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Full Length Article

Advancements in Precision Agriculture for Foaling with Automated Water Break Detection using Image Recognition Technology

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Abstract

This research presents a foaling detection system based on a deep learning-based image recognition algorithm for pregnant mares in precision agriculture. The system aims to predict water breaks and critical events before foaling and provide real-time monitoring to improve animal welfare. The experiment was conducted in a stable, using two camera devices capturing thermal images. The dataset of 5,618 infrared images was carefully selected to represent events before and after water breaks. The chosen deep learning model achieved an overall accuracy of 95.40% and an F1-score of 76.77%, indicating its effectiveness. However, challenges were identified, such as misidentifying urine and heat as water breaks. Rule-based corrections were introduced to address this, resulting in an improved F1-score of 79.02%. The foaling detection system's practical applications in precision agriculture include labor-saving benefits for ranchers and enhanced animal health during the foaling process. Furthermore, integration into existing farming practices could lead to timely interventions during horse births, improving overall farm productivity. © 2023 Friends Science Publishers

Keywords: Precision agriculture; Horse farming; Deep learning; Agriculture management

Introduction

Precision agriculture is a transformative approach to modern agriculture that integrates advanced technologies such as information and communication technology (ICT), the Internet of Things (IoT) and artificial intelligence (AI) to optimize the health and productivity of livestock and crops (Abu *et al.* 2022). This innovative system aims to maximize returns on inputs while conserving resources, thereby increasing the sustainability and efficiency of agriculture. These technologies can monitor livestock health in real-time, and precision agriculture has opened new avenues of innovation in livestock management, particularly in the management of horse husbandry. An essential element of horse management, mainly, is the detection of foal estrus. The ability to accurately predict the onset of labor, especially when the fetlock ruptures or water breaks, significantly improves labor management in horses. Currently, traditional methods of delivery detection have several challenges and limitations, often require constant monitoring by experienced professionals, which is time-consuming and may delay or miss detection. It may include visual observation for behavioral changes, manual palpation for physical changes, or monitoring for changes in body temperature, all of which require considerable human intervention and expertise. In addition, improper labor management can have severe consequences for the health and survival of mares and foals, highlighting the need for more accurate and efficient detection methods.

Research in precision agriculture and foaling detection systems has been extensive, with notable advancements in machine learning, sensor technology (Jung *et al.* 2021; Jung *et al.* 2022; Myrthe 2005) and image recognition techniques. However, each of these methods presents unique strengths and challenges. Foaling detection has dramatically benefited from technological advancements, particularly in sensor technology. Jung *et al.* (2021) developed an alarm system using sensors to detect specific motion patterns in mares during pre-foaling. Further, Jung *et al.* (2022) used an accelerometer to analyze and detect behaviors related to foaling. Temperature changes have also been observed as potential indicators of foaling. Müller *et al.* (2022) reported an increase in skin temperature within 90 min of birth. Similarly, using a wireless temperature monitoring device, Korosue *et al.* (2012) monitored body temperature changes before parturition. Auclair-Ronzaud *et al.* (2020) also explored the use of body temperature as an indicator of foaling in horses. Significant decreases in body temperature

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were observed 12 h before and at birth, allowing early detection with a high degree of accuracy. Behavioral changes were also observed, suggesting that temperature monitoring may be a new tool to predict foaling in mares. Additionally, while the focus has been on foaling, machine learning and image recognition techniques have been used for calving detection in other animals. These techniques use patterns and trends in the collected data to predict future outcomes and events. Domino *et al.* (2022) and Bowers *et al*. (2009) investigated how infrared thermography (IRT) can be used to detect early and accurate pregnancy in equids, especially native and wild species. Image recognition has been used extensively in precision agriculture for crop and livestock management (Atalla *et al*. 2023), providing a basis for its application in foaling detection.

Despite the advancements in precision agriculture and animal husbandry, there is a clear need for an improved, automated system that integrates multiple predictive parameters for foaling detection. This gap presents an opportunity for further research and development in this area. The main objective of this study is to develop and implement an automatic water break detection system for mares using deep learning algorithms and infrared cameras. The implementation of this system will enable more accurate prediction of calving and timely intervention to improve farm management.

Materials and Methods

Experimental setup

The experiment was conducted in a stable located on a farm in the Niikappu-cho, Hokkaido, Japan. The exterior of the stable is shown in Fig. 1 and is approximately 4 m square and 3 m high. In order to optimally monitor the mares, two camera devices were installed in the stables on a diagonal line, as shown in Fig. 2. The devices were developed for record-keeping purposes for the experiments in this study. A total of six surveillance cameras were installed in the three stables. The video recording period was from April 18 to June 15, 2022, during which 12 video data sets were collected and 11 foal births were confirmed. During the filming period, 50,686 images were acquired for analysis.

Two types of cameras, a visible light camera, and an infrared camera, were attached to the device and used in the experiment. Fig. 3 shows the actual appearance of the developed device. As shown in the basic information for each camera in Table 1, the visible light camera is the Raspberry Pi Camera NoIR V2, a photography module for the Raspberry Pi, with a resolution of 1024 x 544 and an angle of view of 62.2°. The infrared camera was a Seek Thermal Compact PRO module developed by Seek Thermal, with a resolution of 240 x 320 and an angle of view of 32.0°. Two types of cameras were used in the experiment.

The Raspberry Pi, a versatile and cost-effective computer, controlled the cameras and managed image capture. A dedicated recording and storage device was developed. Both cameras were time-synchronized, capturing images at around one frame per second. Captured images were sent to a CentOS7 server PC on the same network for storage. Python 3 and OpenCV were used for image processing, while EfficientNetV2 (Tan and Quoc 2021) was used for water break detection in infrared thermal images. Two thermal images were taken, one with water cutoff and one without, showing distinct heat signatures of the water break in Fig. 4.

Data collection/acquisition: description of the dataset of foaling images

The dataset used in the study consists of thermal images captured in an experimental environment to develop an automatic water break detection model. The dataset was carefully selected based on the presence or absence of water breaks, which typically occur 20–30 min before foal birth (Myrthe 2005; McCue *et al*. 2012). Continuous 24 h videography was conducted to ensure critical events like water breaking were captured. Training data was primarily extracted from the 30 min before water breaking, focusing on signs of impending delivery. This approach aims to increase the efficiency and accuracy of the water break detection model. The data set consists of 5,618 infrared images with a 320 x 240 pixels resolution, corresponding to 12 delivery events. Of these images, 3,038 were taken after the water shutoff and 2,580 were taken when the water was not shut off. These images were carefully selected from the 50,686 images taken during the period of photography. The image capture rate was approximately one frame per second and all images were temporally synchronized with the video data.

Image recognition and model training

The specific image recognition algorithm utilized in this study is a convolutional neural network (CNN), is a deep learning model designed to process and classify visual data such as images. CNNs operate on the principle of hierarchical feature learning, which consists of several layers, including a convolutional layer, a pooling layer, and a fully connected layer The algorithm EfficientNetV2 employed in this study is a variant of CNN that excels in performance and parameter efficiency for computer vision tasks. EfficientNetV2 employs an architectural search method to optimize its width, depth and resolution, and it is a conventional CNN and achieves higher efficiency with smaller model sizes than conventional CNNs.

The input layer of the water break classification model was adjusted to accommodate the resolution of the images captured by the infrared camera, allowing it to handle images of (320, 240, 3) shapes. This model is then connected to the EfficientNetV2 and GlobalAveragePooling layers. The model layers and training parameters are summarized in Table 2. The water break detection model utilizes

Table 1: Camera description used in the experiment

Camera type	Device name	Resolution	Angle of view
Visible light	Raspberry Pi Camera NoIR V2	1024 x 544	62.2°
Infrared	Seek Thermal Compact PRO	240 x 320	32.0°

Table 2: Overview of learning model for water breaking detection

Layer	Output shape	Parameter No.
Input Layer	(None, 320, 240, 3)	0
Efficient Net V2-B0	(None, 7, 7, 1280)	5919312
GlobalAveragePooling2D	(None, 1280)	0
Dropout (0.5)	(None, 1280)	0
Dense	(None, 2)	2562
Activation (softmax)	(None, 2)	0

Fig. 1: Appearance of the farrowing stalls used in the experiment

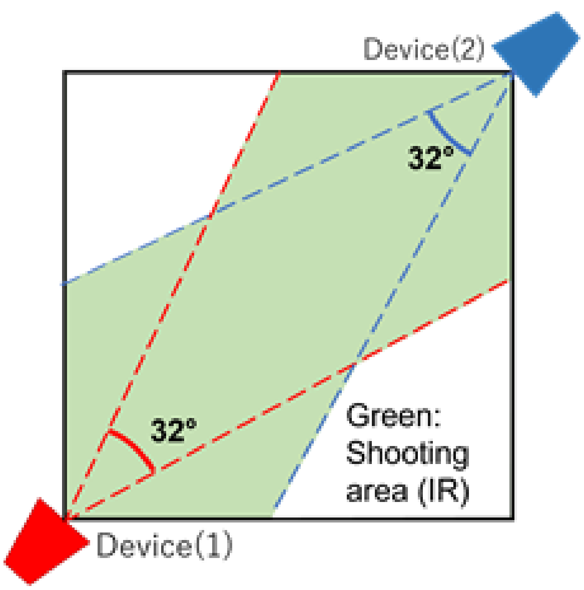

Fig. 2: Location of the two camera-equipped devices in the stables and the range of the thermal imaging camera

EfficientNetV2 architecture and consists of an InputLayer for (320, 240, 3) infrared images, followed by EfficientNetV2-B0 layer producing (None, 7, 7, 1280) output.

Fig. 3: Device used in experiment: Raspberry Pi, visible light and infrared camera

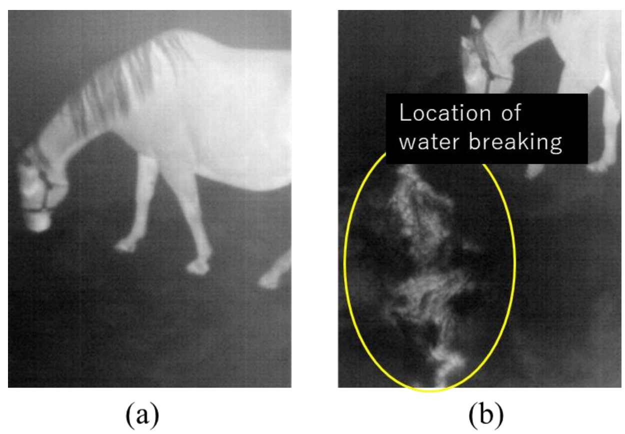

Fig. 4: Example of recorded infrared images: no water break (a), with water break (b)

The GlobalAveragePooling2D layer reduces spatial dimensions (None, 1280). A dropout layer with 0.5 dropout rate prevents overfitting. A Dense layer with softmax activation classifies images into two classes: "with water break detection" and "without water break detection." The model is trained for 20 epochs with a batch size of 64, achieving an optimal trade-off between performance and training time. Categorical cross-entropy loss and Adam optimizer are used. The dataset is partitioned into training, validation, and test sets for unbiased evaluation.

A leave-one-out cross-validation approach was used in this study. Of the 12 events in the dataset, 11 were used for training, and the remaining one was used as test data. The model was trained and tested 12 times, with a different event used as test data each time. The accuracy index of the test data in each pattern was evaluated to provide a comprehensive assessment of the model's performance in various scenarios. In addition, 10% of the training data (validation data) was used to evaluate the performance of the constructed model during training. This allowed us to fine-tune the hyperparameters and evaluate their performance on each video data set. Finally, by carefully selecting the hyperparameters, performing cross-validation, and dividing the dataset into training, validation and test sets, an image recognition system for water break detection could be effectively trained and evaluated, ensuring reliability and practicality in real-world applications. The results of this study were used to ensure the reliability and practicality of the system in real-world applications.

To evaluate the water break detection model, key classification metrics were used. The confidence score plays a crucial role in quantifying the model's certainty, with values above 50% indicating a water break and below 50% indicating its absence. True positives and true negatives represent correct predictions, while false positives and false negatives indicate erroneous predictions. High false predictions can impact model performance and practicality. To address this, a rule-based correction method was proposed, adjusting confidence levels and applying temporal correction. This correction reduces false predictions, enhancing the model's practicality and reliability for water break detection.

Correction Step 1: The confidence score threshold for detecting water breakage is increased from 50 to 75% or lower. This is based on confidence intervals, where the model needs to be more confident in its predictions. The vertical axis in Fig. 5 represents the confidence value of the Deep learning model for water breakage detection and the horizontal axis shows the time series nature of the video frames. Correction 1 reduces false positives by adjusting the confidence level to 0 if it's below 75%. This results in a more accurate detection of water breakage after the 14th frame.

Correction Step 2: Following Correction 1, if 6 or more frames out of the last 11 consecutive frames have a confidence level of 0%, the confidence level of the current frame is also set to 0. This helps improve accuracy by considering sequences of time-series frames for water break detection, reducing spontaneous false positives. As shown in Fig. 6, false detections prior to the actual water breaking period are eliminated with this correction.

Results

Table 3 shows parameter settings used in the experiment, and Table 4 shows the evaluation values for each calving event when no correction was made: the mean of the evaluation values for each of the 12 events was 95.40% for Accuracy, 78.06% for Precision, 86.44% for Recall and 76.77% for F-score, indicating the overall effectiveness of the water break detection model. The evaluation of individual events revealed that some had low Precision (No.05, No.09 and No.12) indicating erroneous water break predictions, while others had low Recall (No.06, No.08 and No.11)

Table 3: Parameters when training the water breakage detection model

Optimization algorithm	Adam
Loss function	cross entropy
Evaluation function	Accuracy
Batch size	64
Number of epochs	20

Table 4: Accuracy and Precision and Recall and F-score for each water break detection model with test data from 12 videos

Number of video	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
1	92.17	65.92	99.20	79.12
2	99.93	98.53	98.53	98.53
3	99.14	99.82	94.80	97.24
4	98.77	98.56	84.71	91.11
5	98.13	52.00	100.00	68.42
6	97.34	76.62	62.77	69.01
7	98.38	95.09	78.28	85.87
8	96.88	98.24	63.50	77.14
9	77.18	21.82	100.00	35.82
10	99.69	100.00	95.48	97.69
11	93.69	100.00	60.00	75.00
12	93.47	30.07	100.00	46.24
Average	95.40	78.06	86.44	76.77

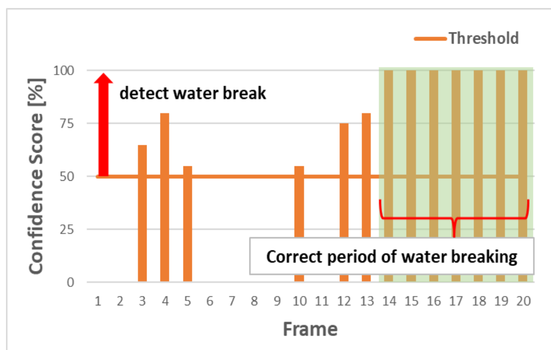

Fig. 5: Example of each image frame and its confidence score: without correction (when the threshold for water breakage determination is greater than 50%)

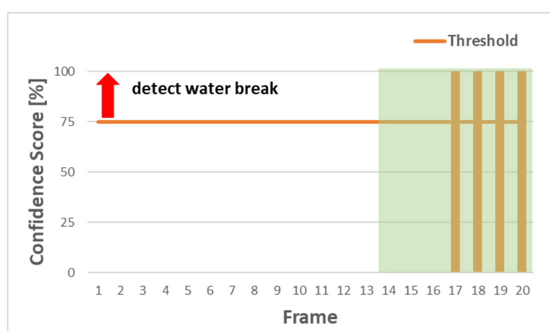

Fig. 6: Example of each image frame and its confidence score: water break detection considering continuity by correction 1, and 2

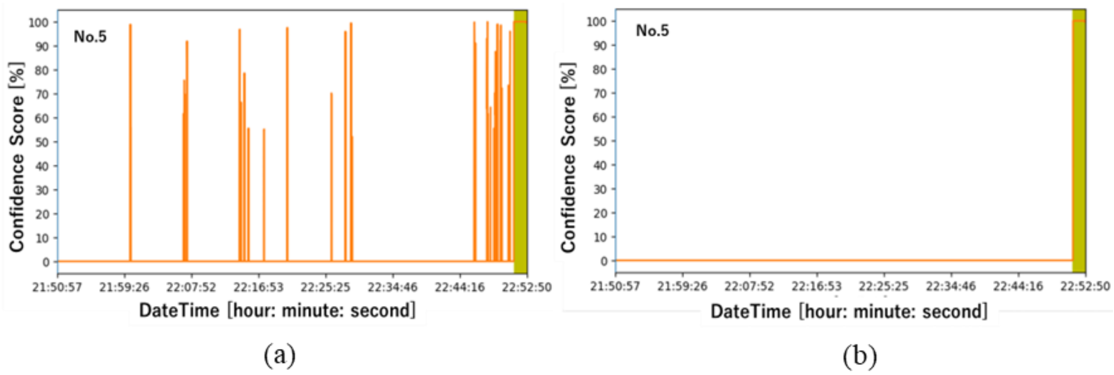

Fig. 7: Example 1 of time variation of confidence scores for calving events (Video No. 5): (a) without correction (b)after correction 1 and 2

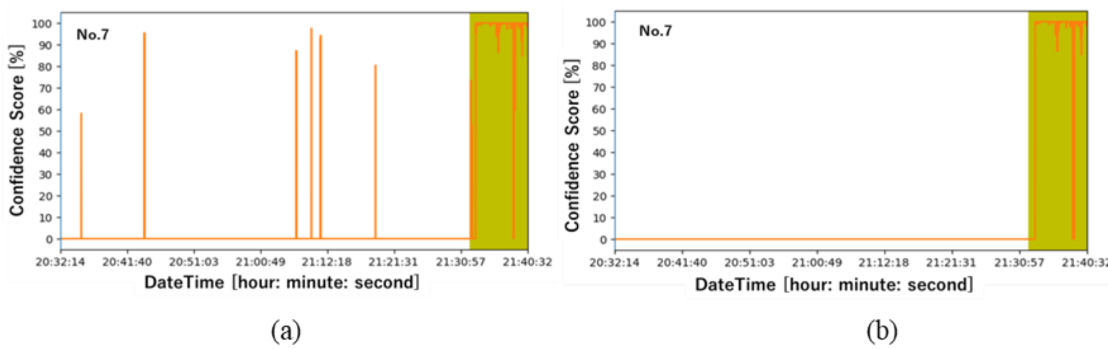

Fig. 8: Example 2 of time variation of confidence scores for calving events (Video No. 7): (a) without correction (b) after correction 1 and 2

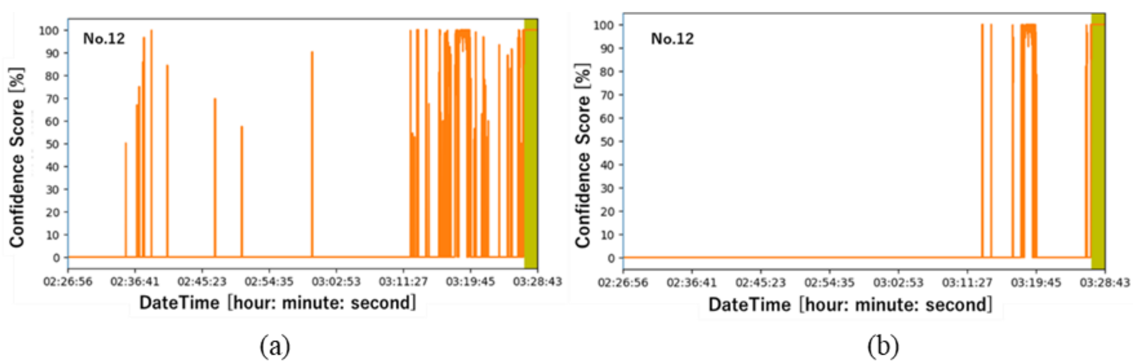

Fig. 9: Example 3 of time variation of confidence scores for calving events (Video No. 12): (a) without correction (b)corrected 1 and 2

suggesting oversights during water break detection. However, applying correction steps 1 and 2 improved Accuracy, Precision, and Recall in the water break detection model. The F-score, representing overall performance, improved by 2.25 after correction. Figs. 7–9 illustrate examples of confidence scores at different times from the three water break detection models. Before correction, false detections occurred before the actual water break, but after the two-step correction, the model accurately detected the water break occurrence. This improvement in detection led to the enhanced Precision in Table 5. The corrected models provided practical and accurate predictions for real-world applications, making them useful tools for horse farmers.

Discussion

The study revealed some interesting patterns in the water shutoff predictions. In particular, there were marked differences in accuracy and recall among individual events; implementing a two-step correction process improved these measures, indicating that the model applies to all events. Interestingly, the correction, which improved precision and accuracy, inadvertently reduced recall slightly. This suggests a more complex relationship between these metrics than initially anticipated.

Our method shows promising results compared to previous studies on pup detection systems, especially for

Table 5: Comparison of each accuracy score with and without correction

Correction method	Accuracy (%)	Precision (%)	Recall (%)	F-score (%)
No correction	95.40	78.06	86.44	76.77
Correction 1	95.65 (+0.25)	80.88 (+2.82)	84.06 (-2.38)	77.33 (+0.56)
Correction1 and 2	96.20 (+0.68)	87.48 (+9.42)	80.53 (-5.91)	79.02 (+2.25)

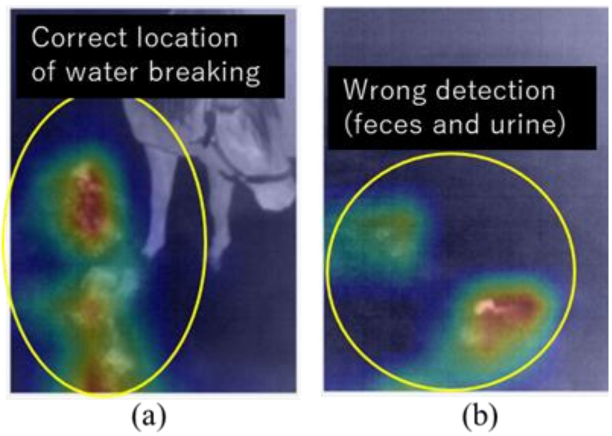

Fig. 10: Visualization of reasons for water breakage using Class Activation Map (CAM):
(a) Thermal image of correctly detected water break and (b) false water breakage detection due to heat in feces and urine (b)

model accuracy. While several studies have shown comparable results, the unique strength of our model lies in implementing a correction method that significantly improves accuracy. The proposed image recognition algorithm is similar to existing methods in using deep learning. However, it differentiates itself by using corrections to deal with false positives, a novel and practical approach that helps improve overall performance. Despite the promising results, several limitations were identified during the study. One of the most significant limitations was that the model sometimes misidentified urine and heat as water breaks. This was revealed using class activation maps (CAM) (Zhou *et al*. 2016), a visualization technique highlighting the regions of the input image that contribute the most to the model's predictions. This technique revealed that on the right side of Fig. 10, specific patterns associated with feces and heat were misidentified as water breaking, creating false positives and affecting the model's reliability. These limitations sometimes reduced accuracy and recall and affected the study results. To mitigate these limitations, a correction method was employed. However, more sophisticated techniques must be developed to distinguish between urine, heat, and water breaks. For example, future studies could consider using multi-class classification models or specific feature detection algorithms.

Our foal birth detection system significantly contributes to precision agriculture and animal monitoring by providing a reliable and automated method of predicting the critical event of horse birth. The originality of this research lies in developing and implementing correction methods that significantly improve model performance.

Conclusion

The study developed a foaling detection system using an EfficientNetV2-based image recognition algorithm to automatically detect water breaks in pregnant mares. The system achieved competitive performance with an overall F1-score of 76.77%. It showed high accuracy, precision and recall in most cases, but false positive predictions occurred in certain scenarios. Rule-based corrections improved precision, resulting in an enhanced F1-score of 79.02%. The system's adoption of EfficientNetV2 algorithm contributed to its efficiency and real-time capabilities, making it a valuable tool for precision agriculture. Integrating this technology can improve ranchers' monitoring and management of pregnant mares, leading to labor-saving benefits and enhanced animal welfare. In conclusion, our foaling detection system represents a significant advancement in precision agriculture and animal monitoring. It showcases the potential of EfficientNetV2-based image recognition algorithms in real-time detection tasks. However, further research and refinement are essential to address the identified limitations related to misclassification. By continuously improving the system's accuracy and reliability, we can enhance its practical applicability and facilitate its adoption on farms to ensure the well-being of pregnant mares and their foals.

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Author Contributions

TU, HO and TH conceptualized experiments, TU curated and analyzed data, TU and NPM write and review manuscript.

Conflicts of Interest

All authors declare no conflicts of interest.

Data Availability

Data presented in this study will be available on a fair request to the corresponding author.

Ethics Approval

Not applicable in this paper.

Funding Source

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