Topic: Multimodal machine learning for calving detection

In dairy farming, monitoring calf births is essential to ensure animal health, optimize operational efficiency, and achieve financial sustainability. Recent studies [1] have highlighted a concerning trend in various parts of the globe: the rising incidence of dystocia [2]. These conditions, coupled with improper cattle supervision, result in approximately 38 calf fatalities per 1,000 births, contributing to a premature calf death rate of 10-12% within three months post-birth in Bavaria alone [3]. Timely assistance can significantly reduce the impact of such medical conditions on calf mortality and morbidity on dairy farms.

Traditional calf birth detection methods, largely grounded in manual observations and physical examinations, exhibit limitations in accuracy, scalability, and labor efficiency [4]. While they retain significance, these methods are often outperformed by the precision of non-conventional data indicators. Specifically, indicators such as cow movement patterns [5], body temperatures [6], and eating habits [7] have demonstrated superior accuracy in predicting calf birth timings. Nevertheless, these advanced methods predominantly depend on wearable sensor data and are often categorized into neck-worn inertial sensors, leg-worn, and tail-worn inertial sensors [8][9][10]. However, wearable sensors, which can only capture the movement of individual body parts, have proven to be unreliable [10].

Attaching sensors to every cow incurs high costs and necessitates a time-consuming setup. In contrast, camera-based calving detection offers several advantages. First, it provides a non-contact method of monitoring that is both humane and cow-friendly, ensuring that the animals are not distressed or harmed by the technology. Second, it is scalable, capable of handling multiple calving signs, and offers a comprehensive view of various attributes and behaviors of cows—such as standing, lying, raising tails, rotations, and movements—which are recognized as calving signs. Furthermore, the camera-based approach can potentially monitor multiple animals simultaneously, providing a scalable and efficient solution for farmers. The research study [11] has further enhanced this approach by introducing a deep multi-stream network architecture that effectively integrates expert knowledge into a deep neural network, thereby reducing detection errors. However, despite these technical advantages, the complexity of the architecture, which involves multiple components in calving sign extraction, poses significant drawbacks. It can be computationally intensive, challenging to implement and manage, and dependent on high-quality video data and optimal environmental conditions, potentially limiting its practicality and widespread adoption in various farming contexts.

In a parallel context, a study [12] employed the YOLOv5 model [13] for monitoring piglet farrowing, yielding results that align with the aforementioned research. However, applying the same method to bovines presents unique challenges due to the distinct nature of their birthing processes. Pigs, being prolific, produce multiple offspring in a brief timeframe, contrasting sharply with the solitary birthing nature of cows. Moreover, animals, even within the same species, can exhibit varied behaviors and physical responses during birthing, adding an additional layer of complexity to the monitoring process. Cows, in particular, can be especially challenging to monitor due to their size, the potential for obstructed views in monitoring devices, and the variability in physical and behavioral signs during parturition. Additionally, while the intrinsic complexity of YOLOv5 is effective in certain contexts, it poses challenges for its utility in real-time, large-scale monitoring, particularly in diverse and dynamic farming environments, where individual animal characteristics and behaviors must be meticulously accounted for to ensure accurate birth detection.

Environmental variables, such as inconsistent lighting and potential physical obstructions, can compromise the integrity of visual data. Concurrent research underscores a significant correlation between bovine vocalizations and behavioral and physiological states during parturition [14][15]. Therefore, the objective extends to the detection of cows' vocalizations, specifically "moo calls," during birth, integrating audio data to augment the monitoring systems. This integration aims to counterbalance the limitations of visual data, providing an auxiliary data layer to refine detection algorithms and enhance system robustness. Consequently, exploring a multimodal approach, synthesizing visual and audio data, becomes imperative in future research to develop a technically robust and comprehensive livestock monitoring mechanism.

This thesis introduces a multimodal strategy for calf birth detection, employing the EfficientDet architecture [16]. Utilizing EfficientDet for visual data and a separate neural network for audio call classifications, this multimodal approach synergizes audio and visual data to optimize detection reliability and accuracy. Aimed at enhancing both efficiency and scalability, the research objective encompasses designing, refining, and benchmarking EfficientDet for calf birth detection, followed by its subsequent deployment on edge devices. Moreover, the research elucidates the salient features of vocal patterns prevalent during bovine parturition, providing a comprehensive analysis of their spectral and temporal characteristics. It further explores various architectural constructs for synthesizing a robust multimodal system that cohesively integrates both auditory and visual cues, ensuring a comprehensive and reliable detection mechanism in the context of livestock management.

The research will follow a logical and technical structure centered on the following key objectives:

- **Literature Review**: Conduct a literature review on automated calving detection using different sensor modalities and machine learning.
- **EfficientDet Implementation**: Train and fine-tune EfficientDet models tailored specifically for calf birth detection.
- **Comparative Analysis**: Perform a comprehensive comparative analysis, evaluating the performance of the developed EfficientDet models considering sensitivity, specificity, and model complexity.
- **Integration of Audio Data:** Design, train, and optimize methods for integrating audio data into the machine learning model.
- **Construction of a Multimodal Pipeline:** Develop a framework that integrates both audio and visual data for calving detection.

The thesis will contain a detailed description of all developed and used algorithms as well as a profound result evaluation and discussion. The implemented code will also be documented and provided. Extended research on literature, existing patents and related work in the corresponding areas has to be performed.

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