Machine Learning Based Computational Analysis Method for Cattle Lameness Prediction

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Abstract. A significant problem that the systematic cattle farming is facing and the science of Livestock Precision Farming is trying to solve, is the identification of lameness in cattle. The aim of this research is to present a novel integrated computational analysis for lameness prediction based on machine learning methods. The new algorithm was tested on data sets of healthy and unhealthy cattle. The new computational analysis uses four features: «steps per day» (dimensionless), «overall walking per day» (m), «lying per day» (min) and «eating per day» (min). The aim of these four features was to help the algorithm to separate the samples, in the best possible way. The result which was obtained was encouraging since the algorithm can identify equally well the positive samples (healthy cattle) and the negative samples (cattle suffering from lameness).

Keywords: Lameness, Cattle, Random Forest, ANN, LIBSVM.

1 Introduction

Every year, computer science shows great progress in hardware as well as in software level but mainly in the field of machine learning. Thanks to this rapid development of computer systems and machine learning algorithms, sectors from other scientific domains have evolved. In recent years, significant studies have been developed on Precision Livestock based on machine learning method solving real-life problems in an automated manner.

Machine learning has been applied mainly to issues relating to the science of Precision Agriculture. For example, the machine learning applied for the exact calculation of soil temperature (Nahvi, 2016). Another application of the machine learning deals with the calculation of the soil drying (Coopersmith, 2014) or for the correct prediction of the dew point on a daily basis (Mohammadi, 2015). Machine learning is applied even for the accurate prediction in the production of wheat (Pantazi, 2016) and for the correct prediction of the evapotranspiration (Patil, et al. 2016).

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In the field of Precision Livestock Farming, machine learning is rarely applied and mainly concerns the automated individual monitoring of the livestock. Some studies where machine learning was applied in Precision Livestock Farming relate to the behavior recognition in cattle. Specifically, in research (Dutta, 2015) machine learning is applied to data which is collected from 3-axis accelerometers and magnetometers to distinguish when the cattle search for food, graze, rest and walk. Other studies which machine learning is applied relate to the right identification of cattle with biometric characteristics. For example in the study (Gaber, 2016) with the help of machine learning methods, they try to identify the characteristics of the head of a bovine by using biometrics features. Also machine learning is applied to biological studies on Precision Livestock Farming. For example, in the research (Meher, 2016) their purpose is the correct identification of coding regions from non-coding regions for the cattle, with the help of two features, the structure of the codons and the mutations of the methylation. However, one of the most important issues that concern the Precision Livestock Farming is the creation of automated systems which relate to the welfare and health of animals.

Lameness is one of the most important issues with regard to the health of farm animals. Problems created in production derived from lameness are catastrophic for the farmer. A decrease in profit was noted (Bruijnis, et al. 2010), due to the decrease in milk and meat production and cost increase, due to the healthcare of the cattle. The diseases which are associated with the lameness, costs 66 € per cattle with 32% of that given for the healthcare (Bruijnis, et al. 2010). It is important to detect the lameness in time and with reliability (Booth, 2004, Holzhauer, 2004 and Tasch & Rajkondawar, 2004), in order to reduce the cost but also to ensure the health of the animal. It has been observed that animals which suffer from lameness presents various symptoms, such as difficulty in walking (Walker, 2008), they lie down more compared to healthy animals (Walker, 2008, Ito, 2010 and Chapinal, 2009), stand less (Walker, 2008) and graze less (Miguel-Pacheco, 2014). Until now many studies have been concerned on correct prediction of lameness in cattle. Nevertheless, the existing methods are unclear and unreliable (Schlageter-Tello, 2014) and mostly those which try to approach lameness with computational analysis.

The methods which try to predict the lameness in cattle vary from study to study. Some studies approach the lameness with optical technologies. For example, (Song, 2008) tried to observe the lameness with the usage of high resolution pictures and videos or in research (Viazzi, 2014) they try to identify the lameness with the usage of 2 dimensional and 3 dimensional cameras. Another way of dealing the lameness is by using sensors, as it reported in (Pastell, 2008), in which with the usage of force sensors authors tried to record and distinguish the cattle with lameness.

The purpose of this study is the creation of an integrated computational analysis based on machine learning methods with the aim of distinguishing correctly the healthy cattle from cattle which suffer from lameness.

2 Methods

In this section a new integrated computational analysis is presented, based on machine learning methods. Initially, the algorithm consists of two computational models, the (LP1, Table 1) and (LP2, Table 2). Next, the algorithm uses the model which returns the highest results. For the training and the prediction, the two models was tested in three machine learning methods, namely, Artificial Neural Networks, Random Forest, and Library for Support Vector Machine (LIBSVM) to determine which will be the final model, which will return the highest results. For the SVM machine learning method we used an innovative parallel programming model, the GPU-LIBSVM (Athanasopoulos, et al. 2011).

It's the first time in which the GPU-LIBSVM model is used for the computational analysis of lameness in cattle. The GPU-LIBSVM model is applied for the training and the prediction of the two computational models (LP1) and (LP2). This innovative SVM machine-learning model enables more computational models with a lot of features to be created and to be tested 30 times faster.

The models (LP1) and (LP2) are different in the number of features they use to distinguish the samples. The purpose was to ascertain how affected the two computational models from their features and what features help the computational models to distinguish with bigger accuracy the healthy cattle from cattle which suffer from lameness.

Table 1. Computational Model LP1.

Computational Model LP1	
Feature 1	Steps per day
Feature 2	Walking per day (m)
Feature 3	Lying per day (min)

Table 2. Computational Model LP2.

Computational Model LP2	
Feature 1	Steps per day
Feature 2	Walking per day (m)
Feature 3	Lying per day (min)
Feature 4	Eating per day (min)

Table 3. Example from a positive and negative sample for a set with four features.

State of cattle	Steps per day (dimensionless)	Walking per day (m)	Lying per day (min)	Eating per day (min)
Healthy	2900	3700	660	178
With problem in hooves	600	2350	830	168

For the training and the prediction of the two models, two sets are used: one set for training and one set for prediction. The two sets are small in samples because based on an assumption according to the method (Frondelius, 2015). This has as a result the test set to return unusually high values. Main purpose in future is to create a large dataset based on the above-mentioned four features and to observe how effective these are on a large scale. The training and prediction sets are presented in Table 4 and Table 5.

Table 4. Training set 1.1.

Training set 1.1	
Positive	6 healthy cattle
Negative	6 with lameness cattle

Table 5. Prediction set 1.2.

Prediction set 1.2	
Positive	2 healthy cattle
Negative	2 with lameness cattle

The training set 1.1 and the prediction set 1.2 are used for the training and the prediction of the computational models LP1 and LP2. The features from the two models was converted with scale method and then provided for the training and prediction processes at the three machine learning methods. For the Library for Support Vector Machine method the best option returned from SVM type: One-Class and Kernel type: Linear.

3 Results

The final results of the two computational models LP1 and LP2, are presented for the sets of training and prediction, in order to observe what computational model and which machine learning method could predict with highest accuracy the lameness in cattle.

The two computational models were created in the programming languages Perl, Python and R.

3.1 LP1 Computational Model

The first table presents the threshold used for the three machine learning methods of each computational model and also the results which were returned for the specific threshold such as: True Positive, False Positive, True Negative, False Negative, Sensitivity, Specificity, Precision, Recall, Accuracy and AUC (Area Under Curve).

Table 6. Threshold of machine learning methods for the computational model LP1 and the training set 1.1.

LP1 computational model & training set 1.1											
M.L Method	Threshold	TP	FP	TN	FN	Sensitivity	Specificity	Precision	Recall	Accuracy	AUC
ANN	0.5	5	1	5	1	0.83	0.83	0.83	0.83	0.83	0.83
RF	0.5	6	0	6	0	1.00	1.00	1.00	1.00	1.00	1.00
LIBSVM	0.4	5	2	4	1	0.83	0.66	0.71	0.83	0.75	0.75

The pie chart presents the average prediction score produced for each set from the three machine learning methods.

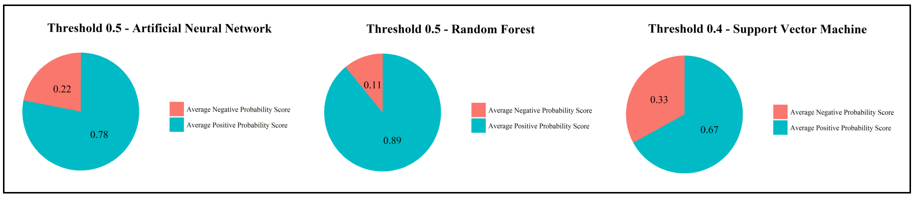

Fig. 1. The average prediction score which is returned from the machine learning methods for the computational model LP1 and the training set 1.1.

Table 7. Threshold of machine learning methods for the computational model LP1 and the prediction set 1.2.

LP1 computational model & prediction set 1.2											
M.L Method	Threshold	TP	FP	TN	FN	Sensitivity	Specificity	Precision	Recall	Accuracy	AUC
ANN	0.5	2	0	2	0	1.00	1.00	1.00	1.00	1.00	1.00
RF	0.5	2	0	2	0	1.00	1.00	1.00	1.00	1.00	1.00
LIBSVM	0.4	2	0	2	0	1.00	1.00	1.00	1.00	1.00	1.00

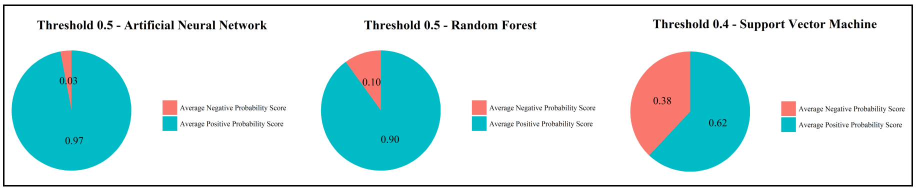

Fig. 2. The average prediction score which is returned from the machine learning methods for the computational model LP1 and the prediction set 1.2.

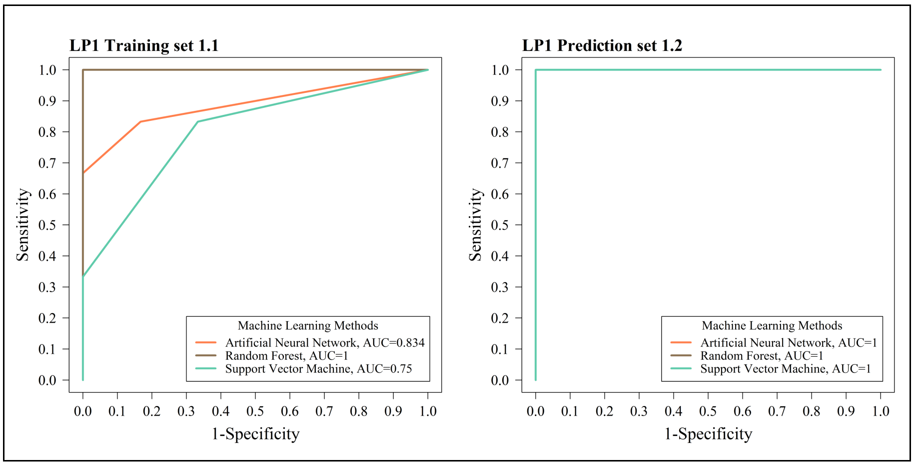

Fig. 3. Sensitivity 1-Specificity plot of the machine learning methods for the computational model LP1 and for the training set 1.1 & prediction set 1.2.

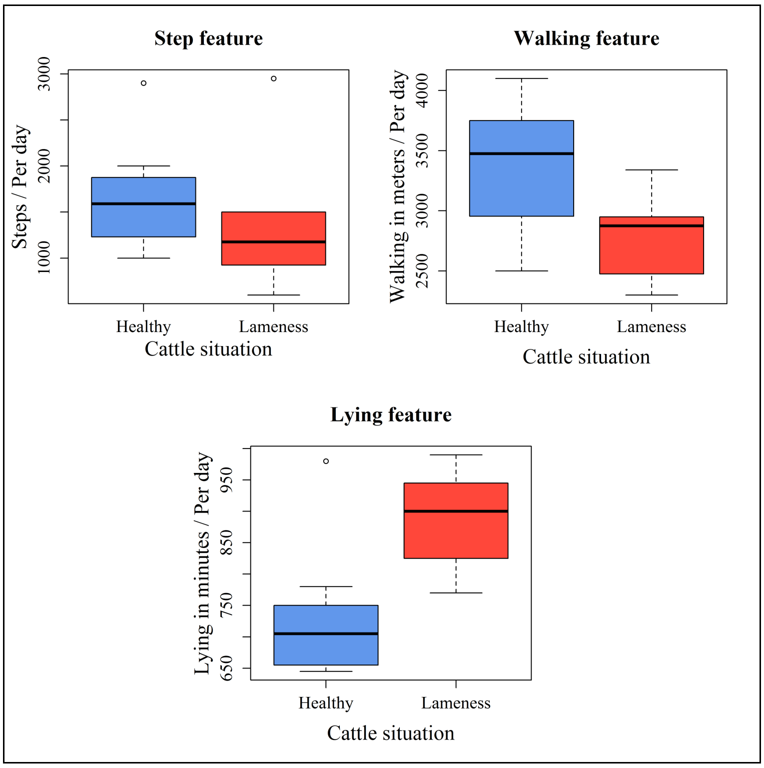

Fig. 4. Box plots with the 3 features from training set 1.1 and prediction set 1.2.

From Figure 3 and Table 6, it is observed that the machine learning method Random Forest can distinguish the training set (1.1, Table 4) with the highest score, with Accuracy=100%. The prediction set (1.2, Table 5) can be distinguished equally well from all the three machine-learning methods (Figure 3 and Table 7). Another positive aspect is that the Random Forest machine learning method can identify with significant difference the positive samples from negative samples for both sets. That result is obtained from the average prediction score of positive samples and from the average prediction score of negative samples (Figure 1 and Figure 2). In (Figure 4), the differences between the healthy and infested cattle are presented in steps, walking and in lying. Also from Figure 4, it is revealed that from the three features «steps per day» (dimensionless), «overall walking per day» (m), «lying per day» (min), the most significant feature is the «lying per day» (min), because it has the bigger difference in concentration between healthy and infested cattle and therefore, it supports the computational model LP1 to distinguish with bigger accuracy the samples.

3.2 LP2 Computational Model

In this section, the results for the second computational model (LP2, Table 2) and the training set (1.1, Table 4) & the prediction set (1.2, Table 5) are presented.

Table 8. Threshold of the machine learning methods for the computational model LP2 and the training set 1.1.

LP2 computational model & training set 1.1											
M.L Method	Threshold	TP	FP	TN	FN	Sensitivity	Specificity	Precision	Recall	Accuracy	AUC
ANN	0.5	6	0	6	0	1.00	1.00	1.00	1.00	1.00	1.00
RF	0.5	6	0	6	0	1.00	1.00	1.00	1.00	1.00	1.00
LIBSVM	0.5	6	0	6	0	1.00	1.00	1.00	1.00	1.00	1.00

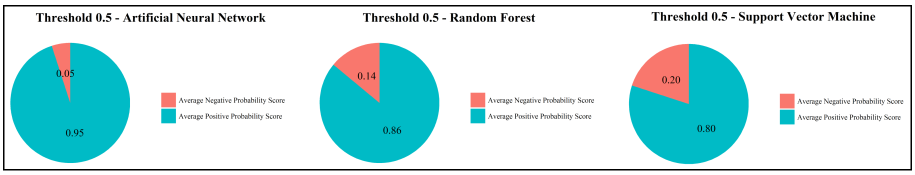

Fig. 5. The average prediction score which is returned from the machine learning methods for the computational model LP2 and the training set 1.1.

Table 9. Threshold of the machine learning methods for the computational model LP2 and the prediction set 1.2.

LP2 computational model & prediction set 1.2											
M.L Method	Threshold	TP	FP	TN	FN	Sensitivity	Specificity	Precision	Recall	Accuracy	AUC
ANN	0.5	2	0	2	0	1.00	1.00	1.00	1.00	1.00	1.00
RF	0.5	2	0	2	0	1.00	1.00	1.00	1.00	1.00	1.00
LIBSVM	0.5	2	0	2	0	1.00	1.00	1.00	1.00	1.00	1.00

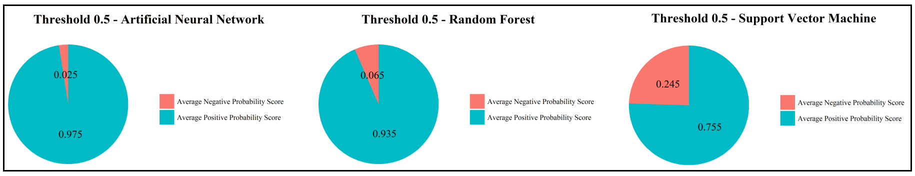

Fig. 6. The average prediction score which is returned from the machine learning methods for the computational model LP2 and the prediction set 1.2.

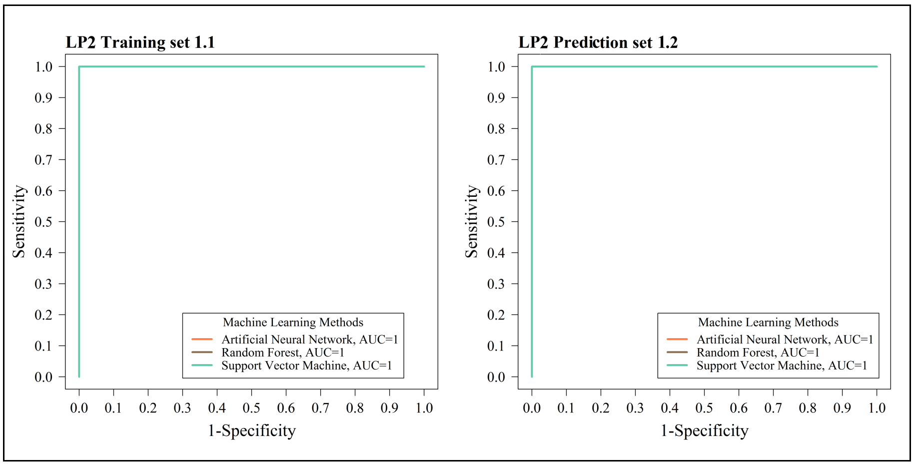

Fig. 7. Sensitivity 1-Specificity diagram of the machine learning methods for the computational model LP2 and for the training set 1.1 & prediction set 1.2.

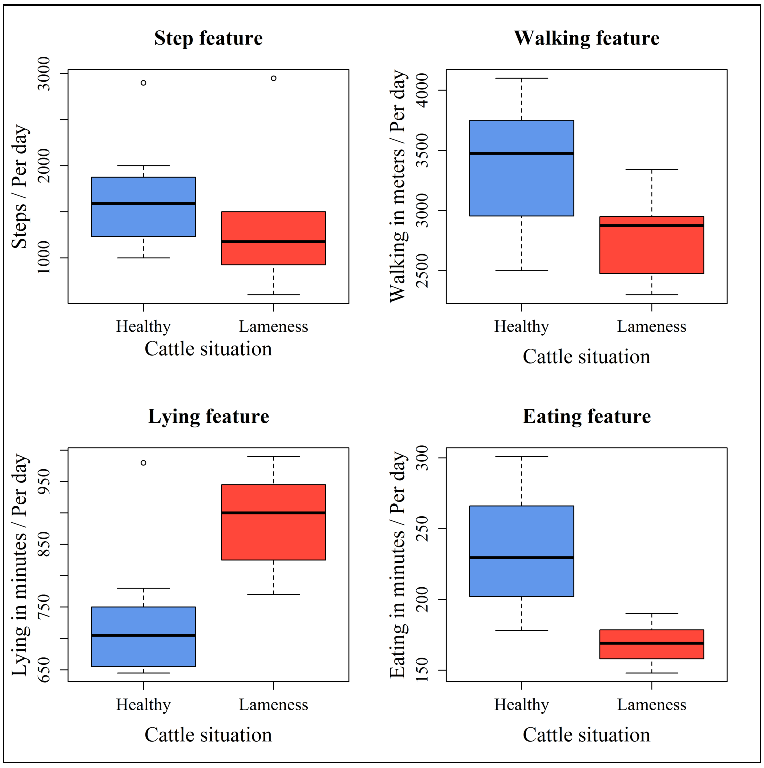

Fig. 8. Box plots with the 4 features from training set 1.1 and prediction set 1.2.

The results listed at Table 8 and Table 9 and depicted at Figure 7 are considered as optimistic. The reason is that the three machine learning methods can distinguish equally well the training set (1.1, Table 4) and the prediction set (1.2, Table 5), for the computational model (LP2, Table 2). The most significant conclusion which is obtained from these results and from Figure 8 is that the fourth feature, «eating per day» (min), is a crucial feature and helps all three machine learning methods to distinguish more accurately the positive from the negative samples. The second most crucial feature is «lying per day» (min). A second positive result that was observed is increase in the variation of prediction scores between positive and negative samples from the three machine learning methods (Figure 5 and Figure 6) for both sets, mainly in ANN and LIBSVM methods, the reason is the fourth feature.

The conclusions obtained from the observation of the tables and figures for the two computational models (LP1, Table 1) and (LP2, Table 2) are, that the three machine learning methods, Artificial Neural Networks, Random Forest, and Library for Support Vector Machines, can distinguish with remarkable results the positive from negative samples. As a result, the features which are used from the two computational models are crucial, mainly the «eating per day» (min) and the «lying per day» (min) and these features enhance the algorithm such as to distinguish with bigger accuracy the positive from the negative samples.

The machine learning method which returned the highest results for the two computational models was the Random Forest.

From the two computational models which were compared, the best results were returned from the (LP2, Table 2) model. The reason is that the fourth feature «eating per day» (min) is used by the model to distinguish the positive from negative samples. The fourth feature helps significantly the three machine learning methods to identify the healthy from non-healthy samples, as was obtained from the great variation for the prediction scores between the positive and negative samples.

4 Conclusion

The result of this study, was the development of a new integrated, powerful and reliable computational analysis, which is used for the identification of the lameness in cattle based on machine learning. Two computational models, Lameness Potential 1 and Lameness Potential 2, were created. The computational model which excelled was the (LP2) which uses four powerful features, «steps per day» (dimensionless), «overall walking per day» (m), «lying per day» (min) and «eating per day» (min), to distinguish the positive from negative samples. The aim of these four features was to support the algorithm to distinguish the samples in the best way possible. The final result which was obtained is considered as optimistic, because the algorithm can distinguish equally well the positive (healthy) and negative (infested) samples, as indicated from the great variation of the prediction scores between the positive and negative samples. As a result, the algorithm is able to identify with high accuracy the healthy cattle from cattle with lameness.

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