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Improving Feedlot Profitability Using Operational Data in Mortality Prediction Modeling

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Feedlot managers make difficult culling decisions using their best subjective judgment together with advice from animal health professionals. Using routinely collected operational feedlot data and five well-known classification methods, we construct mortality predictive models to aid managers in making objective culling decisions. Simulation results suggest that net return per head for calves having been treated at least once for any health incident would increase on average by \$14.01 if the best-performing model were used as a culling decision aid. The probability of a positive return is 60.9%. Using cost-sensitive learning, the average value may increase to \$45.27/head.

Key words: cost-sensitive learning, feedlot culling, railers, realizers

Introduction

There are many components to profitability in the cattle feeding industry. A feedlot's mortality rate has been shown to have a significant effect on many aspects of feedlot profitability. Irsik et al. (2006) found that for each percentage-point increase in a feedlot's mortality rate, the feed conversion ratio and added costs increased by 0.27 lb and \$1.00/head, respectively, while average daily gain would be expected to decrease by 0.08 lb. These results taken collectively demonstrate how mortality rate can have a pronounced impact on a feedlot's bottom line. The price of feeder cattle alone represents a sizable investment for a feedlot. Mortality within the feedlot eliminates an individual calf's expected return on investment and is a large cost for the operation. Therefore, efforts to decrease a feedlot's mortality rate are often worthwhile. If a feedlot manager were able to predict which calves were going to die before the end of the feeding period, then naturally the manager would look to alter their management practices or market these animals prematurely in order to recoup a portion of the investment.

Cattle that are culled and marketed prematurely are often referred to as *realizers* or *railers*. Though often quite thin, markets for railers do exist and offer an outlet for feedlot management to unload culled cattle. Railers are often comprised of the lame or chronically sick cattle and, therefore, are typically sold at a sizable discount from market prices (McCollum, 1998). Conventional wisdom pushes mangers to accept the heavily discounted prices for railers, as any revenue is better than no revenue in the event of premature death. The disparity in fat cattle and railer cattle prices demonstrates the value in knowing whether an animal will die prior to finishing.

However, there is a large difference in knowing versus predicting with some level of uncertainty. Under conditions of certainty, the manager is always better off culling those animals that will not survive through finishing. Under conditions of uncertainty, the decision to cull is much more ambiguous. If the manager culls an animal and the prediction is correct, then the manager has

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successfully mitigated loss of revenue. However, if the prediction is incorrect, then the feedlot incurs a large opportunity cost by not allowing the animal to finish. Therefore, in considering this dilemma, the question is not whether a model could be created for predicting whether cattle will finish fully or die prematurely but rather whether such a model could have a high enough degree of certainty to be economically practical for a feedlot to implement as a decision aid within their culling protocol.

Using diagnostic predictive models in a feedlot setting is not a new concept. Amrine, White, and Larson (2014) assessed the ability of different classification algorithms to predict an individual calf's outcome based on data available at first identification of and treatment for bovine respiratory disease (BRD). Their models focused on predicting animals that were treated for BRD with an antimicrobial but ultimately did not finish (DNF) the production cycle with their cohort. Their definition for DNF included any animal that died following BRD treatment or any animal that was removed from the feeding phase prior to cohort harvest following initial treatment for BRD. Accuracies of their best-performing algorithms ranged from 63% in one dataset up to 95% in a different dataset. They found that by pairing the correct classifier with the data available, accurate predictions could be made that would provide feedlot managers with valuable information. However, they did not go as far as to demonstrate the economic consequences of implementing algorithm predictions as a method of making culling decisions.

Moya et al. (2015) used feeding behavior pattern recognition techniques to predict morbidity in newly arrived feedlot cattle with varying degrees of success for different model types. As noted by the researchers, for this method to have value to a feedlot operator, more work is needed to integrate systems that would automatically process data collected from automated feed bunk monitoring systems.

Theurer et al. (2014) created a mixed general linear model to evaluate associations of rectal temperature at first treatment for BRD and the probability of not finishing the production cycle. Their results indicated that the probability of DNF increases as rectal temperature increases. However, the model demonstrated that the relationship is not linear and is influenced by quarter of the year at feedlot arrival, sex, and number of days in the feedlot at time of BRD diagnosis. Ultimately, the researchers concluded, rectal temperature has limited value as an indicator of whether calves will finish the production cycle.

Cernicchiaro et al. (2013) created an economic model to estimate net returns per animal in a feed yard. Their objective was to evaluate associations between economic and performance outcomes with the number of treatments after an initial diagnosis of BRD. They found that net returns decreased with increasing number of treatments for BRD. The differences in net returns were attributed to differences in carcass traits such as weight and quality grade. With increasing number of treatments, carcass quality and weight decreased, resulting in a lower net return relative to animals treated on fewer occasions.

Theurer et al. (2015) created a stochastic simulation model to determine the economic value of changing diagnostic test characteristics (sensitivity and specificity) for identifying cattle to be treated for BRD. When considering diagnostic testing accuracy, the test's accuracy is often discussed in terms of sensitivity and specificity. Sensitivity refers to the proportion of truly positive cases the test identifies as "test positive"; specificity refers to the proportion of truly negative cases the test identifies as "test negative." If a predictive test is applied to a group of known truly positive and truly negative animals, the sensitivity and specificity of the test are easily calculated post-prediction. For their study, these researchers used data from multiple feedlots to create true ranges of respiratory disease prevalence and mortality. Then the input variables were combined into a single model that calculated net returns for each diagnostic outcome (true positive, false positive, false negative, and true negative) based on prevalence, sensitivity, and specificity for each iteration. They concluded that for both high ($\geq$15%) and low (<15%) prevalence, increasing diagnostic specificity increased net returns at a faster rate than increasing sensitivity.

This study builds on the current literature and extends health predictive modeling within feedlots to demonstrate the expected economic consequences of using such modeling as a culling decision support tool. The objective is to construct a mortality predictive model and evaluate whether the model is strong enough to ensure a positive financial impact if the model is incorporated into a feedlot's current culling protocol.

Data and Methods

The primary data source for this study comes from data gathered through the Noble Research Institute's Integrity Beef Sustainability Pilot Project. The aim of this project was to improve the sustainability of the entire beef production value chain. In this 2-year project, cattle were managed according to U.S. Roundtable for Sustainable Beef metrics. Cattle were tracked, allowing for data collection across the animal's entire life. In year one, 2,246 head from 25 ranches participated, while in the second year 2,237 head from 29 ranches participated, for a total of 4,483 head over the 2-year project. Herd health and preconditioning information were captured from cow-calf producers as well as animal performance and carcass characteristics from the feedlot and packer. The cattle were fed by Innovative Livestock Services, Inc., in Great Bend, Kansas. The feedlot collected lot-level performance data as well as individual health data for animals that were pulled from their lots for health-related incidents.

This study aims to create mortality predictive models using various classification models, similar to Amrine, White, and Larson (2014). However, the model objectives for this study will differ from their objectives. Their paper focused on predicting when animals would not finish (through either death or culling) with their cohort after initial diagnoses of BRD and treatment with an antimicrobial. Thus, their study population dataset (SPD) was a subset of the original data and included all calves identified as being treated for BRD with an antimicrobial. This study broadens the scope of interest and application of model output. This study is interested in predicting mortality for any calf having been pulled from their cohort for any health-related incident, with a new prediction being made each time a calf is pulled. Thus, the SPD for this study includes the subset of 847 calves that were pulled at least once from their cohort for health incident and represents 19.3% of all cattle in the full dataset. The main contribution of this work centers on evaluating the economic viability of using mortality predictive models to make feedlot-culling decisions. The model output is intended to be used by feedlot management as an aid in making culling decisions. Anytime a calf is given a positive DNF prediction, it is assumed that management would then take steps to cull and market the calf as a railer. Thus, instead of comparing and contrasting various model accuracies, this study focuses on using the model predictions and associated diagnostic outcomes to simulate the change in net returns per animal if the feedlot were to have followed the model predictions as compared to keeping the status quo culling protocol in place.

Procedures

Using the SPD, we test and train five classification models: logistic regression, J48 decision tree, random forest, $k-$ nearest neighbor ($k = 3$), and naïve Bayes. The best-performing classification model is then used to complete and present the economic simulation analysis. All of the models are trained and tested using 10-fold cross-validation, in which the dataset is randomly split into 10 partitions. The learning algorithm is trained on nine of the partitions and then tested on the tenth partition. This process is repeated 10 times so that at the end all 10 partitions have been tested. Using 10-fold cross-validation provides a better understanding of the model's accuracy and generalizability while still using all of the available data. A short description of each classification model follows.

Logistic Regression

Logistic regression is a statistical linear regression method, which is used to predict a dichotomous variable (only two possible outcomes). The probability of outcome occurrence is estimated by fitting data to a logistic function. From the estimated probabilities, researchers can then make predictions for the dichotomous outcome.

Decision Tree

Decision trees are easily understood and relatively simple to implement for regression and classification tasks, making them one of the most widely used methods of supervised learning. Decision trees are a nonparametric algorithmic approach to identify ways to divide a dataset based on different conditions. Decision trees predict the target variable by learning simple decision rules inferred from the data characteristics.

Random Forest

A random forest takes an ensemble-learning approach as it operates by creating many individual decision trees during training. The final output decision for the random forest is essentially the mode or mean prediction for all of the individual trees (majority vote). Random forests have the potential benefit of correcting the overfitting issues that can sometimes plague decision trees.

k-Nearest Neighbor ($k = 3$)

The $k-$ nearest neighbor algorithm does not build a traditional model. Instead, the training data are simply stored for future reference. To make an output decision, the $k-$ nearest neighbor measures the distance from the instance in question to all of the training instances. The k closest instances are selected and the most prevalent classification label in the k neighbors is chosen as the output.

Naïve Bayes

The naïve Bayes algorithm builds a probabilistic model in which it computes the probability of the class given the observed features by estimating the class prior and the likelihood of observing those features for a given class. The model uses the "naïve" assumption that all features used in the model are conditionally independent given the class label. This assumption greatly simplifies the model, reduces the amount of data needed to estimate the model parameters, and reduces the computational resources required to build and evaluate the model.

Variables Included

In total, the models include 39 variables. Many of these variables (e.g., treatment weight, sex, initial weight) come straight from the data provided by the feedlot. Some of the variables (e.g., *Trtcasestothispoint* and *propdailyallpulls*), however, are constructed from the given data. Table 1 lists the variable names included in the models and describes what they represent.

All of the models are run using Waikato Environment for Knowledge Analysis (WEKA) (Witten, Frank, and Hall, 2016). Among other summary statistics, WEKA output for each classifier includes specificity, sensitivity, and overall accuracy percentages as well as counts of the diagnostic outcomes: true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Economic Analysis Procedure

The primary objective of this paper is to determine whether by following the predictions of the best-fitting classification model a feedlot could realize increases to expected net return per calf in

Table 1. Variables Included in the Five Classification Models

Variable Name	Description
Treat_Weight	Weight (lb) of calf when treated
Treat_Temperature	Temperature (ÂřF) of calf when treated
Sex=Steer	Sex of the calf: = 1 if steer, = 0 if heifer
Treatment_Number	Running total of number of treatments calf has received
Head_Lot	Number of head in calf's home lot
Arrival_month	Month calf arrived to the feedlot
Arrival_quarter	Quarter calf arrived to the feedlot
Arrival_year	Year calf arrived to the feedlot
Arrival_Weight	Weight (lb) of calf upon arrival to the feedlot
Disttrtcasestothispoint	Sum of distinct animals from the calf's lot that have been treated for any health-related incident as of the current treatment date of the calf
Txfailure	= 1 if the animal has been previously treated, = 0 otherwise
Txfailuretothispoint	Count of *Txfailure* within the cohort up to this point in time
Txsuccessrate	(*Dsttrtcasestothispoint* − sum of *TxFailure*)/*Dsttrtcasestothispoint* ×100
Trtcasestothispoint	Sum of animals from calf's lot treated for any health-related incident as of the current treatment date of the calf
Proptrtcasestothispoint	Proportion of treatment cases to this point = (*Trtcasestothispoint*/*headin*) ×100
Propdisttrtcasestothispoint	Proportion of distinct treatment cases to this point = (*disttrtcasestothispoint*/*headin*) ×100
Deathstothispoint	Sum of deaths in calf's home lot to this point
Propdeathstothispoint	Proportion of deaths to this point = (*deathstothispoint*/*headin*) ×100
Dailyallpulls	Sum of the number of pulls from calf's home lot pulled on the event day
Propdailyallpulls	Proportion of lot pulled for any reason on this event day = (*Dailyallpulls*/*headin*) ×100
Lot	Lot number of calf
Dayssincearrival	Number of days since calf arrived at the feedlot
Treatment_variablea	Categorical variable that includes 17 treatments (i.e., medication types) administered at time of treatment

Notes: [a] For logistic regression, *Treatment_variable* was converted to 17 dummy variables for each specific treatment administered. Each dummy variable was equal to 1 if the treatment was administered, and 0 otherwise.

the SPD. To accomplish this objective, the diagnostic outcomes are used to simulate net returns per animal; this value is then compared with the simulated status quo (i.e., following current railing protocols) net return per animal. If the difference between the two estimates for net returns is positive, this would indicate that the feedlot could expect a positive return above the status quo by culling according to the predictions of the classification model. If, however, the difference is negative, then the feedlot can assume a better net return per animal in the SPD by retaining the current culling practices. The intended application of the culling classification model for a feedlot would be that for any time a calf is pulled from its cohort for a health incident the appropriate data can be collected and input into the classification model and the feedlot manager could use the prediction to make the culling decision. Table 2 summarizes the possible model predictions with the associated decision that would be made by the manager and the expected financial result that would apply to the decision made.

The SPD for this study includes any animal that was pulled from its cohort at least once for any health incident. It is important to consider that many calves are pulled multiple times and could represent multiple observations in the SPD. Not every calf will be appropriately classified on its first pull. If a feedlot manager were using a classification model to make culling decisions, they would continue treating the calf up until the model gave a DNF prediction (indicating that the animal should be sold). If no DNF prediction were made, then the calf would continue to be treated either until premature death (false negative) or until finishing and slaughter (true negative). Thus, within the SPD, each health incident of a calf is treated as a new opportunity to classify the calf regardless of how many times the calf had previously been classified, unless previously classified as DNF. When

Table 2. Classification Model Predictions, Ground Truth, Diagnostic Outcomes, Management Decision, and Result of Adherence to Model Predictions

Model Prediction	Ground Truth[a]	Diagnostic Outcome	Decision	Financial Result
Do not finish	Do not finish	True positive	Cull	Animal is sold in the railer market. This option allows some revenue to be made while reducing medication and management costs on an animal that was not going to make it to harvest.
Finish	Finish	True negative	Continue treatment	This animal is treated and subsequently harvested with its cohort at market price. This is the optimal financial result with the highest expected net return.
Do not finish	Finish	False positive	Cull	Animal is sold in the railer market but should have been kept, as it would have completed the finishing period and would have been harvested with its cohort. This results in an added opportunity cost equal to the difference between the profit the feedlot could have made on the animal if it had been allowed to fully finish versus the profit made by selling prematurely as a railer.
Finish	Do not finish	False negative	Continue treatment	Animal is kept and treatments are continued. However, it dies before the end of the finishing period, resulting in a financial loss due to no revenue being obtained but costs being incurred. A large opportunity cost is incurred and equal to the difference between the production costs lost and the railer profit that could have been made.

Notes: [a] The ground truth represents the actual outcome (finish or do not finish) a calf experienced at the feedlot.

training and testing the classification models, each health incident is treated as an independent event. After a model has been trained and predictions have been made for the test data, the final assigned diagnostic outcome can be adjusted according to the presumed behavior of the feedlot manager. At any point, if a calf is classified as DNF, it is assumed that a manager would then make the decision to cull the calf and any further predictions made for that animal are ignored. Thus, only one diagnostic outcome is assigned to each calf regardless of how many times it may have been pulled and classified by the model.

To begin building the simulation of change in net return, the estimated net return per head by diagnostic outcome must first be calculated. The equations used to calculate the net return for TP, TN, FP, and FN are

$$NR_{TP} = (RW \cdot RP) - ((IW \cdot SP) + (FC \cdot DOF_{DNF}) + TC_P); \tag{1}$$

$$NR_{TN} = (DP \cdot CW) - ((IW \cdot SP) + (FC \cdot DOF) + TC_N); \tag{2}$$

$$NR_{FP} = NR_{TP} - (NR_{TN} - NR_{TP}); \tag{3}$$

$$\begin{aligned} NR_{FN} = &- [(IW \cdot SP) + (FC \cdot DOF_{DNF}) + TC_P]; \\ &- [NR_{TP} + ((IW \cdot SP) + (FC \cdot DOF_{DNF}) + TC_P)]; \end{aligned} \tag{4}$$

where NR_{TP}, NR_{TN}, NR_{FP}, and NR_{FN} represent the estimated net return per head of a true positive, true negative, false positive, and false negative calf, respectively; *RW* is the railer weight (lb); *RP* is the railer price ($/lb); *IW* is the initial weight (lb); *SP* is the stocker price ($/lb); *FC* is the feed costs ($/day), including feed, yardage, and interest; *DOF* and DOF_{DNF} are the days on feed of a calf who did and did not finish with its cohort, respectively; TC_P and TC_N are the treatment costs ($)

for treating a positive (DNF prediction) and negative predicted calf, respectively; DP is the dressed price (\$/lb); and CW is the carcass weight (lb).

Simulating Net Returns per Hea.d Using Model Predictions

By using equations (1)–(4) and evaluating all variables at their averages, we can estimate the average net returns the feedlot could expect for a calf for each diagnostic outcome. The diagnostic outcome prevalence percentages could then be used as weights for the net return values. The sum of the weighted net return values would be the expected average net return per head for calves in the feedlot that were pulled at least once for any health-related incident. However, simply evaluating at the averages does not properly account for risk. By allowing variables within the net return equations to vary stochastically (fitted distributions from the data) and simulating the net return per head over multiple iterations, a better picture of the distribution of returns per head could be expected. For the simulation, fitted distributions using the data provided by the feedlot are used for all variables other than stocker price, dressed price, and treatment costs. For stocker price and dressed price, we use historical price data for Kansas from the Livestock Marketing Information Center (2019b,a). For the treatment costs, we use triangle distributions with the minimum, most likely, and maximum values set at \$6.90, \$28.50, and \$76, respectively, for positives (DNF prediction) and \$6.90, \$38, and \$95, respectively, for negatives. Appendix A explains how the treatment cost distributions were determined. Appendix Table A1 contains all variables used in the simulations and a description of their fitted distributions. The equation that estimates the net return per head when following the model predictions is

$$(5) \qquad NR_A = NR_{TP}\,(\%TP) + NR_{TN}\,(\%TN) + NR_{FP}\,(\%FP) + NR_{FN}\,(\%FN),$$

where NR_A is the expected net return (\$/head) for cattle experiencing at least one health incident when following the model predictions; NR_{TP}, NR_{TN}, NR_{FP}, and NR_{FN} are the net returns (\$/head) for true positives, true negatives, false positives, and false negatives, respectively as outlined in equations (1)–(4), only allowing for the variables to vary stochastically; and $\%TP$, $\%TN$, $\%FP$, and $\%FN$ are the percentages of animals with diagnostic outcomes of true positive, true negative, false positive, and false negative, respectively.

Simulating the Status Quo

After simulating equation (5), we must also simulate the net return per animal if the manager were to retain the status quo culling protocol for comparison. This is accomplished using one assumption: Under current culling protocol, every animal was treated as a negative by the feedlot and either survived until finishing (true negative) or died prematurely (false negative). Therefore, to calculate the estimated net return per head when following the status quo, equation (5) is updated to weight appropriately the net returns to fit the status quo protocol as in

$$(6) \qquad NR_{SQ} = NR_{TN}\,(1 - \%mortality) + NR_{FN}\,(\%mortality),$$

where NR_{SQ} is the expected net return (\$/head) when following the status quo culling practices, $\%mortality$ is the percentage of the SPD that died prior to finishing, and all other variables are as outlined in equation (5).

Notice in equation (6) that net returns from both false and true positive animals are not included in the calculation of net returns under the status quo. While in reality the feedlot did rail a small percentage of animals, there is no way of identifying the correct diagnostic outcome for railed animals (true positive vs. false positive) once they have left the yard. Additionally, there is no record of which specific animals were railed within the data. This suggests that the relatively small number of railer animals have been incorrectly assigned the true negative diagnostic outcome both within

Table 3. Performance Measures of the Classification Models and Counts of Diagnostic Outcomes

Model	True Pos.	True Neg.	False Pos.	False Neg.	Sensitivity (%)	Specificity (%)	Accuracy (%)
Logistic	73	737	36	1	98.6	95.3	95.6
Random forest	71	714	59	3	95.9	92.4	92.7
J48 decision tree	63	739	34	11	85.1	95.6	94.7
k-nearest neighbor ($k = 3$)	44	712	61	30	59.5	92.1	89.3
Naïve Bayes	46	638	135	28	62.2	82.5	80.8

Notes: The true prevalence percentage (mortality rate of SPD) is 8.7%.

the status quo and predictive model net return results. Discussions with professionals in the feedlot industry have informed us that feedlots target somewhere in the range of 4:1 to 10:1 ratio of deads to railers depending on current market conditions. If death percentages for feedlots are assumed to be in the range of 1%–3%, then the railer percentages would typically be somewhere between 0.1%–0.75%. Thus, the overall impact of the unknown outcome for railed animals as either true or false positives is limited and its effect has been held constant within the simulation of net returns for both the status quo and predictive model culling method.

Results

Table 3 summarizes the performance measures for each of the five classification models. Model accuracies ranged from 80.8% to 95.6%, reflecting good overall accuracy. The naïve Bayes algorithm had much lower accuracy relative to the others for these data. As the logistic regression had the highest accuracy, we use it in the simulation of change in net returns per head. As many of the accuracy rates for the various models are similar, the simulation results using different model predictions are also similar.

To complete the objective of this study, we simulate the difference $NR_A - NR_{SQ}$ (i.e., the difference between equation 5—net return per head when following the model predictions—and equation 6—net return per head when following the status quo culling practice). If this difference is positive, then the model should be considered to aid in making culling decisions. If negative, the culling practices in place would be expected to outperform the model predictions. Figures 1 and 2 show the simulated (10,000 iterations) probability density function (PDF) and cumulative distribution function (CDF) for the expected change in net return per head, respectively. All simulations were conducted using Palisades @Risk Decision Tools Suite 7.6 (2019).

Looking at the PDF and CDF in Figures 1 and 2, respectively, it is apparent that on average the feedlot could expect a $14.01 positive change in net return per head of calves pulled at least once for any health-related incident when following the model predictions. This change in net return is found to be statistically significant at the 1% level (p-value = < 0.01). The probability of a positive change in the return per head is 0.609. By analyzing the sensitivity of the results to individual input parameters, the inputs that have the largest effect on the simulation results can be identified. Figure 3 contains a "tornado" graph ranking the inputs by effect on the change in net return. Railer weight and price together with dressed price and carcass weights have the largest impact on the simulation results. This points to the large disparity between the return of a true negative and a true positive calf. The average railer price per pound is heavily discounted relative to average liveweight finished cattle prices. On top of a discounted price, depending on when the calf is culled, the railer weight is potentially much less than the average finished liveweight. Thus, the simulation of net returns is highly sensitive to the culling market price and weight as well as the dressed price and weight. If

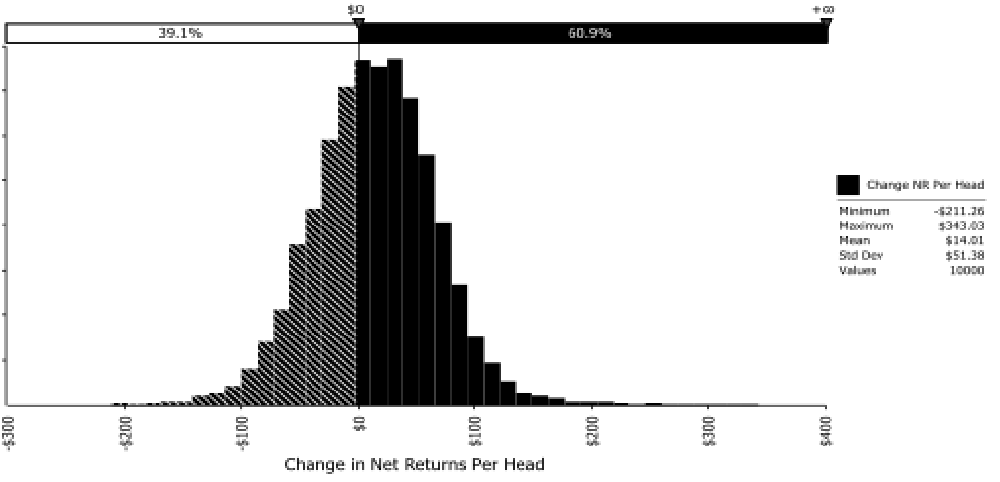

Figure 1. Probability Density Function of Simulated Change to Net Return from Following Logit Model Predictions

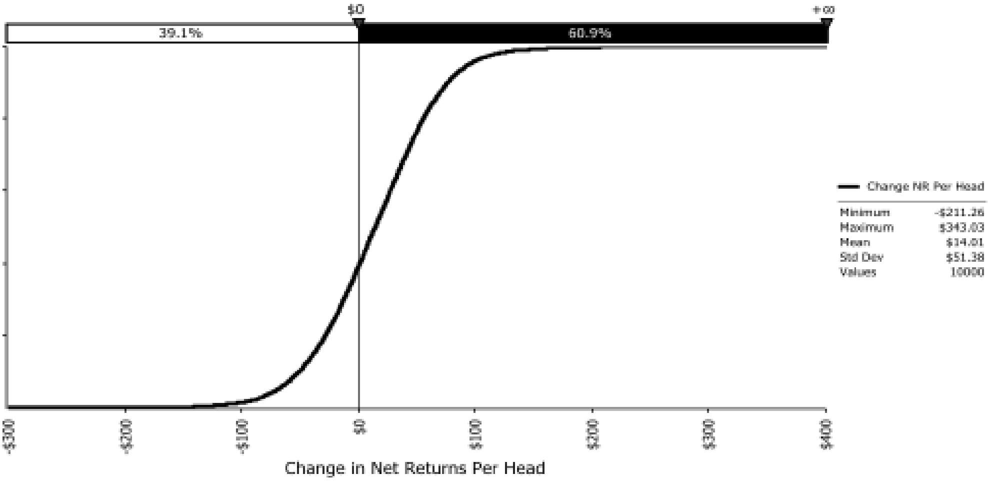

Figure 2. Cumulative Distribution Function of Simulated Change to Net Return from Following Logit Model Predictions

a feedlot is able to garner above-average prices for railers or if liveweight finished cattle prices are down, then an increase to the change in net returns could be expected from following the model. The further along a positively predicted calf is in the growth production cycle, the less negatively impacted the feedlot will be as a result of culling.

We also evaluate the marginal effects of changing sensitivity and specificity. By manually adjusting the counts of the simulation diagnostic outcomes (TP, TN, FN, and FP) incrementally, we increase/decrease sensitivity or specificity by 1% while holding the other constant and resimulate the net return. Through multiple iterations of this exercise, the average change in net return can be calculated for a 1% change (marginal effect) in specificity/sensitivity. In this simulation, the marginal value of sensitivity is found to be $0.77, while the marginal value for specificity is $13.42. This indicates that while an increase in the change in net return per animal can be expected with an increase in either sensitivity or specificity, increases in specificity are expected to have a significantly larger marginal effect. This result is similar to the conclusions drawn by Theurer et al. (2015).

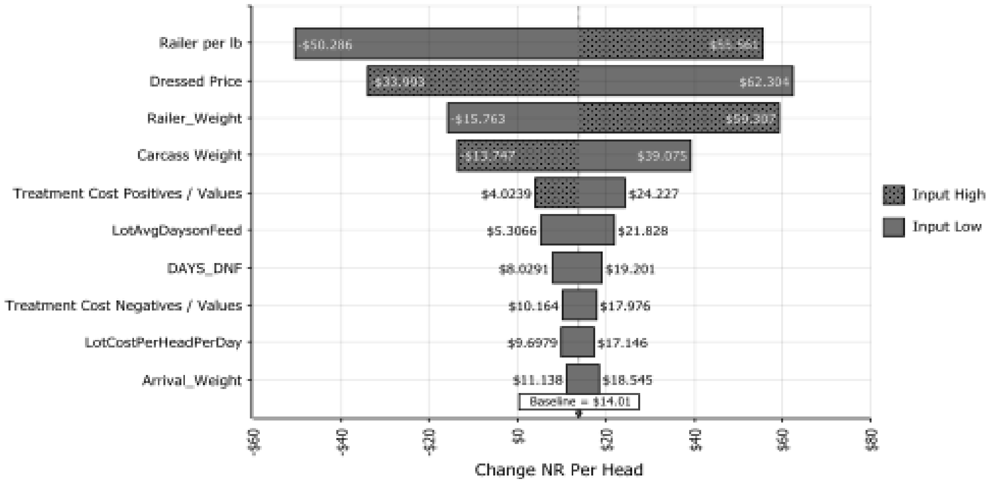

Figure 3. Inputs Ranked by Effect on Change in Net Return from Following Logit Model Predictions

Cost Sensitive Learning

Based on the estimated results of the marginal value for sensitivity versus specificity, it is clear that increases to the change in net return per head could be expected if the models would prioritize increasing specificity over sensitivity. To demonstrate how such an approach could benefit model performance, the models are trained and tested again within Waikato Environment for Knowledge Analysis (WEKA) using the Metacost approach as described by Domingos (1999) to value specificity over sensitivity at a 10:1 ratio. Metacost is a cost-sensitive learning algorithm that can be used in conjunction with any error-based classifier. It works by relabeling the training data with cost-optimized labels based on a given cost-matrix. For each instance x in the original training data, a cost-optimized label is determined by calculating the expected cost (conditional risk) of predicting class label i, $R(i|x)$ as the product of the estimated conditional class probability $P(j|x)$ for each class label j and the cost of the label $C(i,j)$ as specified in the cost matrix, $R(i|x)=\sum_j P(j|x)C(i,j)$. Essentially, Metacost relabels the training instances with the class label estimated to produce the lowest cost for a given cost matrix. The label with the lowest expected cost is then assigned to the training instance. Once all the training data have been relabeled to consider the expected cost, the classification model is then trained.

Table 4 summarizes the performance measures for each of the five classification models using the Metacost approach. The simulation is then updated with the logit performance measures obtained using cost-sensitive learning to calculate the expected change in net return per head. Figures 4 and 5 show the simulated PDF and CDF for the expected change in net return per head using the cost-sensitive approach, respectively.

As can be seen in Figures 4 and 5, the financial results for a feedlot following the model predictions to aid in making culling decisions are expected to improve significantly when using a cost matrix to value specificity over sensitivity at a 10:1 ratio. The results indicate that when following the model predictions, the net return of a calf having experienced at least one health-related incident is expected to be \$45.27 (p-value <0.001), more than a similar calf if the feedlot had kept the status quo culling protocol in place. Additionally, the probability of a negative change to net return per calf is expected to only be 0.006, indicating that following the model predictions is expected to have a positive financial effect greater than 99% of the time relative to the status quo protocol.

Table 4. Performance Measures of the Classification Models and Counts of Diagnostic Outcomes Using Cost Sensitive Learning

Model	True Pos.	True Neg.	False Pos.	False Neg.	Sensitivity (%)	Specificity (%)	Accuracy (%)
Logistic	46	772	1	28	62.2	99.9	96.6
Random forest	11	772	1	63	14.9	99.9	92.4
J48 decision tree	53	749	24	21	71.6	96.9	94.7
k-nearest neighbor ($k = 3$)	2	766	7	72	2.7	99.1	90.7
Naïve Bayes	27	692	81	47	36.5	89.5	84.9

Notes: The true prevalence percentage (mortality rate of SPD) is 8.7%.

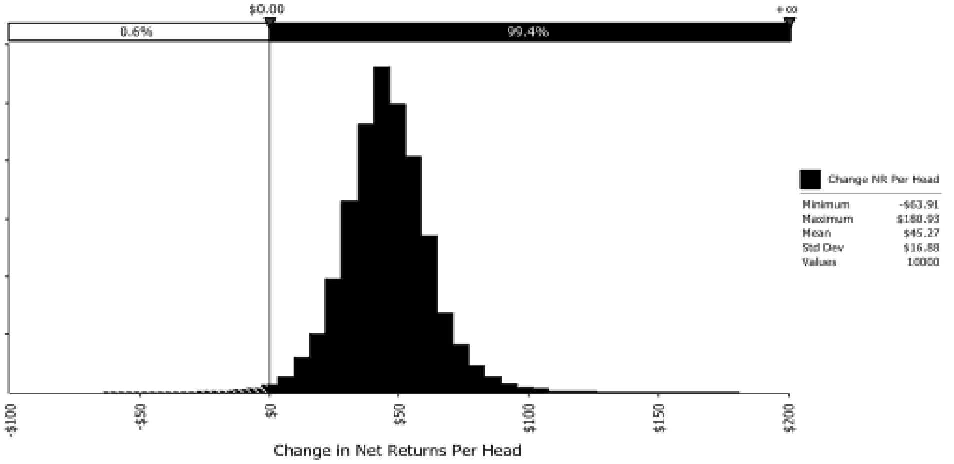

Figure 4. Probability Density Function of Simulated Change to Net Return from Following Logit Model Predictions with Cost Matrix of 10:1 (specificity: sensitivity)

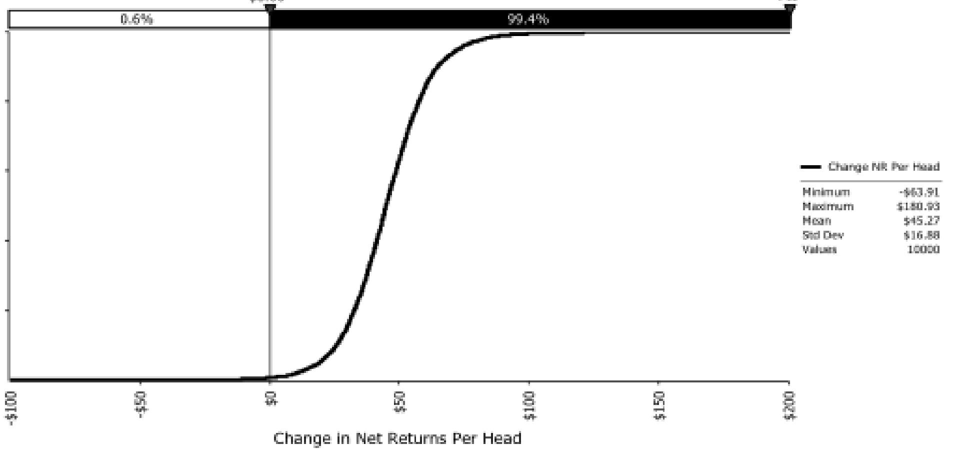

Figure 5. Cumulative Distribution Function of Simulated Change to Net Return from Following Logit Model Predictions with Cost Matrix of 10:1 (specificity: sensitivity)

Limitations

This predictive method has not actually been applied as a method of making culling decisions. The results are only the expectations for one feedlot using 2 years or data given the model output and assumptions. More research is needed to refine the modeling techniques and ensure robustness of the results. Additional data are needed to evaluate the expected change to net return per head using this same method for different feedlots across multiple years.

Conclusions

Feedlot managers attempting to maximize profits face difficult culling decisions. Operational data collected by feedlots have the potential to aid managers in making culling decisions. Most feedlots rely on visual inspection as the primary determinant for making culling decisions. This introduces subjectivity into the process and allows for human error. The classification models used in this study are objective. Though the accuracies of the best performing models were high (>94%), the simulated change to expected net return per head when following the logistic regression model predictions versus maintaining the status quo culling protocol was only $14.01. This positive change indicates that—based on the feedlot data for this study and the assumptions included in the simulation—following model predictions in making culling decisions would be expected to increase the net returns over the current culling protocol for calves having experienced at least one health-related incident. This positive result can be further increased when the cost matrix for specificity/sensitivity is adjusted to favor specificity over sensitivity. Using a ratio of 10:1, the simulated change to expected net return per head improved to over $45. This suggests that using operational data to form predictive models to make culling decisions shows promise as a method for increasing feedlot profitability.

The profit incentives for feedlots considering implementing modeling techniques as demonstrated in this research are greatest for larger-scale feeding operations. The expected change in net return per head of calves pulled for at least one health incident (using cost matrix approach) is approximately $45. Assuming a morbidity rate of 20%, as is approximately the case in this dataset (847/4,427), then the expected annual change in total revenue for 1,000-, 10,000-, and 100,000-head feedlots would be $9,000, $90,000, and $900,000, respectively. Even considering the added costs needed to collect the necessary data and actively manage the new culling model, as the size of the operation increases, at some point the benefits would greatly outweigh the costs. Additional research is warranted to determine the minimum efficient size of a feeding operation necessary to be economical in implementing classifier modeling in culling protocols.

The estimated marginal effects of sensitivity and specificity demonstrate the importance of making the correct culling decisions. While improvement of overall accuracy should always be the goal for any management protocol, when it comes to making culling decisions in a feedlot, specificity has a much larger marginal effect on net returns. Therefore, feedlot internal culling protocols should prioritize minimizing false positives over minimizing false negatives. Railer markets are thin and the discount received for a culled calf compared to a fully finished steer or heifer is large, making the false positive error relatively costly. While costs increase for a feedlot with false negative calves, the opportunity cost of a false positive is much larger; therefore, feedlots can overcome costs of false negatives by minimizing false positives.

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Appendix A: Treatment Cost Distributions

In 2013, the U.S. Department of Agriculture (2013) estimated the feedlot cost per treatment of cattle for respiratory disease at $23.60, acute interstitial pneumonia at $21.70, digestive problems at $9.90, bullers at $6.90, lameness at $13.40, and central nervous system problems at $20.10. The same report also provided prevalence estimates of each of these conditions. Using the prevalence estimates as weights, we are then able to arrive at the average treatment cost (per incident) of $19.00. The treatment cost triangle distribution for positive predicted animals (DNF) was defined with minimum, most likely, and maximum values of $6.90, $28.5, and $76, respectively. The minimum is set at the cost of treating a buller, as it is the lowest estimated treatment cost and we assume that every animal must receive at least one treatment before being predicted either positive or negative. The most likely value for positives is set at $28.50, which assumes positives are treated on average 1.5 times. The highest value for positives is $76, which is equivalent to 4 treatments. The triangle distribution for treatment cost of negative predicted animals is defined with a minimum value of $6.90 (cost of buller treatment), a most likely value of $38 (cost of two average treatments), and high value of $95 (cost of five average treatments). Table A1 reports the stochastic variables used in the simulation and descriptions of their assumed distributions.

Table A1. Simulation Variables and Their Distributions

Variable Name	Probability Density Function	Function	Min.	Mean	Max.
Stocker price (700 lb)[a]		Weibull	75.09	124.05	+∞
Carcass weight (lb)		Normal	−∞	848.45	+∞
Dressed price ($/cwt)		Uniform	101.8	174.47	247.1
Initial weight (lb)		Laplace	−∞	693	+∞
Feed cost ($/head/day)		Kumaraswamy	2.62	2.89	3.3
Days on feed		Uniform	139.99	169.5	199
Days on feed DNF[b]		Pearson	(40.72)[c]	63.7	+∞[d]
Railer weight		Log logistic	218.1	835.5	+∞
Railer price ($/lb)		Extreme value	−∞	0.52	+∞
Treatment cost negatives ($)		Triangle	10	25	40
Treatment cost positives ($)		Triangle	0	8.33	15

Notes: [a] Negatively correlated (−0.5) with initial weight.
[b] Positively correlated (0.5) with railer weight and treatment cost positives.
[c] Truncated to 0.
[d] Truncated to 200.