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AI Analysis Method Utilizing Ingestible Bio-Sensors for Bovine Calving Predictions

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Abstract

Parturition is an important event for farmers as it provides economic gains for the farms. Thus, the effective management of parturition is essential to farm management. In particular, the unit price of cattle is higher than other livestock and the productivity of cattle is closely associated to farm income. In addition, 42% of calving occurs in the nighttime so accurate parturition predictions are all the more important. In this paper, we propose a method that accurately predicts the calving date by applying core body temperature of cattle to deep learning. The body temperature of cattle can be measured without being influenced by the ambient environment by applying an ingestible bio-sensor in the cattle's rumen. By experiment on cattle, we confirmed this method to be more accurate for predicting calving dates than existing parturition prediction methods, showing an average of 3 hour 40 minute error. This proposed method is expected to reduce the economic damages of farms by accurately predicting calving times and assisting in successful parturitions.

요 약

가축의 분만은 농가의 재산을 늘릴 수 있는 중요한 수단이므로 이를 관리하는 것은 농업 경영에 필수적인 항목이다. 특히 축우는 다른 가축에 비해 단가가 높고, 생산성 측면에서 농가의 소득과 밀접히 연관되어 있으며 축우의 42%는 밤에 분만이 이루어지고 있어 정확한 분만 예측은 더 중요하다고 할 수 있다. 그리하여 본 논문에서는 경구 투여용 센서를 통해 반추위 내의 심부 체온을 외부 환경의 간섭 없이 안정적으로 실시간 측정하고 이를 딥러닝에 적용함으로써 분만 시점을 예측하는 방법을 제안 하였고, 실제 축우를 대상으로 실험을 수행한 결과 실제 분만 시간 대비 평균 3시간 40분의 오차만 보여 기존 분만 예측 방법보다 정확하게 분만일을 예측하는 것을 확인하였다. 제안하는 방법을 통해 축우의 분만을 정확하게 예측하여 난산의 위험 없이 성공적으로 분만 하도록 도움을 줌으로써 농가의 경제적 피해를 절감할 수 있을 것으로 기대한다.

Keywords

bovine parturition/calving, body temperature, ingestible sensor, deep learning, LSTM-FCN

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Ⅰ. Introduction

Bovine parturition is an important event for a farmer as the process produces a calf and increases a farm's wealth, and also decides the milk production period of the particular cow that could not milk during its pregnancy period. The gestation length of cattle is about 280 days, which is similar to humans. The calving process involves the delivery of the calf after it passes through the cervix, vulva and birth canal. However, if the cow does not receive proper care during parturition, calving complications such as dystocia, stillborn calves and retained placenta may occur. According to statistics released by the U.S., the dystocia rate was higher in primiparous cows(51.2%) than multiparous cows(29.4%). In addition, most calves that experienced difficult deliveries were culled before 30 days. If such cases become more frequent the labor, time and financial support for assisting a pregnant cow is wasted, which in turn damages the farm household economy. Such calving complications can also develop into social issues regarding animal welfare. Therefore, the accurate prediction of calving time is essential for cattle farm management.

Until now, most farms have observed the physical changes in cattle to predict calving times. In general, udder development and swelling of the vulva can be observed 3~5 days before parturition. 1~2 days before calving, relaxation of the pelvic ligaments may become visually evident, giving a sunken appearance of the vulva and some behavioral differences such as discomfort[1]. However, spotting such symptoms in large-scale farms is practically impossible. 42% of calving occurs in the nighttime[2] and so it is difficult for farm owners to manage parturitions on time. Even if the physical or behavioral symptoms are detected such symptoms may be caused by different reasons or may not indicate accurate calving times.

Signs of impending calving in cows include behavioral changes such as discomfort and also other changes such as amount of activity, body temperature, rumination speed, feed ration, etc.[3]. Due to its heavier weight a cow expecting to deliver shows a rapid decline in its activity level, and from about a week before calving its rumination time also rapidly decreases resulting in a drop in feed ration. However, the criteria for each indicator are vague and there is a great deviation among cows, making it almost impossible for an accurate prediction of calving time. Among the various biometric data, body temperature shows a gradually decrease in calving cows 24 hours before the actual parturition process. Body temperature have been confirmed by various researches to show stable changing patterns compared to other indicators [4][5].

The body temperature of cattle is a reliable indicator currently being used to monitor diseases[6] or predict estrus[7], in which for both cases the body temperature rises. However, in the case of calving, the body temperature drops. Parturition can be predicted with accurate measurements and monitoring of cattle body temperature. However, existing methods such as the usage of rectal thermometers or thermal cameras have difficult measurement processes with limited usage and are not safe from external environmental interferences, making it unfit for practical use.

In this paper, we propose a method to make an accurate prediction of calving times utilizing ingestible sensors and applying collected body temperature data to deep learning algorithm. The proposed method orally applies ingestible sensors into the rumen of cattle and measures deep body temperature on a regular basis. The collected body temperature data is applied and analyzed to deep learning and with this algorithm the parturition time can be predicted so the farm manager can care for the calving cow in a timely manner. Also, the manager can prepare for any difficulties that many arise during the calving process and provide any care that is necessary for a safe delivery. Thus, the proposed method is expected to contribute in increasing a farm's income.

This paper continues to examine related researches in the following chapter. In Chapter 3 the proposed calving prediction method is explained. Chapters 4&5 describe the experiments conducted on dairy cattle. And lastly, Chapter 6 provides the conclusion and plans for future researches.

II. Related Works

2.1 Existing Prediction Methods for Bovine Calving

The most widely used calving prediction method is a calculation method that subtracts 3 months from the final insemination month and adds 10 day to the final insemination day[1]. However, this calculation method shows a deviation of 15 days maximum according to cow. Also the actual calving date can differ according to the number and sex of fetuses, and calving season.

The calving period can also be predicted by observing the physical and behavioral changes in cows. Impending cows show swelling of the vulva and udder development[8]. About 6 hours prior to calving, behavioral changes such as elevation of the tail or frequent lowering of the head to see the stomach can be observed[9]. However, it is difficult to observe every cow in a large-scale farm with vast numbers of cattle. Also some calving occurs at night or dawn, making this prediction method ineffective. Another method that analyzes vaginal temperature, rumination time, lying time, and lying bouts to predict calving times[10] has complex measurement processes and a low accuracy rate of 74%.

There have been active researches on predicting calving times by analyzing body temperature changes before calving. Study[11] measured the rectal and vaginal temperatures of impending cows in regular intervals 48 hours prior to calving, however, the measurement process was difficult and the small drop size of body temperature made accurate prediction impossible. Research[12] concluded that if the rumen temperature drop was greater than 0.2℃ there was a high probability that calving would occur within 24 hours. Vaginal sensor is inserted to measure and analyze temperature to predict calving time[13]. The vaginal sensor transmits an alarm message to the farm manager when it is discharged with the ruptured ventral sac and detects a change in temperature. This method transmits an alarm at the actual time calving starts and thus makes it possible for an accurate prediction of parturition. However, it accompanies the danger of bacterial infection during the process of inserting the sensor in the vaginal area.

2.2 Automated Calving Prediction Method Utilizing AI

Existing calving prediction methods require regular data analysis by the user and so there have been continuous attempts to automate this process using AI. However, such studies have focused on externally installed acceleration sensors and cameras, and due to inaccurate data and sensor durability issues, practical use and case studies have started to be presented after 2016.

Study[14] proposed an algorithm predicting insemination outcomes of Irish dairy cows using 5 variables including milk genetic trait. The logistic regression algorithm was applied but the method showed low results with an F-Score of 52.03%. Study[15] monitored activity, condition, etc. of dairy cattle by using random forest algorithm with data collected from acceleration sensors installed on the necks of cattle. Also, Heat detectors was installed near the vulvar area and predicted cattle diseases using deep learning from color changes caused by temperature change[16]. This method has low accuracy as it indirectly measures temperature and has issues such as difficulties in measuring at nighttime.

Study[17] proposed a disease prediction method by applying data such as deep body temperature, amount of activity, feed ration to deep learning(4-layer neural network). This method showed a performance rate of more than 80% and giving rise to the potential of deep learning application in the area of cattle condition detection.

In this paper, we propose a calving prediction method using ingestible sensors to measure deep body temperature and applying such collected data to deep learning to provide an accurate calving time for impending cows.

III. Proposed Method

3.1 Calving Prediction Process

The proposed calving prediction process is outlined in Fig. 1. The ingestible sensor measures the rumen temperature and the measured data is transmitted to the remote server through the LoRa Gateway. The data transmitted by the sensor through the LoRa Gateway guarantees safe transmission with no data loss to the server. The data transmitted to the server is saved to each database according to entity, location, and farm. Such categorized data is transmitted to the analysis server for real-time analysis. This data is analyzed with deep learning and the final calving prediction date is calculated. Cows with impeding calving are notified to farm managers so proper assistance can be provided.

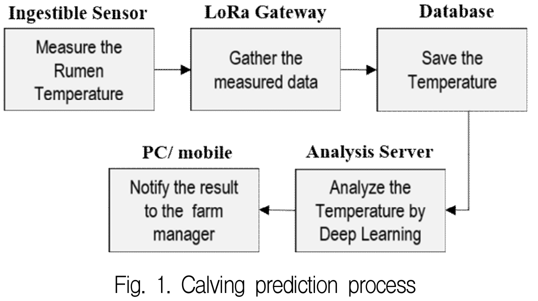


Fig. 1. Calving prediction process

3.2 Ingestible Sensor

Ingestible bio-sensors(LiveCare, uLikeKorea Co., South Korea) were used to measure the deep body temperature of cattle. Bolus guns were used to orally administer the sensors while preventing any saliva contamination. The orally administered sensors settle in the rumen as in Fig. 2. Ingestible sensors once settled in the rumen are free from any external influences and measure deep body temperature in 10-minute intervals. The bio-sensors can detect minute changes in core body temperature up to 0.1℃. The bio-sensor is installed in a non-toxic plastic capsule that protects it from gastric fluids and pressure. The capsule does not have any rough surfaces or sharp corners making it safe to install in cows[18].

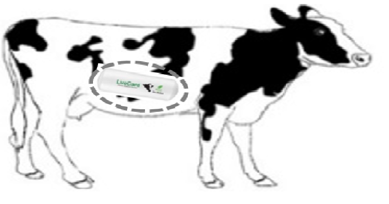


Fig. 2. Ingestible sensor settled in rumen

3.3 Deep Learning Analysis Method

The data measured and collected in this proposed method is time-series data. The purpose of this method is to analyze the collected data and provide accurate predictions of calving time(determining whether calving is imminent or not). This method can be defined with single input and binary classification problems.

LSTM(Long short-term memory) is frequently used in natural language processing, and it is especially useful in processing time-series data where data correlation is important.

This paper promoted higher performance by augmenting FCN(Fully convolutional networks) to LSTM as in Fig. 3[19]. The LSTM-FCN model has proved to offer outstanding performance for open data ECG200.

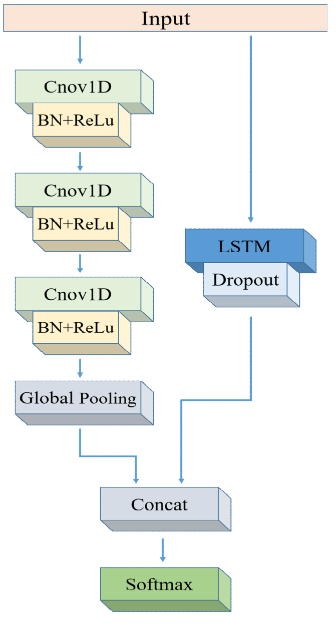


Fig. 3. LSTM-FCN model

The input time-series data is normalized by expressing the difference from the average value using the average and standard deviation. The normalized value is entered into LSTM and the one-dimension convolution layer according to each time frame. Both outputs are concatenated and processed through the softmax function for a probability value [probability of calving condition, probability of normal condition]. If the cow is definitely in calving condition the output value will be [1, 0], and for normal condition the output will be [0, 1]. The probability of calving condition = 1 – probability of normal condition.

IV. Experiment

4.1 Experiment Subject

The experiment was conducted from August 1, 2018 to October 31, 2018 on 4 pregnant cows over 24-months-old bred in a domestic cattle farm in Chungnam province, Korea. Information of the entities including breed, sex, age, and expected calving date are illustrated in Table 1. Entities A&D and B&C have similar ages and calving dates and thus will be compared and analyzed for body temperature patterns.

Table 1. Information of entities

Entity	Breed	Sex	Age (month)	Expected Calving Date
A	Korean Native Cattle	Female	27	2018-09-20
B			36	2018-09-18
C			38	2018-09-15
D			22	2018-10-02

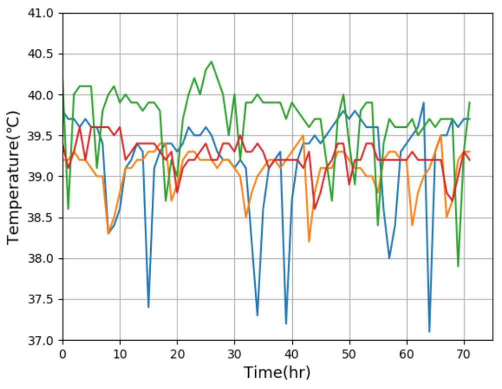
4.2 Experiment Method

Ingestible sensors were orally administered to all 4 entities on July 31, 2018. The bio-sensors measured deep body temperatures of each cow in ten minute intervals and transmitted the data to the server. The collected data was analyzed for deep-learning based calving predictions.

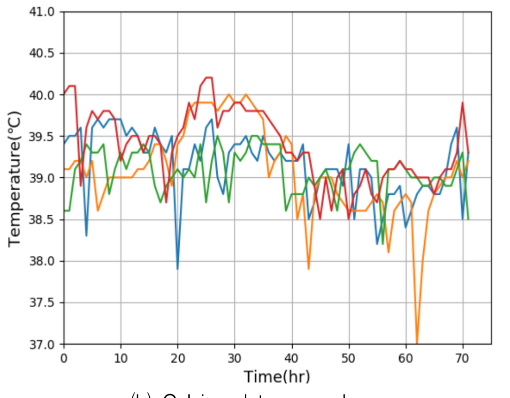
AWS EC2(Amazon Elastic Compute Cloud) was used for deep learning training and testing. Specifications are as follows: Intel Xeon E5-2686 @ 2.3GHz CPU, 61GB RAM, NVIDIA Tesla K80 GPU, Windows Server 2016 OS. AWS EC2 is a web service that provides stable and scalable computing resources. Recently, the system has provided GPU instances which is optimal for deep learning computing, making it the preferable system for many researchers and developers.

The temperature data collected every 10 minutes are converted into one-hour unit data by calculating the average value of each hour. Each hour unit that accompanies calving symptoms is checked. If the number of temperature data with calving symptoms exceeds a certain number it is labeled as calving condition 1, and if not normal condition -1.

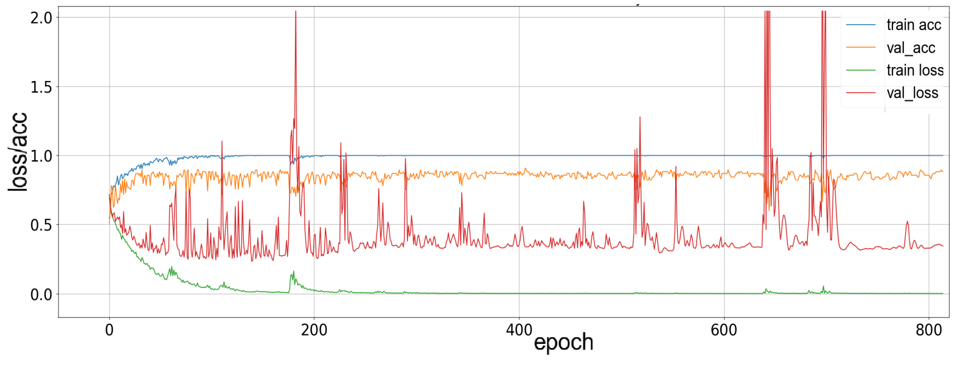
The deep learning structure was realized using Keras with Tensorlflow backend. A total of 369,154 parameters were used with 3 one-dimension convolution layers and 1 LSTM layer. In addition the early learning rate was 0.001, with a batch size of 128 and the epoch number for repeated learning of the total data set was 3000.



(a) Normal data example



(b) Calving data example



(c) Training data

Fig. 4. Training examples and history

He initialization was used for each parameter initialization. Fig. 4 displays the training examples and history of each unit hour and temperature data with calving symptoms. Training wasconducted for a model that detects calving when temperature data with calving symptoms exceed 15 within a 72-hour unit. Also, we used 3 methods ike below to avoid the overfitting problem.

1) Splitted the data and performed cross validation
2) Added a drop-out in each layer
3) Applied L2 normalization

The early learning rate of 0.001 rose to 0.000125 in the final learning session. The accuracy rate for the training data set was 100%, and 97% for the data set. In addition, this model showed over 97% accuracy when applied to a separate experiment data set (Table 2).

Table 2. Experiment data set accuracy rates according to time frame

Time frame	symptom hours	Accuracy
48	10	0.974859
48	15	0.974939
72	10	0.979912
72	15	0.984459

4.3 Experiment Results

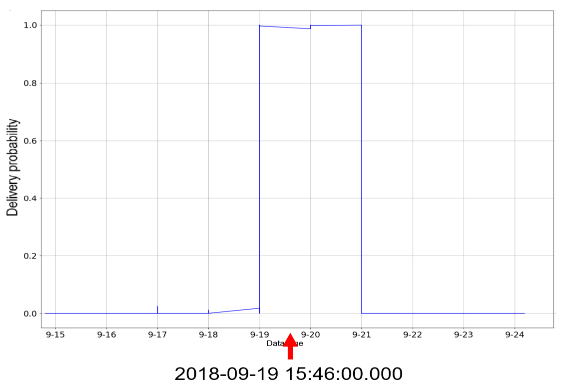
During the experiment period, the deep body temperature of all 4 entities were measured in a stable manner without the bio-sensors being lost or entities showing any abnormal behavior. A total of 17,280 deep body temperature data was collected by the data collection device, and an average of 4,320 data was analyzed per entity. Table 3 is a summary of the experiment results and all 4 cows completed parturition during the experiment period.

The average body temperature of the entities during the experiment period was 39.25℃ and showed temperature changes within the normal body temperature range. There were some differences among entities, however most entities recorded an average body temperature of 39.42℃ from 10 days prior to 1 day prior to calving, which was about 0.2℃ higher than the overall average body temperature during the experiment period. In addition, most entities experienced fall in body temperature 24 hours prior to calving, recording an average of 38.79℃ which was about 0.5℃ lower than the overall average.

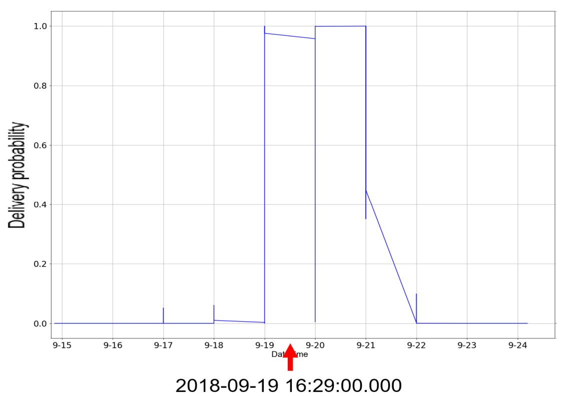
Fig. 5 shows the results of the calving probability rates of each entity that was predicted through the deep learning model based upon the hour-unit body temperature data.

Table 3. Summary of experiment results

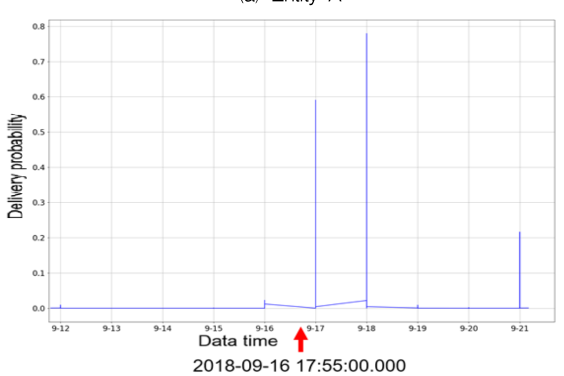
Entity	A	B	C	D
Average temperature (℃) during experiment period	39.12	39.33	39.28	39.26
Average temperature (℃) of 10 days prior ~ 25 hours prior to calving	39.32	39.53	39.43	39.40
Average temperature (℃) of 24 hours prior to calving ~ actual calving	38.52	38.77	39.09	38.78
Recorded time for actual calving	2018-09-19 15:46	2018-09-19 16:29	2018-09-16 17:55	2018-09-26 09:02
Predicted calving time by system	2018-09-19 06:00	2018-09-19 11:00	2018-09-17 00:00	2018-09-26 00:01
Probability of calving condition	0.9953941	0.9973894	0.99612683	0.9978048



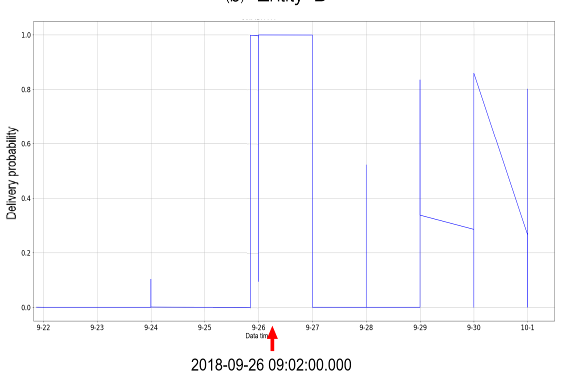
(a) Entity A



(b) Entity B



(c) Entity C



(d) Entity D

Fig. 5. Calving probability graph by entity

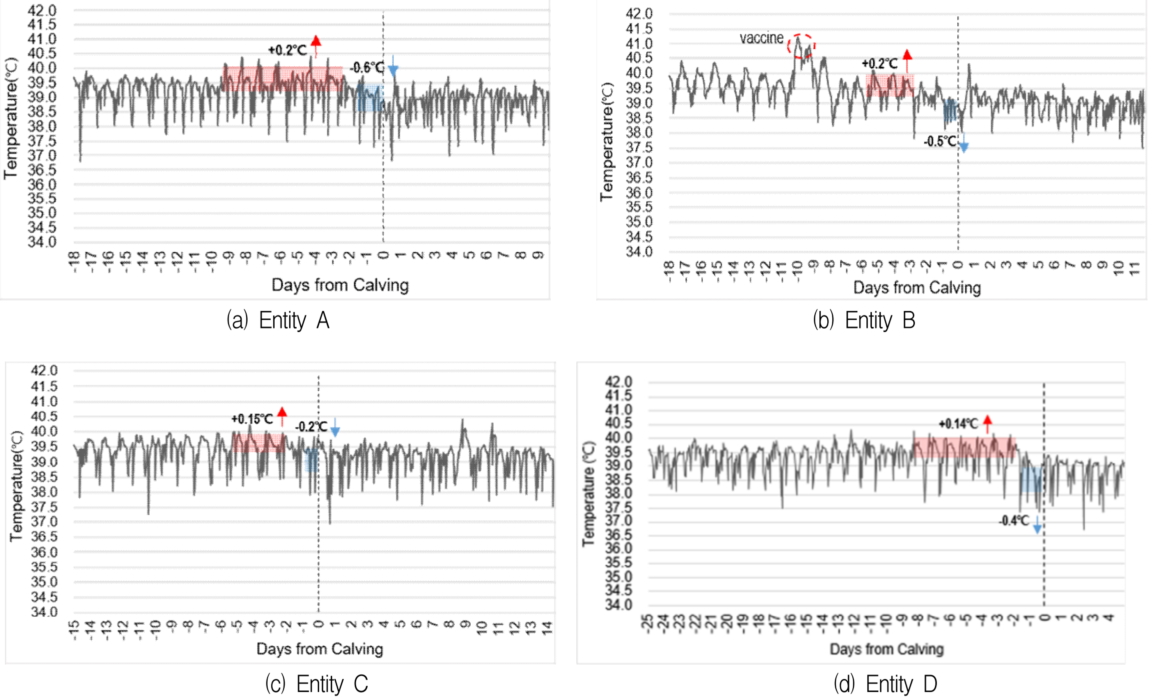
The probability value is expressed from 0~1 and the higher the calving probability, the closer the value is to 1. The red arrow indicates the actual calving time. The unit hour is 72 hours and the entity was decided to be in the calving process when the number of calving condition body temperature exceeded 15. Experiment results show that with the exception of Entity C, the model accurately predicted the calving date.

Ⅴ. Consideration

Experiment results show that with the exception of Entity C, the system predicted calving on the same date as the actual calving. Entities A, B and D followed the typical pattern of gradually rising body temperatures 10 days prior to calving and then a rapid drop in body temperature 1 day prior to calving. However, Entity C showed almost no body temperature changes during the same period and so the system seems to have made an inadequate prediction. The system will be remedied by updating and analyzing additional data in the future. Fig. 6 are graphs of the average body temperature of each entity that can be compared with the calving date(dotted line). Although there are deviations among entities, the graph displays a gradually increase in body temperature 10 days prior to calving and a drop in body temperature 1 day prior to calving.

Fig. 6(a), 6(b), 6(d) show the body temperature of all 3 entities rising 10 days prior to calving and sharply declining 1 day prior to the actual calving date. Such typical temperature change patterns can increase the accuracy of calving predictions.

The expected calving date for Entity A was September 20, 2018 and the system predicted the calving time to be September 19, 6 A.M.(calving probability: 0.995). The actual parturition occurred on the 19th at 3:46 P.M. and the system predicted calving 9 hours 46 minutes in advance. Entity B was expected to delivery on September 18, 2018.



(a) Entity A

(b) Entity B

(c) Entity C

(d) Entity D

Fig. 6. Average body temperature data graph by entity

Entity B was vaccinated about 9 days prior to parturition and experienced a rapid rise in body temperature which was followed by normal temperature. The system detected a drop in body temperature on September 18 and predicted the calving time to be 11 A.M. on September 19(calving probability: 0.997). The actual delivery occurred at 4:29 P.M. on the same date of prediction. The expected parturition date for Entity D was October 2, 2018. However, the system detected a sharp drop in body temperature starting on September 25 and predicted calving to occur on September 26, 12 A.M.(calving probability: 0.998). The actual parturition occurred 9 hours later and so the manager was ready to assist the calving process.

However, accurate prediction can be difficult if the body temperature changes are weak or irregular. In the case of Entity C, the expected calving date was September 15, 2018. Entity C did not show any distinct rises or falls in body temperature as seen in Fig. 6(c). From 10 days prior to calving to 1 day prior to calving the body temperature increase of Entity C recorded only 0.1℃. While other entities showed a fall in body temperature of 0.7~0.8℃ 1 day prior to calving, the body temperature of Entity C fell only 0.2℃. The system analyzed Entity C's data and predicted its calving time to September 17, 12 A.M. The actual delivery date occurred on September 16 at 6 P.M. For Entity C, the system predicted the calving time with a 9-hour delay. However, the system reduced the error rate of existing prediction methods by 7-days. Thus, the system can be said to have a better prediction rate than existing methods.

Entities A&D and B&C with similar ages and calving dates were chosen for future comparisons. While entities A&D showed similar body temperature patterns, Entities B&C did not. There are no studies on pregnant cows with similar ages and calving dates having similar body temperature patterns. Thus, additional researches on this issue seems necessary.

Through this experiment, the proposed calving prediction method was evaluated by comparing the actual calving time and system predicted calving time of cows. The existing calculation method based on the final insemination date of the cow has large deviations, while the proposed calving prediction method shows an average of 3 hour 40 minute error according to the experiment. Thus, the proposed method has been confirmed to be a more accurate calving prediction method than existing methods.

Ⅵ. Conclusion & Future Researches

The management of bovine calving is very important for increasing a farm profitability and livestock welfare. Thus, timely management of calving time is necessary. Farm managers have used observation methods to predict calving periods. However, such prediction methods make it difficult for the manager to provide timely care. Even with the same insemination date, calving periods can differ according to the sex and number of fetuses, and calving can occur at night or dawn.

This paper proposed a calving prediction method utilizing deep learning of body temperature data measured by ingestible sensors. The ingestible sensors settled in the rumen of cattle could measure deep body temperature in a stable manner without the interference of the ambient environment. Such collected temperature data was analyzed to provide accurate predictions on calving times.

Experiment was conducted on 4 pregnant cows with impending calving dates. The body temperatures of these cows were measured and analyzed to predict calving times. The body temperatures of the cows gradually rose during the 10 days prior to calving, and then 24 hours prior to parturition the body temperatures dropped sharply. The proposed body temperature monitoring and deep learning-based calving prediction system made an accurate prediction of the parturition time and provided feedback to the farm manager, allowing for timely care.

Future studies will include the development of the proposed calving prediction algorithm by analyzing the relationship of biometric data and body temperature. In addition, the calving prediction system will be improved by adding data of cows with similar ages and calving numbers to deep learning.

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