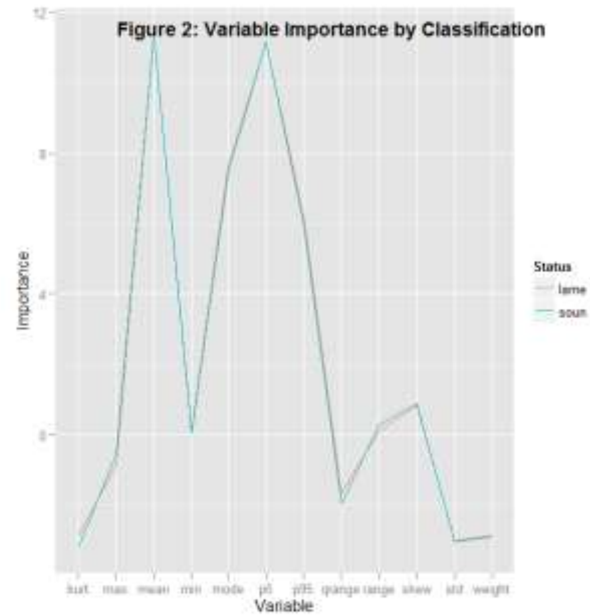


Figure 2: Variable Importance by Classification