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Determination of Estrus in Cattle with Artificial Neural Networks Using Mobility and Environmental Data

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Abstract: Detection of estrus with high accuracy directly affects the possibility of cows becoming pregnant and so also milk production. Most milk is obtained in the early lactation period, after calving. Animals in estrus are more active than others. This mobility can be measured by a testing device called "pedometer." Estrus can be estimated using detected movement changes with artificial neural networks (ANN) models. This study aims to create and assess the effectiveness of a neural network model to estimate estrus in cattle by using movement and environmental data. Movement data of 78 cattle, which showed 184 estruses have been captured along with climatic data during a seven-month period at a private agricultural organization. Data such as cow age, lactation number and number of days elapsed from estrus were also taken into account and evaluated. ANN models were compared with accuracy, precision and F-scores. Two-layer classification networks were tested for feed-forward neural network model. Optimal inputs to the neural network model were found to be motion data, motion data of the previous period, the number of days after the previous estrus, temperature and humidity. Two-layer network with 37 for the first layer and 40 neurons in the second layer has been the most successful model with a 0.1775 F - score. The study has shown that the accuracy of estrus prediction is increased by evaluating movement data along with climate data.

Keywords: Dairy cattle, estrus detection, artificial neural networks

Hareketlilik ve Çevre Verileri Kullanılarak Yapay Sinir Ağları ile Sığırlarda Kızgınlık Tespiti

Öz: Kızgınlığın yüksek doğrulukla tespiti, ineklerin gebe kalma olasılığını ve dolayısıyla süt üretimini doğrudan etkiler. Sütün çoğu, doğumdan sonra erken laktasyon döneminde elde edilir. Kızgınlık dönemindeki hayvanlar diğerlerinden daha aktiftir. Bu hareketlilik, "pedometre" adı verilen bir test cihazı ile ölçülebilir. Yapay sinir ağları (YSA) modelleri ile tespit edilen hareket değişiklikleri kullanılarak kızgınlık tahmin edilebilir. Bu çalışma, hareket ve çevresel verileri kullanarak sığırlarda kızgınlığı tahmin etmek için bir sinir ağı modelinin etkinliğini oluşturmayı ve değerlendirmeyi amaçlamaktadır. Özel bir tarım kuruluşunda yedi aylık dönemde 184 kızgınlık gösteren 78 büyükbaş hayvanın hareket verisi ve çalışma dönemindeki iklim verisi elde edilmiştir. İnek yaşı, laktasyon sayısı ve kızgınlıktan sonra geçen gün sayısı gibi veriler de dikkate alınmış ve değerlendirilmiştir. YSA modelleri doğruluk, kesinlik ve F-skorları ile karşılaştırılmıştır. İki katmanlı sınıflandırma ağları, ileri beslemeli sinir ağı modeli için test edilmiştir. Sinir ağı modeline en uygun girdilerin hareket verileri, önceki döneme ait hareket verileri, bir önceki kızgınlıktan sonraki gün sayısı, sıcaklık ve nem olduğu anlaşılmıştır. Birinci katmanda 37 ve ikinci katmanda 40 nöron bulunan iki katmanlı ağ, 0,1775 F-skoru ile en başarılı model olmuştur. Çalışma, iklim verileriyle birlikte hareket verilerinin değerlendirerek kızgınlık tahmininin doğruluğunun arttığını göstermiştir.

Anahtar Kelimeler: Süt Sığırı; Kızgınlık Tespiti, Yapay Sinir Ağları

1. Introduction

The use of sensors, big data, artificial intelligence and machine learning is making a significant contribution to animal farmers reducing production costs, increasing productivity, improving animal welfare and raising more animals per hectare (Neethirajan, 2020). Estrus detection is one of the most important factors affecting the reproductive performance of dairy herds (Senger, 1994). Inadequate or inaccurate determination of estrus in time leads to delayed insemination, decreased pregnancy rate and prolongation of birth interval (Özgüven, 2018For this reason, automatic systems have been developed for high accuracy detection of estrus (Dulyala et al., 2014). Detection of estrus with high accuracy directly affects the possibility of cows becoming pregnant. The high rate of the breeding ability of cows primarily increases the production of calves. It also affects the milk production. Most milk is obtained in the early lactation period, after calving. Controlling reproduction allows for longer periods and higher milk production (Daniel, 2006). Additionally, as the number of heifers cannot be provided due to the increase in the calving interval, so the herd will age and gets smaller. The success of the selection will be adversely affected. Thus, the determination of estrus should be accurate and not-estrus animals should not be perceived as in estrus.

The rate of detection of estrus is between 43% and 52% and this value can reach up to 80%. Factors such as air temperature, milk yield and some diseases affect the determination of estrus (Orman, 2011). In the summer, conception rates may be half that of colder months (Peralta et al., 2005). In some enterprises, 5%-30% of animals are inseminated even though they are not in estrus (Tömek, 2007). In their study, Shahriar et al. (2016), obtained 82-100% estrus accuracy in pasture areas. The estrus period is more difficult than other species in the cows due to the short and variable estrus period (Demirci, 2007). Many methods are used in the determination of estrus. Direct research by observing (inspection), determining by using the search bulls, placed instruments in the sacrum region, the measurement of electrical resistance of vaginal mucosa, determination of hormone (progesterone, estrogen) in blood and milk, rectal examination and determining by pedometer are methods for detecting estrus (Firk et al., 2002; Demirci, 2007). It is also possible to perform estrus detection with electronic devices such as video cameras, mounting detectors, temperature sensors and hormonal fragrance sensors (Williamson et al., 2006). The most common method of estrus detection is done by cow-keeper observation. Specialized personnel are needed in this method (Sarıbay & Erdem, 2008). Automatic detection of estrus by using mobility is also possible. In the literature, the results of estrus detection by sensors and cameras range from 51% to 86% (Roelofs et al. 2005). Animals in the estrus are more mobile than other animals. This mobility is measured by the step-counting devices called “pedometer” that are attached above the dew claws of the cows.

Today, artificial intelligence methods are an effective solution for complex and time-consuming problems. Artificial intelligence is a research area that examines the mental functions of people in decision-making processes by using computer models and formulates. Artificial intelligence methods can be used in order to determination of estrus (Mitchell et al., 1996; De Mol et al., 1999; Firk et al., 2002; Brunassi et al, 2010; Yin et al., 2013; Shahriar et al., 2016; Thanh et al, 2018). Artificial Neural Network (ANN), which is one of the effective and widespread methods of artificial intelligence, can be used in the classification of animal and herd behavior (Nadimi et al., 2012). It is thought that ANN models can determine the estrus status by detecting changes in animal behavior (Krieter et al., 2005). But, although animals have general behavior determined, they can react differently in most cases (Hulsen, 2012). Shelter conditions, climatic conditions, and animal population density can affect mobility and consequently estrus prediction.

Walking activity and behavioral measures of estrus are affected by many individual and environmental factors such as lactation-related social interactions, housing, age, genetics and physiological aspects (Galina & Orihuela, 2007; Aungier et al., 2012). It is thought that accuracy will be increased by evaluating environmental conditions and animal data as input in the ANN model. Thus, this study establishes an ANN model that will determine the estrus period in cows by using motion and environmental data and to investigate its effectiveness. In addition to the movement information obtained using the pedometers, the data of the climate and animals were included in the study. Different input sets have been evaluated using ANN models in different topologies and thus it is aimed to determine the most suitable model and data types.

2. Materials and Methods

Observations made for the study were conducted in a commercial dairy cattle farm in Tokat province. Using the Dairy Plan (GEA Westfalia Surge) herd management software, all kinds of veterinary records such as birth and calving dates, vaccine and drug histories, as well as data on lactation numbers and milk yields were recorded. To monitor estrus, 78 healthy animals of Holstein cows, which were in the first three lactation periods were observed. The study was approved by the Animal Experiments Local Ethics Committee of Tokat Gaziosmanpaşa University (2012-HADYEK-028). Climatic data on barns and farm were recorded during the study period. To measure and record the climate data, iMetos 300 climatic measuring station (Metos, Hassfurt) was established in the open area in the middle of the barns. iMetos 100 climatic measuring stations (Metos, Hassfurt) were established inside the barns. Stations were used to measure humidity, temperature and dew point values. Measurements were made for every minute and recorded in the database using an internet connection. Then, hourly averages of the data from the database were obtained and recorded for the training of ANN models. The humidity of the air affects the sensation of temperature. Thus, to define the comfort and stress conditions, the Temperature Humidity Index (THI) was used to show the effect of humidity on temperature (Garcia, 2006). THI was calculated using Equation 1.

$$THI = s + (0.36) + 41.2 \quad (1)$$

In equality, s is the hourly average dry thermometer temperature in °C, and c is the dew point. The wireless pedometer system (Robolab MOO, Konya) was used to track the movement of the cows. The system consists of pedometers attached to the wrists of cows, interconnection hubs and central server. Pedometers hourly send data to the interconnection hubs in the barns with wireless data transfer. The interconnection hubs collect the data from pedometers then transmit the central server, where the received data are stored in the database. The motion tracking system calculated the number of movements with the values read from the acceleration sensor in the pedometers and evaluated this number as motion data. Movement data were recorded hourly, such as climate data. In the dataset, the outputs were set to be [1,0] if the cow is in estrus and [0,1] if it is not.

All data were divided into three sets: 10% test, 10% validation and 80% training. While training the networks with the training set, performance was evaluated with the validation set for each epoch of training. "The validation error" is recorded if the performance value obtained from the validation set was worse than the previous iteration. If the training gives a certain number of validation errors, the training was terminated. So, the network was prevented over-learning. The success of the final network was evaluated using the test set that was not used in the training process. All inputs were normalized between -1 and +1 before being used in ANN training. Min-max method was used for normalization (Equation 2).

$$P_n=2(P-Pmin)\div(P_{max}-P_{min}) -1 \quad (2)$$

In Equation 2, P is the actual input. P_{min} represent the smallest value and P_{max} represent the maximum value of the input variables. The result of the equation P_n means the normalized value.

The ANN model structure was selected as hierarchical feed forward multilayer network, which was reported to be successful (Nadimi et al., 2012). The output layers of the investigated ANN models were determined as two neurons to express the estrus condition.

2.1.Investigation of Input Types

To examine the effects of inputs on the model and determine the most appropriate inputs, input sets were arranged in different combinations of input types. For this, the input data were divided into three basic groups. The movement-related group has three motion data for the last hour, one hour before and two hours before. The climate group has the average temperature, humidity and THI data calculated for the last hour. In the animal information group; The number of lactations, the age of the animal (in days) and the number of days after estrus was obtained. Using these input types, three basic input groups were prepared in different combinations with 3 for motion data, 3 for climate data and 7 for animal data. Based on the movement group as the master group, 96 different input clusters were created because of the combinations of these groups. These clusters were tested with a network, which has 15 neurons in the single-hidden layer. The input cluster that gave the best result was selected as the optimum input.

2.2.Determination of ANN Topology

It was stated that finding optimal topology for ANN could be a time-consuming process depending on the computer processing power and problem complexity (Madadlou et al., 2009). Chegini et al. (2008) reported that the two-layer ANN was more successful. Thus, two-layer models were investigated in the study. More than two hidden layers or many more neurons in the layers are not recommended as it will directly increase the processing (Alpaydın, 2010). The number of neurons in the hidden layer was increased in certain amounts and their performance was evaluated to find the optimal number of neurons. The network with the lowest error was selected because of these tests.

The method that Chegini et al. (2008) used in their study, was applied to determine the most appropriate two hidden layered networks: The second layer was increased to the end for each neuron increase in the first layer. So that, all possible conditions were tried sequentially. The first number of neurons was 1-1 for the first and second layers, respectively. Neurons were increased by three to 52-52. The best training algorithm for classification problems is the scaled conjugate gradient (SCG) backpropagation (Moller, 1993; Bishop, 1995). Thus, each network, which was generated by this method was trained using the SCG backpropagation algorithm. The σ parameter, which is the weight change between cycles of the algorithm, was determined as 5.0e-5 and the μ that adjusts instability, as 5.0e-7. The terminating limit of the training algorithm was arranged as 1000 epochs. Validation was performed in all trainings. 6 validation errors received consecutively was chosen as the termination criterion of training. The target performance criterion was selected as zero. Another termination parameter, the smallest gradient value of the error function was determined as 1e-66.

The hyperbolic sigmoid tangent function, which was reported for the best performance in previous studies, has been used as a transfer function in the hidden layer neurons of the ANN models (Alpaydın, 2010; Bishop, 1995). The "Softmax" transfer function was used in the output layer of the networks. This function, which mathematical expression is given in Equation 3, takes the ANN outputs as probability associated with classes.

$$f\left(n_i\right) = \exp\left(n_i\right) \div \sum_{j=1}^{s} \exp\left(n_i\right) \quad (3)$$

In the equation, *S* gives the number of the class, *j* is the index. *i* is the index of the output. The outputs of the Softmax function are between 0 and 1. The sum of one output set is equal to 1. The function identifies classes by making the value of the highest output neuron as 1 and the others as 0.

2.3.Comparison of ANN Models

To demonstrate success in the classification networks, it is necessary to show whether the classification has been done correctly. There are two kinds of correct estimates for the estrus classification: First is " True Positive" when the cow is in the estrus class also predicted as estrus. And the second is " True Negative" when cows are not in the estrus class also predicted as not estrus. Accuracy of the classification models is calculated by dividing the sum of positive and negative trues by the all-estimates sum. Although accuracy is accepted as a general criterion, it is insufficient to demonstrate the success of the classification model. The number of negative classes (for this problem, the animals, which were not in the estrus state) can be much more than the positive. As a result of this excessive, the estimation of the negative trues raises the accuracy rate. The model may be supposed as successful even if the prediction of positive class, which is valuable for the problem is not in the desired success. "Sensitivity," "Precision" and "F-Score" calculations were used to evaluate the performance of classification networks and to make their comparison objective. Sensitivity is an indicator of how many estruses are predicted by the model. Precision is an indication of how many predictions are predicted correctly. Because of the importance of the positive class (estrus), both the sensitivity and precision should be high for a successful classification model.

F-score was used to compare the success of ANN models. The F-score, which is given in Equation 4 is a sufficient criterion for evaluating sensitivity and precision.

$$F = 2 \text{ x} \frac{p \ x \ s}{p + s} \quad (4)$$

In the equation, *P* defines precision. *S* defines sensitivity. And result gives the F-score between 0 and 1. If the both two values are large, the F-score approaches 1. The reduction of at least one reduces the F-score pretty. Accuracy, sensitivity, Precision and F-score calculations were made with the test set before separation from the data. Then, using the most successful networks, the same calculations were made for all data and confusion matrices were created.

The designing, training and testing of ANN models, statistical calculations, tables and graphs for the evaluation of the results were made with MATLAB software and NNTool plugin.

3. Results and Discussion

3.1.Climatic observations

If THI is above 80, it causes cows to be in a condition called “High Stress.” The situation between 70 and 80 is called “Low Stress.” Stress status affects animal mobility (Sönmez et al., 2005).

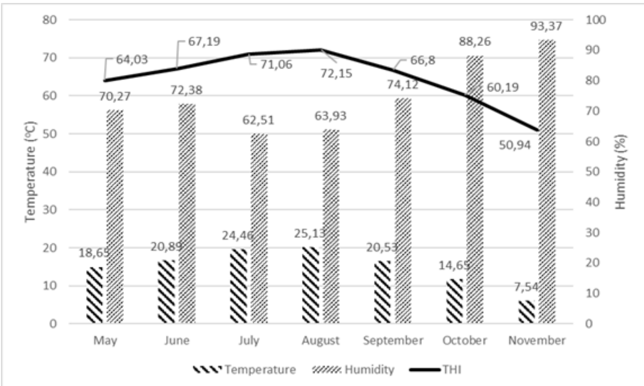

Figure 1. Average of temperature, humidity THI values

Şekil 1. *Sıcaklık, nem ve SNİ değerlerinin ortalaması*

Figure 1 shows the average temperature, humidity and THI values for the months observed. In June, July, August and September, the average of THI increased to over 70. If THI values are evaluated momentarily during these months, it can be mentioned that the animals were in a stress state most of the time.

3.2.The Optimal inputs types for ANN

Between May and November, 184 estruses were reported for 78 cows during a seven-month observation period. The 96 different input clusters previously identified were trained with ANN models with 15 neurons in the single hidden layer and with the same characteristics (transfer function, initial weight values, etc.). The input clusters were compared for the F-score. The movement data, one-hour previous motion data, the number of days after the estrus, temperature and humidity averages were chosen as the most successful inputs. A total of 87685 lines, corresponding to 80% of the 109605-row data generated by these inputs, were used in the training of networks. The rest was used as two equal parts (10960 lines for each) for validation and testing.

3.3.ANN Model Trainings

The number of neurons increased three for every step, in the range of 1-1 to 52-52 in order to test the two-layer networks. The graph in Figure 2 shows the F-score change according to the number of neurons in the layers.

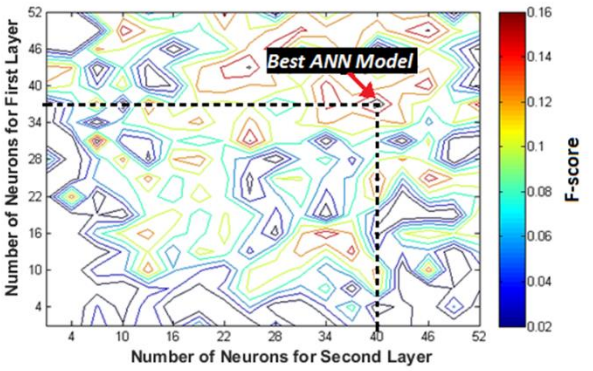

Figure 2. F-score change according to neuron numbers for two-layer ANN
Şekil 2. *İki katmanlı YSA için nöron sayılarına göre F-skoru değişimi*

As shown in Figure 2, the most successful network with a 0.1775 F-score was the network with 37 neurons in the first layer and 40 in the second. The training was terminated with validation error warnings. The 6th validation error was reached at the 63rd epoch. The confusion matrix of the network for all data is given in Figure 3.

4. Conclusion

In this study, the most suitable inputs for ANN training were investigated firstly. The movement data, the movement data of the previous period, the number of days after the previous estrus, temperature and humidity were found as optimal inputs. The F-score of this input cluster was calculated as 0.1706, which is the highest among other input clusters.

Cows have been stressed for some days due to temperature and humidity. This situation, which directly affected their mobility, was due to the climate effect as indicated by Sönmez et al. (2005). The F-score was calculated as 0.1488 by subtracting the temperature and humidity values from this input set. It was seen that environmental factors were important for determining estrus with ANN. Also, it was more successful to use temperature and humidity as separate inputs instead of THI alone. F-score was 0.1020 for the input cluster, which climatic data were only THI. Another type of input that affects success is the number of days after estrus. The F-score was reduced to 0.0995 when this input was removed from the input. The number of days after estrus had a significant effect on the F-score. The movement data with the previous period, increase the success of the estimate due to its ability to show the sudden increase in the movement.

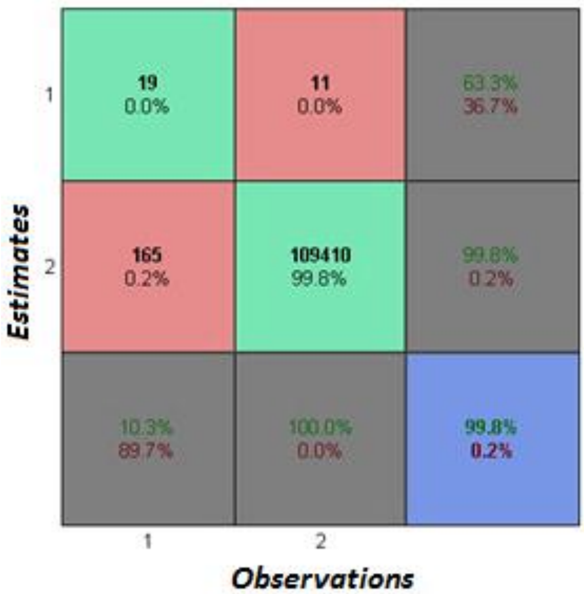

Figure 3. Confusion matrix of the most successful two-layer network. ("1" indicates estrus and, "2" indicates non-estrus class)
Şekil 3. *En başarılı iki katmanlı ağın hata matrisi. ("1" kızgınlığı ve "2" kızgınlık olmayan sınıfı belirtir)*

After finding the most suitable inputs for ANN, then the best model topology was studied using this input cluster. According to the F-score, the best result was obtained by an ANN model, which has 37 neurons in the first layer, and 40 neurons in the second layer, with a value of 0.1775. Its sensitivity was obtained as 0.1032 and precision as 0.6334. Its accuracy was 0.9983. The accuracy of all models was over 0.99. The reason for this was that the negative predicted number of negative classes increased the accuracy rate because the number of negative classes was much greater than the positive class.

Movement data, which were essential for estrus estimation used for ANN training in the current system, were a numerical value produced by motion sensors. Although these data were related to the movements of animals, it did not specify the exact number of steps. Previous studies have shown good results with the number of steps (Krieter, 2005; Nadimi et al., 2012). It is thought that more successful results will be obtained by an ANN model where direct step information is taken, including environmental and animal data.

Besides the evaluation of environmental data, another important point in this study is the use of hourly data. In many herd-management systems, reading movement data from the pedometer is performed at specific times and places, such as milking. With the help of wireless data transfer, hourly data were collected independently of location, so that estrus estimation could be made earlier.

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