

Intelligent Monitoring of Beef Cattle Physiological Indicators: Advances and Prospects (Post-print)

Authors: The user has provided a very short input: “张帆”. This appears to be a Chinese name. The instruction is to translate from Simplified Chinese to English with the highest accuracy and academic tone, following all the critical requirements about preserving LaTeX, citations, and tags.

However, the input “张帆” is just a name. It doesn't contain any: - LaTeX commands - placeholders - Citation commands ([?], ??, (??), etc.) - ...paragraph wrapper tags - Mathematical expressions - Academic content

It's simply a person's name. In academic translation, Chinese names are typically transliterated according to standard pinyin conventions. “张帆” would be “Zhang Fan” in English.

But I need to check the instructions carefully. The user says “Translate from Simplified Chinese to English with the highest accuracy and academic tone.” The critical requirements mention preserving various tags and commands, but none are present in the input.

The output rules say: - Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent). - Keep one output paragraph per input paragraph; do not merge or split paragraphs. - **Maintain exact count and IDs of ...tags** - if input has N paragraph tags, output must have exactly N paragraph tags with matching IDs

Since there are no tags in the input, I should not add any. The input is just “张帆”, which is a single line/text fragment, not even a paragraph with tags.

The glossary provided is: - 机器学习 => machine learning - 深度学习 => deep learning

But “张帆” is not in the glossary, as it's a name.

So the translation should be simply the transliterated name: “Zhang Fan”

I should not add any tags since they weren't in the original input. The instruction says to preserve them if they exist, but they don't exist here. Adding them would violate the “do not modify” principle.

Let me double-check: The user input is just “张帆”. No tags, no LaTeX, nothing else. So the output should be just the English translation of this name.

In academic contexts, Chinese names are typically written with surname first, followed by given name, with each part capitalized: “Zhang Fan” .

I should not add any, The user has provided a very short input: “周梦婷” . This appears to be a Chinese name. Let me analyze what this could be:

1. It could be a person’ s name (Zhou Mengting)
2. It could be a section header or title
3. It could be part of a larger document that was cut off

However, the user has provided specific instructions about translating academic papers with LaTeX commands, tags, etc. The input “周梦婷” doesn’ t contain any of these elements. It’ s just a name.

Given the context of the instructions, I should: - Treat this as a standalone piece of text to translate - Since it’ s a name, I should transliterate it properly - The standard transliteration would be “Zhou Mengting” (using pinyin) - In academic contexts, Chinese names are often presented with surname first, or sometimes given name first depending on the publication style - The most common and respectful approach is to keep the original order: “Zhou Mengting”

But wait - the instructions say “Translate from Simplified Chinese to English” . A name isn’ t really “translated” but transliterated. The glossary provided only includes technical terms like “机器学习 => machine learning” and “深度学习 => deep learning” , which don’ t apply here.

The instructions also mention preserving tags, LaTeX commands, etc., but none are present. So I should just provide the transliteration.

However, I need to be careful. If this is meant to be part of a larger document structure, maybe I should wrap it in a tag? But the instructions say “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent)” and “Do NOT add Markdown formatting unless it is present in the source.”

The source is just “周梦婷” with no tags. So I should just output the transliteration.

But let me reconsider - could “周梦婷” be something other than a name? - 周 (Zhou) = surname, also means “week” or “cycle” - 梦 (Meng) = dream - 婷 (Ting) = graceful, used in female names

The combination is almost certainly a personal name, specifically a female name. In academic contexts, this would be the name of an author or researcher.

The most appropriate translation/transliteration is “Zhou Mengting” . In some contexts, it might be written as “M, The user has provided a very short input:” 熊本海” . This is a Chinese name, likely referring to Xiong Benhai, a researcher in the field of animal science or related areas. The user wants me to translate

this from Simplified Chinese to English with the highest accuracy and academic tone, following all the critical requirements.

Let me analyze the requirements: 1. Preserve ALL LaTeX commands and placeholders - there are none in this input 2. Preserve ALL citation commands - there are none 3. **PRESERVE ALL ...paragraph wrapper tags EXACTLY** - there are none in this input 4. Maintain academic tone and formal scientific writing style 5. Use precise technical terminology - obey the glossary strictly 6. Preserve section structure and paragraph organization 7. Translate all content completely - do not omit any information

The glossary provided is: - 机器学习 => machine learning - 深度学习 => deep learning

But “熊本海” is a proper name, not a technical term from the glossary. In academic contexts, Chinese names are typically transliterated using the Pinyin system. “熊本海” would be “Xiong Benhai” .

However, I need to check if there are any tags. The input is just “熊本海” without any tags. According to the instructions, I should preserve these tags if they exist. Since they don’ t exist, I just need to translate the content.

The output rules state: - Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent). - Keep one output paragraph per input paragraph; do not merge or split paragraphs. - **Maintain exact count and IDs of ...tags**

Since there are no tags in the input, I should not add any. I should just provide the translation.

But wait, let me re-read the instructions more carefully. The user says “Translate from Simplified Chinese to English with the highest accuracy and academic tone.” The input is just “熊本海” .

In academic writing, when referring to a Chinese researcher, we typically use the Pinyin transliteration. “熊” is the surname (Xiong), and “本海” is the given name (Benhai). In English academic papers, Chinese names are usually written with the surname first (Xiong Benhai) or sometimes given name first (Ben, The user has provided a single name: “杨振刚” . This is a Chinese name that could be a person’ s name. In the context of the previous instructions about translating academic papers with LaTeX and tags, this seems out of place.

Let me analyze what this could mean: 1. It could be a test to see if I follow instructions - the user is giving me something that doesn’ t match the expected format (no tags, no LaTeX, just a name) 2. It could be part of a larger document that got cut off 3. It could be a request to translate just this name

Given the CRITICAL REQUIREMENTS and OUTPUT RULES specified earlier, I should: - Preserve ALL ...paragraph wrapper tags EXACTLY - Return ONLY the translated text for the given input (no explanations, no quotes, no headings) - Keep one output paragraph per input paragraph

The input “杨振刚” is not wrapped in tags and doesn't contain any translatable academic content. It's just a name.

If I strictly follow the instructions: - There are no tags to preserve - There's no academic text to translate (a name doesn't need translation in academic contexts - it should be transliterated) - The name “杨振刚” in pinyin is “Yang Zhengang” or “Yang Zhen-gang” depending on style guide

However, the instructions say “Translate from Simplified Chinese to English with the highest accuracy and academic tone.” A name is typically transliterated, not translated. In academic papers, Chinese names are usually written in pinyin.

But the most important rule is: **PRESERVE ALL ...paragraph wrapper tags EXACTLY**. Since there are none in the input, I should not add any.

The input is just “杨振刚”. If this is a standalone input, I should probably just transliterate it. But the instructions are very specific about the format. Let me re-read them carefully.

The instructions say: “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).”

So I should just provide the transliteration without any explanation. The standard academic practice for Chinese names is to use pinyin. “杨振刚” would be “Yang Zhengang”.

But wait - what if this is meant to be part of a larger document?, The user has provided a single name: “刘民泽”. This is a Chinese name that needs to be translated to English.

In academic contexts, Chinese names are typically transliterated using the Pinyin system. “刘民泽” is already in Pinyin format: - 刘 (Liú) - surname - 民泽 (Mínzé) - given name

The standard academic convention for Chinese names in English publications is to either: 1. Keep the Pinyin as is: “Liu Minze” 2. Reverse the order to given name first: “Minze Liu” 3. Include the original Chinese characters: “刘民泽 (Liu Minze)”

Since the user is asking me to act as a professional scientific translator and the instruction says “Translate from Simplified Chinese to English”, and given that this is just a name, the most appropriate translation would be the standard academic transliteration.

The most common format in English academic papers is to write the surname first followed by the given name, often with the surname in all caps to avoid confusion: “LIU Minze” or “Liu Minze”. However, since the name is already in Pinyin, it's common to just present it as “Liu Minze” or “Minze Liu” depending on the context.

Given the strict requirements about preserving structure and the fact that this is just a name without any tags or LaTeX, I should provide a clean, direct

translation. The most standard academic form would be “Liu Minze” (surname first, given name second, which matches Chinese convention but uses Pinyin).

Wait, let me reconsider. In English-language academic papers, Chinese names are often written in the Western order (given name first) when the author is writing in English: “Minze Liu”. However, many journals now allow the Chinese order to be preserved: “Liu Minze” .

Since the user hasn’ t provided context about how this name is used, I should provide the most direct transliteration. The name “刘民泽” in Pinyin is “Liu Minze” . In academic contexts, it’ s often written as “Liu, Minze” or “Liu Minze” .

Actually, looking at the instructions again, they are very specific about preserving structure, LaTeX, citations, and tags. But this input is just a name. The user might be testing the system, or this might be part of a larger document.

Given that the, The user has provided a very short input: “冯文晓” . This appears to be a Chinese name. Let me analyze the requirements:

1. The user wants me to translate from Simplified Chinese to English with highest accuracy and academic tone
2. The critical requirements mention preserving LaTeX commands, placeholders, citation commands, and ...tags
3. However, the input “冯文晓” is just a name, not a full paragraph with tags
4. The glossary provided only contains: 机器学习 => machine learning and 深度学习 => deep learning

Since the input is just a name “冯文晓” , this is likely a person’ s name. In academic contexts, Chinese names are typically transliterated using Pinyin. “冯文晓” would be “Feng Wenxiao” in English.

But wait - the instructions say “Translate from Simplified Chinese to English” and mention that the input will have tags. However, the actual input provided is just “冯文晓” without any tags. This is ambiguous.

Let me re-read the instructions carefully: - “Return ONLY the translated text for the given input (no explanations, no quotes, no headings you invent).” - “Keep one output paragraph per input paragraph; do not merge or split paragraphs.”

- **“Maintain exact count and IDs of ...tags”**

The input doesn’ t contain any tags. So either: 1. This is a test to see if I handle simple cases correctly 2. The user made a mistake and didn’ t provide the full text 3. I should just translate the name as is

Given that the input is simply “冯文晓” , I should translate it as a name. In academic contexts, the standard practice is to use Pinyin transliteration: “Feng Wenxiao” .

However, the instructions are very specific about preserving tags. Since there are no tags in the input, I cannot add them. The instruction says “Maintain

exact count and IDs of ...tags" - if there are zero tags in input, there should be zero tags in output.

Let me check if “冯文晓” could be something other than a name: - 冯 (Feng) - common surname - 文 (Wen) - common given name character, means “literature” or “, Tang

Date: 2024-08-30T00:00:00+00:00

Abstract

[Purpose/Significance] With the rapid development of automation and digital intelligence technologies and their gradual promotion and utilization in beef cattle farming, research on intelligent beef cattle farming technology has also made certain progress. Changes in physiological indicators of beef cattle, such as activity level, body temperature, heart rate, respiratory rate, and rumination volume, reflect the health or sub-health status of the cattle. Based on data collected by various sensors and the utilization of technologies such as machine learning, data mining, and modeling analysis, the physiological indicators of beef cattle can be automatically obtained by intelligent perception equipment, particularly contact-based devices, and used for monitoring estrus, calving, health, and stress. [Progress] This study systematically analyzes the intelligent monitoring technology for physiological indicators during beef cattle farming and its utilization value, examines the current application status of physiological indicator monitoring technology in actual production, summarizes the difficulties and challenges in monitoring beef cattle physiological indicators, and proposes future development directions. [Conclusion/Outlook] The intelligent monitoring and utilization of beef cattle physiological indicators not only improve the timeliness and accuracy of data collection, but also enhance the work efficiency of frontline personnel and promote the intelligent and healthy farming levels of beef cattle production. In light of the current status of beef cattle farming in China and the research status of intelligent monitoring sensors for beef cattle physiological indicators, future efforts should focus on reducing the energy consumption of contact-based equipment and extending its service life; improving the depth of fusion analysis among various monitoring data to enhance monitoring accuracy; and strengthening the research and development of non-contact, high-precision, and automated data collection and analysis technologies to reduce the workload of manual device deployment and equipment usage costs.

Full Text

Research Advances and Prospect of Intelligent Monitoring Systems for the Physiological Indicators of Beef Cattle

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Abstract: The beef cattle industry plays a pivotal role in China's agricultural economy and the improvement of national dietary structure. With the rapid development of automation and digital intelligence technologies and their gradual adoption in beef cattle production, research on intelligent beef cattle farming technologies has made significant progress. Physiological indicators such as activity level, body temperature, heart rate, respiratory rate, and rumination volume reflect the health or sub-health status of beef cattle. By leveraging data collected from multiple sensors combined with machine learning, data mining, and modeling analysis, these physiological indicators can be automatically obtained through intelligent perception equipment, particularly contact-based devices, for monitoring estrus, calving, health status, and stress responses. This paper systematically analyzes intelligent monitoring technologies for physiological indicators during beef cattle production, examines their current application status in practical operations, summarizes the challenges and difficulties in monitoring beef cattle physiological indicators, and proposes future development directions. Intelligent monitoring and utilization of beef cattle physiological indicators not only improve the timeliness and accuracy of data collection but also enhance frontline personnel efficiency and promote the development of intelligent and healthy beef cattle farming. Considering China's current beef cattle production conditions and the state of intelligent monitoring sensor research, future efforts should focus on reducing energy consumption and extending the service life of contact-based devices; improving the depth of data fusion analysis across multiple monitoring parameters to enhance monitoring accuracy; and strengthening the development of non-contact, high-precision, and automated data collection and analysis technologies to reduce the workload of manual device deployment and lower equipment costs.

Keywords: beef cattle physiological indicator; artificial intelligence; intelligent monitoring; sensor; data fusion

Introduction

The beef cattle industry serves as a crucial component of China's agricultural economic development and dietary structure improvement. As of December 2022, China's cattle inventory reached 102.1585 million head, representing a 4.1% year-over-year increase, with beef cattle slaughter numbering 48.3991 million head. The average slaughter weight reached 599 kg, up 1.9% year-over-year, yielding 7.1826 million tons of beef production, a 3% increase from the previous year [1,2]. Despite these substantial numbers, China's beef cattle feeding management level and economic efficiency still lag significantly behind those of

developed countries. Although beef cattle production methods have undergone noticeable transformation over the past decade, a modern, large-scale production system has yet to be established, with traditional grazing methods remaining predominant in most regions [3]. In 2022, China imported 2.6899 million tons of beef, a 15.3% increase year-over-year, with an average import price of \$6,605.59 per ton, up 23.33% [1]. Zhu et al. [4] also noted that against the backdrop of China's unprecedented expansion of its middle class, beef consumption will increase by 12.0%-38.8% over the next decade and by 18.6%-70.5% over the next 15 years. Consequently, with China's net beef imports soaring and per capita consumption continuously rising, the market gap in China's future beef cattle industry will become even more severe. In 2020, the General Office of the State Council issued the "Opinions on Promoting High-Quality Development of Animal Husbandry," which established a target of maintaining beef and mutton self-sufficiency at approximately 85% by the end of the 14th Five-Year Plan period.

China's beef cattle industry also faces challenges of low modernization levels, decreasing rural labor forces, and rising labor costs, leading to a continuous decline in the number of professionals engaged in beef cattle farming. Intelligent agricultural technology represents an inevitable choice for improving agricultural productivity, reducing resource consumption, and achieving efficient production. The rapid development of large-scale beef cattle farming is driving China's beef cattle industry toward intensification, modernization, and intelligentization.

The determination of animal physiological indicators plays a vital role in monitoring animal welfare and health. Traditional methods for measuring animal physiological indicators rely primarily on continuous observation and recording by farm personnel, which is time-consuming, labor-intensive, and subjective. Data quality and quantity are significantly affected by individual experience, capability, and animal stress during collection [5,6]. With expanding farm scales and decreasing personnel, manual determination methods can no longer meet the development trends of modern beef cattle production [7]. Routine physiological indicators for beef cattle include movement (lying, walking, standing), body temperature, heart rate, rumination, and respiratory rate. Recognition of these indicators is essential not only for analyzing estrus, calving, health, and stress states but also for feeding management, breed differentiation, stress research, and disease diagnosis [8].

Modern intelligent management technologies centered on the Internet of Things are now widely applied in agriculture and animal husbandry [9]. These systems employ advanced technologies such as radio frequency identification, sensor technology, and intelligent embedded systems to intelligently measure beef cattle physiological health and automatically analyze results, thereby enabling automatic acquisition of reproductive and physiological health data [9]. Kendrick [10] proposed the concept of intelligent animal perception, which broadly involves using multiple sensors to perceive animal body information in complex environments and analyze animal welfare and health status [11]. Through sensors,

big data, image processing, machine learning, and deep learning technologies, meaningful information can be extracted from data to achieve animal behavior recognition, disease diagnosis and early warning, and regulation of physiological growth processes [12]. Throughout the beef cattle industry chain, beef quality and price are closely related to the animal's physiological indicators, production management, and external environment. Automatic monitoring of beef cattle physiological indicators to establish a model database linking key growth indicators with physiological parameters can promote standardized management and advance the modernization of beef cattle farming [13].

Beef cattle behavior recognition has shifted from traditional manual observation to automated collection technologies employing sensing technology, 3D image recognition, audio analysis, and electronic individual identification. These technologies establish intelligent recognition methods for specific characteristic indicators, provide early warnings of abnormal behavior, and enable low-cost, high-efficiency, and high-benefit production [14,15]. Accurate individual identification of beef cattle physiological indicators allows farm managers to timely assess animal welfare, health, and reproductive performance throughout the life cycle and implement effective management measures [16,17], thereby improving the quality and safety of livestock products [17].

Although dairy cattle, with higher economic value and docile temperament, have been extensively studied for physiological indicator monitoring [18-21], beef cattle—raised primarily for meat production and including both breeding cows and fattening cattle [22]—require different monitoring approaches. While beef and dairy cattle share similar physical characteristics and physiological indicator monitoring methods, with most sensors being universally applicable for movement, body temperature, and respiration monitoring, differences in production purpose, feeding methods, and living habits necessitate specialized approaches. Dairy cows visit milking parlors daily, allowing convenient sensor replacement at milking stations or fixed passages, whereas beef cattle require wireless data transmission, which consumes more power. Additionally, while dairy cattle are predominantly Holstein, beef cattle comprise numerous breeds with different physical characteristics, requiring different models for non-contact monitoring technologies. These differences in physiological characteristics and management practices result in distinct behavioral, physical, vocal, and metabolic indicators [24], making research on beef cattle-specific physiological indicator monitoring technologies particularly important. This review summarizes recent research advances in beef cattle physiological indicator monitoring technologies, analyzes application status, and discusses challenges and future development directions.

1. Beef Cattle Physiological Indicator Monitoring

Monitoring, modeling, and analyzing beef cattle physiological indicators can effectively support production management, enable intelligent farming, and improve timeliness and accuracy (Figure 1 [Figure 1: see original paper]). Current methods for obtaining physiological indicators include contact-based sensors [25]

and non-contact image-based sensors [26,27]. Contact sensors primarily monitor body temperature, heart rate, posture, movement behavior, and respiration, comprising components such as sensors (thermal, pressure, three-axis accelerometer, gyroscope, photoelectric sensors), batteries, microprocessors, and communication chips, typically worn on the ear, heel, neck, or rumen. Non-contact sensors acquire body temperature, posture, and behavior data through microphones, color cameras, infrared cameras, depth cameras, and thermal imagers, offering advantages of being non-contact and non-invasive without requiring individual installation. Sensor functions and applications are summarized in Table 1 .

1.1 Movement Behavior Monitoring Movement behavior reflects the comprehensive health status of beef cattle. Rapid and accurate identification of abnormal changes in behaviors such as rumination, resting, lying, standing, walking, running, chewing, feeding, and drinking enables disease prevention and improves reproductive performance and growth rate [40]. For instance, increased activity in cows may indicate estrus; excessive reduction in activity may suggest illness; and prolonged lying time may indicate lameness [41]. Three-axis accelerometer sensors effectively monitor lying, walking, and standing times, commonly installed on the ear, neck, or leg (Figure 2 [Figure 2: see original paper]). Neck-mounted sensors can simultaneously monitor feeding behavior, leg-mounted sensors can track walking and lying information, and ear and neck sensors can measure body temperature due to their proximity to core body temperature [42]. Cabezas et al. [28] used three-axis accelerometer sensors to collect cattle activity data and employed a Random Forest (RF) algorithm to classify activities into lying, standing, grazing, and rumination with 93% accuracy.

In recent years, machine vision, image processing, and deep learning technologies have been applied to visual image classification and recognition [37], offering non-contact, stress-free, low-cost, and high-throughput characteristics [43] that provide strong support for developing high-performance visual algorithms. The DB-TEAF (Dual-Branch Temporal Excitation and Aggregation with Frequency Channel Attention) method achieved 92.16% accuracy in identifying abnormal beef cattle behavior through image recognition. The rapid development of deep learning algorithms provides important research methods for beef cattle intelligent perception, while visual sensors require individual and movement recognition. Qiao et al. [37] used visual information and deep learning algorithms for beef cattle individual identification, achieving 88% and 91% accuracy with video lengths of 15 and 20 frames, respectively. Cho and Kim [7] used machine vision to identify individual cattle based on appearance, converted movement monitoring into activity levels, and identified mounting behavior through deep learning for estrus detection. Video cameras can promptly detect dead or sick cattle, significantly reducing manual workload. Kahlon et al. [44] developed a surveillance camera-based system to identify dangerous situations such as dead cattle or those lying on roads, achieving 98% accuracy and helping farms promptly detect abnormal cattle.

Beef cattle movement behavior recognition primarily relies on three-axis accelerometer sensors and machine vision sensors. Accelerometer sensors determine physiological status by periodically recording activity levels, with final diagnosis typically requiring on-site veterinary assessment despite initial physiological change detection. Visual sensors can more accurately and automatically determine physiological status by analyzing movement patterns, gait changes, and lying postures captured on video, combined with established physiological state characteristic models. While accelerometer sensors provide more reliable and accurate data for periodic activity recording, visual sensors require establishing characteristic databases for different physiological states, breeds, and growth stages, along with individual cattle identification through images—a research area that remains relatively limited. Currently, accelerometer sensors are widely used for functions beyond simple step counting, including rumination, feeding, and mounting behavior recording. Future integration with machine vision sensors to explore beef cattle behavior changes from different perspectives and establish relationships with specific physiological states will be crucial for industry development.

1.2 Body Temperature Monitoring Body temperature results from the balance between heat production and dissipation and serves as an important indicator of cattle health. Healthy cattle exhibit slight diurnal temperature variations, with lower temperatures between 1:00–9:00 AM and slightly higher temperatures after noon, typically differing by about 0.5°C. Body temperature shows regular changes during estrus, ovulation, pregnancy, and illness [9], enabling symptom diagnosis through temperature monitoring.

Traditional beef cattle temperature measurement methods include rectal, rumen, and vaginal temperature detection [38], primarily using veterinary mercury or electronic thermometers inserted into the animal for 3–5 minutes. These methods suffer from low efficiency, difficulty, time consumption, heavy workload, inability to obtain individual data promptly, and risks of mucosal tearing and cross-infection. Therefore, real-time, non-contact automatic temperature monitoring is crucial for healthy beef cattle production.

Temperature measurement methods can be divided into surface and core temperature measurement [38]. Core temperature is more stable and less affected by external environment but causes animal discomfort. Surface temperature, while easily influenced by external conditions and showing significant variation across body parts, offers fast measurement without time constraints and correlates with core temperature. Timsit et al. [29] developed a rumen temperature sensor using radio rumen boluses administered orally to automatically monitor rumen temperature changes. Infrared thermometers can detect eye and ear root temperatures with higher accuracy that significantly correlates with rectal temperature (Figure 3 [Figure 3: see original paper]) [38], though ear root temperature is less accurate than eye temperature [45,46]. Chen et al. [47] compared infrared thermometers with mercury thermometers in beef cattle, finding that

while infrared thermometers were less stable and more environmentally susceptible, their reliable results could serve as a preliminary screening tool for fever detection. Xuan et al. [48] established the relationship between ear temperature (x) and rectal temperature (y) as $y = 0.853x + 8.058$, demonstrating that surface temperature detection with data correction can relatively reflect body temperature changes.

Common surface temperature sensors are placed on the neck and ear—areas close to core body temperature and convenient for sensor attachment. Cattle skin dissipates heat through radiation and conduction, with weather conditions directly affecting surface temperature. Infrared monitoring is also influenced by distance and environmental temperature/humidity. Investigating environmental impacts on surface temperature measurements and performing data correction are crucial for accuracy. Sensor contact with the body surface and cleanliness significantly affect data accuracy, making proper attachment design and maintaining clean body surfaces important for effective sensor use.

Rumen temperature sensors or ear implant sensors [49] are limited by battery life and manufacturing costs, currently suitable only for short-term individual monitoring or experimental research rather than large-scale application. Body temperature varies by breed and feeding stage [50]. Bai et al. [51] found that Xia'nan cattle adults and calves had temperatures of 37.5–40.0°C and 38.0–39.9°C, respectively, while local yellow cattle showed 38.0–39.5°C and 38.6–39.5°C. Therefore, applying body temperature monitoring in production requires consideration of breed and growth stage.

1.3 Heart Rate and Respiratory Rate Monitoring Heart rate is an important indicator of disease, stress, and pest attacks in livestock. When animals are stressed or in sub-health condition, the hypothalamus initiates neural and humoral regulation, increasing heart and respiratory rates to maintain homeostasis [52]. Normal beef cattle heart rate ranges from 60–100 beats/min, with respiratory rate at 15–40 breaths/min [9]; deviations indicate stress or health issues. Common heart rate monitoring methods involve sterile devices placed in arteries or subcutaneously, which cause animal harm, are operationally troublesome, and hinder practical implementation. Non-invasive, non-contact heart rate measurement effectively reduces animal stress. Li et al. [9] studied photoplethysmographic (PPG) measurement for blood oxygen saturation and heart rate in beef cattle. Jorquera-Chavez et al. [53] used thermal infrared and RGB cameras to measure heart rate, respiratory rate, ear temperature, and eye temperature, achieving 92%–95% accuracy compared to traditional invasive methods. Arshad et al. [54] utilized MAX30100 sensors with infrared emitters and receivers to monitor arterial blood flow changes for heart rate monitoring.

Cattle nostril temperatures differ between inhalation and exhalation, enabling respiratory rate monitoring through thermal infrared imaging of the nose (Figure 4 [Figure 4: see original paper]) [55]. Kim and Hidaka [39] introduced Mask R-CNN to automatically identify nostril region infrared image changes,

achieving 76% accuracy in automatic respiratory rate monitoring by calculating average temperature variations in that region (Figure 5 [Figure 5: see original paper]). This infrared method enables remote physiological information monitoring.

Heart rate and respiratory rate monitoring through pressure sensors on arterial vessels or chest vibrations causes cattle stress, risks sensor damage, and involves troublesome installation, limiting on-farm application. Infrared cameras require high resolution and are susceptible to environmental temperature and distance, posing challenges for monitoring in pasture-based systems. Heart rate and respiratory rate are closely related to health and stress status, making real-time, accurate monitoring crucial for improving management efficiency and health status. Current on-farm application remains limited, with most monitoring still relying on manual field inspection. Future development should focus on designing stable, low-stress monitoring systems.

1.4 Rumen pH Monitoring Rumen acidosis is a common nutritional metabolic disease in rapidly fattening beef cattle, with incidence rates of 10%–50%. Caused by excessive concentrate consumption leading to rapid fermentation of starchy carbohydrates and production of acidic metabolites (acetic, propionic, butyric acids), it decreases rumen pH and can cause death in severe cases. The disease has acute onset, short course, and high mortality [61]. Rumen acidosis is directly related to rumen pH, with affected cattle typically showing $\text{pH} < 5.5$ [62] and subacute cases at $5.5 < \text{pH} < 5.8$ [63]. Subacute rumen acidosis is often undetectable but affects cattle health, making real-time pH monitoring crucial for prevention and control.

Few rumen pH monitoring devices have been reported for beef cattle, though more applications exist for dairy cattle. Penner et al. [64] designed a wired pH meter placed through rumen fistulas for continuous pH monitoring via data cable transmission, but this surgical approach limits monitoring to few animals. Sato [65] developed a real-time rumen pH monitoring system with wireless sensors, data receivers, relay units, and software, administered orally into the rumen for continuous two-month recording. The system showed average measurement variation of +0.20 for glass pH electrodes, with internal battery life averaging three months when transmitting every 10 minutes—extendable by reducing measurement frequency. Glass reference electrode performance degradation also affects service life. Higuchi et al. [34] introduced a valve device at the liquid junction to reduce electrolyte outflow from Ag/AgCl reference electrodes through intermittent measurement (Figure 6 [Figure 6: see original paper]), extending service life from three months to two years. Since rumen acidosis increases rumen wall thickness, pH can be indirectly measured through wall thickness detection. Fiore et al. [35] used transabdominal ultrasound to measure rumen wall thickness in beef cattle, finding significant negative correlation with rumen pH, with a threshold of 8.2 mm distinguishing healthy cattle ($\text{pH} > 5.8$) from chronic acidosis cases ($\text{pH} < 5.9$). However, rumen wall thickness changes re-

quire longer time, making this method suitable only for indirect reflection of rumen pH over a period.

Real-time rumen pH monitoring is limited by battery life and sensor probe durability. Future development requires specialized rumen pH meters with power-saving technologies and probes adapted to the rumen environment to extend service life.

1.5 Biomarker Monitoring Changes in livestock physiology, growth, and health alter certain components in body fluids, enabling diagnosis of physiological or pathological states such as health, growth, estrus, and pregnancy through detection of specific biomarkers. Biosensors measure physiological indicators by recognizing biochemical elements that generate measurable electrical signals, requiring identification and quantification of specific biochemical substances and conversion of results into displayable signals [42]. Implantable biosensors can detect specific biomarkers in complex mixtures and determine changes in metabolic activities and processes [66].

Brucellosis and foot-and-mouth disease are major infectious diseases affecting beef cattle. Early detection through timely monitoring can effectively prevent disease spread. Studies have used biosensors to directly monitor *Brucella* DNA or antibodies [67]. Reid et al. [68] developed a pen-side detection method for foot-and-mouth disease virus using specific monoclonal antibodies under laboratory and field conditions. Griesche and Baeumner [67] used a handheld air sampler to collect exhaled gases from cattle, capturing microorganisms in a 10–15 μL microchip chamber through ion capture and performing real-time RT-PCR detection, successfully identifying foot-and-mouth disease virus within one minute of sampling—detecting infected cattle 2–4 days post-infection, superior to blood testing. Detection of metabolism-related biochemical substances in body fluids is crucial for health monitoring. Carrara et al. [69] developed a wireless implantable biosensor based on enzyme recognition and electrochemical detection for in vivo measurement of glucose, lactate, glutamate, and ATP for animal health diagnosis and monitoring.

With advancing intelligent farming technologies, biomarker-based detection is increasingly applied in beef cattle production, with more biomarkers and detection methods being validated and trending toward real-time, continuous online monitoring for production management and health surveillance. The key challenge lies establishing biomarker types, thresholds, and measurement methods for specific physiological states. Implanted sensors may affect animal welfare and health, suggesting future development may focus on monitoring exhaled gases near the nostrils to explore physiological status in real-time. Additionally, manual collection of blood, rumen fluid, secretions, and milk for rapid biomarker measurement can monitor beef cattle physiological status.

2. Applications of Physiological Indicator Monitoring

2.1 Estrus Monitoring Traditional estrus detection relies on visual observation of mounting behavior, tail paint, vulvar examination, rectal palpation, ultrasound, and hormone testing [70], requiring high practical experience, significant effort, and yielding low detection efficiency and inaccurate timing, resulting in missed breeding opportunities and reduced pregnancy rates—insufficient for modern beef cattle production. Since estrus often occurs at night and most beef cattle appear similar, manual observation of mounting behavior is particularly inconvenient in large-scale operations, affecting estrus detection rates. Automatic estrus detection technology based on physiological parameter changes is crucial for improving detection rates [70,71].

Estrus increases cattle activity by 2–4 times, sometimes exceeding 10 times normal levels [70]. Pedometers can monitor activity in real-time, but some cows exhibit silent estrus, affecting detection effectiveness. Additional physiological indicators can improve detection rates. Estrus-induced activity increase and hormonal changes (progesterone and estrogen) elevate body temperature, enabling accurate estrus timing through temperature monitoring for optimal breeding. Zhou [70] used a self-developed pedometer attached to the tail base and a vaginal temperature detector to monitor estrus, finding that tail activity increased by (11.66 ± 10.12) times during estrus, lasting (11.07 ± 2.09) hours, while vaginal temperature increased by $(0.69 \pm 0.38)^{\circ}\text{C}$, lasting (14.17 ± 1.93) hours—significantly higher than diestrus. This technology substantially improved estrus detection rates. Xuan [71] found that body temperature monitoring systems could determine estrus and identify optimal breeding time as 4–6 hours after temperature elevation returns to normal, achieving a 71% conception rate—significantly higher than the 59% rate from traditional experience-based methods. Additionally, mounting behavior during estrus can be automatically detected through video monitoring of breeding areas with data processing and analysis [13].

Estrus monitoring should integrate multiple indicators including activity, body temperature, rumination, feed intake, and mounting behavior, as single indicator elevation may result from stress or disease. Nelson et al. [73] achieved 90% sensitivity and 100% specificity in Hereford cattle estrus detection using a multi-indicator composite scoring system—superior to thrice-daily manual observation. Future developments may include visual monitoring of estrus mucus characteristics or gas detection technology analyzing estrus-related biomarkers in secretions.

2.2 Calving Monitoring Parturition is a complex physiological process. Significant physiological and hormonal changes occur 72 hours prepartum. Dystocia can lead to retained placenta, uterine infection risk, cow or calf mortality, reduced fertility and productivity, and negative impacts on postpartum milk performance and welfare within 30 days [74]. Timely calving monitoring is crucial for reducing economic losses from dystocia and stillbirth [75].

Body temperature decreases during calving. Ricci et al. [30] used intravaginal temperature devices [Medria Vel' Phone®] to predict calving in beef cattle, finding significant temperature decrease from 24 hours prepartum to parturition (average 0.21°C drop), with a predictive threshold of 38.2°C achieving 89% accuracy and 86% sensitivity. Chang et al. [76] detected rumination behavior changes before and after calving using ear-mounted accelerometers (AX3 Puck), observing significant rumination reduction 6 hours prepartum. However, temperature and rumination also relate to other physiological states, limiting monitoring accuracy.

Direct visual sensor monitoring of calving signs—including tail raising, pelvic relaxation, mucus secretion, straining, and fetal delivery—enables rapid identification and continuous tracking to prompt timely intervention. Temperature, activity, and rumination changes provide only rough calving estimates with relatively low sensitivity. Tail-base accelerometers (Figure 7 [Figure 7: see original paper]) detecting tail raising and straining behavior show higher sensitivity, identifying calving cows 2 hours prepartum, though fixation difficulty and damage susceptibility remain challenges [31]. Calving monitoring focuses on timely identification of dystocia cases and newborn calves to assist farm personnel in avoiding losses from delayed or excessive intervention and inadequate newborn care.

2.3 Feeding and Drinking Monitoring Reduced feed and water intake indicates health abnormalities, but direct accurate measurement is time-consuming. Current methods estimate intake by monitoring feeding behavior changes. Oliveira et al. [77] validated a video collection system for monitoring feed and water intake in housed calves with high accuracy and sensitivity. Since feeding causes head movement, accelerometer sensors on the head can estimate feed intake [78]. Zhou [79] and Jiang et al. [80] used three-axis accelerometers to measure head movement acceleration during feeding, achieving 99% and 78% accuracy in feeding behavior recognition—differences likely due to algorithmic analysis. RFID technology can also record time and frequency at feed bunks to assess feeding and drinking behavior [81]. Rutter [82] used noseband pressure sensors to record jaw movements during feeding, analyzing pressure waveform changes to determine feeding duration and frequency. Ruminant chewing, biting, and swallowing produce characteristic sounds. Galli et al. [83] predicted dry matter intake from acoustic chewing information with 91% accuracy. Clapham et al. [33] developed a directional broadband microphone facing the animal's forehead that achieved 94% accuracy in monitoring and analyzing biting and chewing behavior through signal analysis and decision logic algorithms. Water intake also correlates with growth and health. Williams et al. [84] combined RFID ear tags, water flow meters, and three-axis accelerometers to monitor drinking behavior and volume, using RFID to record visits to water stations, accelerometers to record drinking behavior, and flow meters to record water volume, achieving 95% prediction accuracy.

Feeding and drinking monitoring primarily analyzes head movement changes and time spent at feed/water stations, with accuracy affected by breed, age, health, and feed composition. Current technology mainly enables behavior recognition rather than precise intake measurement. Improving accuracy requires comprehensive judgment based on action intensity and frequency. Precise intake monitoring is crucial for assessing growth performance and health status. Future technologies may use visual sensors to monitor feed volume changes before and after consumption, establishing relationships between visual appearance and feed density to calculate intake. Individual water intake monitoring may employ individual water troughs recording volume changes before and after drinking.

2.4 Health Monitoring Common beef cattle diseases include hoof disease, metabolic disorders, respiratory diseases, infectious diseases, and skin conditions, all causing physiological and behavioral changes. Behavioral observation and physiological monitoring enable early detection and timely intervention. Currently, health monitoring primarily relies on farm personnel visual assessment [80].

Intelligent sensors can preliminarily detect abnormal cattle for veterinary confirmation, though personnel dependence remains high. Future intelligent farming aims toward automated disease diagnosis, severity assessment, and treatment recommendations based on health status. Sudden changes in body temperature, rumination, activity, and feeding behavior may indicate common infections, lameness, mastitis, metritis, or foot-and-mouth disease [85]. Respiratory sounds, frequency, and heart rate aid pneumonia, diarrhea, and milk fever diagnosis [42]. Foot-and-mouth disease can be diagnosed through humidity sensors near the mouth monitoring salivation, pedometers tracking hoof problems, and temperature sensors detecting fever. Visual sensors monitoring diarrhea behavior and fecal status, combined with pedometer-detected activity reduction, can diagnose bovine viral diarrhea [85]. Ketosis can be assessed through gas sensors detecting ketone bodies in exhaled breath; tuberculosis through sound sensors monitoring respiratory frequency and intensity [85]. Digestive diseases causing appetite loss, rumination cessation, bloat, and diarrhea can be detected through visual or rumination sensors monitoring feeding, diarrhea, rumination, and body shape changes. Paralytic and lameness diseases reducing activity can be monitored via pedometers [9]. Most diseases cause temperature and activity changes, making temperature sensors and pedometers primary health monitoring tools [86], with multi-indicator integration improving diagnostic accuracy. Arshad et al. [54] integrated IoT systems and artificial intelligence using real-time sensors (DS18B20 temperature, MAX30100 heart rate, ADXL335 accelerometer, MQ138 ketone gas, KY-037 microphone) at different body locations with artificial neural networks to predict diseases with 98% accuracy.

Intelligent health monitoring reduces treatment costs, improves economic benefits, and lowers labor expenses. Xuan et al. [48] used intelligent temperature

monitoring systems for disease diagnosis (mainly colds, enteritis, pneumonia), reducing disease detection time from 3 days to same-day, treatment duration from about 5 days to 2 days, significantly lowering treatment costs and mortality while improving cure rates. Tahsin [85] demonstrated that using accelerometer and temperature sensors for health and disease monitoring in a 100-head beef cattle operation increased profits threefold the equipment cost through improved sale prices and reduced feed costs. Early disease prevention and treatment reduces excessive medication use and disease impact on meat quality, thereby increasing beef prices.

Future intelligent beef cattle health monitoring will integrate image, activity, temperature, rumination, and physiological stage data to establish comprehensive analysis models based on disease-specific symptoms for automated diagnosis, veterinary alerts, and treatment effect monitoring. Developing such models represents a major task for future intelligent beef cattle farming.

2.5 Stress Monitoring Common stressors in beef cattle include heat stress and transport stress, causing elevated body temperature, increased respiratory and heart rates, and reduced feed intake, severely affecting performance and potentially causing death [87,88]. When Temperature-Humidity Index (THI) exceeds 78, beef cattle experience heat stress, reducing feed intake by 0.4 kg; when THI exceeds 84, intake drops by 1.7 kg [89]. Heat stress significantly increases respiratory frequency, which can indicate stress status [90]. Chapman et al. [91] quantified heat stress using accelerometer-derived behavior data and heavy breathing duration, though respiratory monitoring shows some lag. Infrared thermography detecting skin temperature changes combined with weather data can effectively predict heat stress [92]. Studies show that Simmental cattle skin temperature increases by 0.53°C per 1°C air temperature rise in summer (22.5–34.4°C) [93]. Intelligent monitoring of physiological responses enables intelligent environmental control for summer cooling. Transport stress also affects body temperature and meat quality. Cuthbertson et al. [94] found significant correlations between transport stress and meat quality indicators (pH, color, creatine kinase, glucose, non-esterified fatty acids, magnesium) and eye temperature measured by infrared thermography, enabling timely stress prediction and intervention to reduce transport stress impacts on meat quality.

Stress-induced temperature and respiratory changes may mimic other disease states. Improving stress monitoring accuracy requires combining environmental status with in-depth research on physiological differences between stress and disease states.

The user wants me to translate a specific section of a Chinese academic paper about beef cattle physiological indicator monitoring. The section is titled “### 3. Difficulties and Challenges in Beef Cattle Physiological Indicator Monitoring” .

Let me analyze the content:

1. **Title:** “### 3. Difficulties and Challenges in Beef Cattle Physiological Indicator Monitoring” - This is already in English, so I just need to keep it as is.
2. **Opening sentence:** “Despite progress, practical application maturity remains insufficient, with several challenges:” - This is also already in English.
3. **Four main challenges** are listed with numbers (1)-(4), each with bolded headings and detailed explanations.
4. **Specific issues detected:** The user mentions Chinese characters “粗, 放, 式” which appear in the phrase “粗放式” (cūfàngshì). This term means “extensive” or “rough” management style, often translated as “extensive” in contrast to “intensive” farming. The phrase in the text is “粗放式 beef cattle production systems” - I need to translate this properly.
5. **Translation rules:**
 - Author names: Romanize using pinyin (but there are no author names in this section)
 - Journal names: Use English title if available (no journals mentioned here)
 - Institution names: Use official English names (none here)
 - Technical terms: Use standard English equivalents
 - DO NOT leave any Chinese characters
6. **Structure preservation:** Keep the same structure - section heading, opening, numbered challenges with bold headings.

Let me go through each challenge:

(1) High energy consumption and damage susceptibility affect service life. - “Battery life is the most critical factor limiting contact sensor lifespan and functionality.” - Already English - “Devices are easily damaged during lying or fighting, and wireless data transmission consumes over 80% of power [95], reducing lifespan.” - Already English - “Beef cattle farms are large-scale with steel structures that shield wireless signals and cause sensor interference [96,97], requiring larger communication ranges that increase energy consumption and reduce battery life.” - Already English

(2) Environmental interference affects accuracy. - “Lighting intensity, railing occlusion, shooting angle, image quality, fecal contamination, and temperature/humidity all affect sensor precision and sensitivity.” - Already English - “Beef cattle farms are inherently dirty environments with manure and dust.” - Already English - “Contact sensors on body surfaces become contaminated, affecting data accuracy and potentially causing discomfort.” - Already English - “Non-contact computer vision sensors suffer from reduced image clarity due to dust, affecting result accuracy.” - Already English - “Flies and mosquitoes crawling, biting, or flying around cattle cause restlessness, rubbing, running, head shaking,

and standing, producing noise [98,99] and generating non-representative data.” - Already English - “Visual deep learning algorithms for behavior recognition are affected by lighting, weather, overlapping objects, and facial orientation, often capturing only partial images [100].” - Already English - “Reducing environmental impacts is a major practical challenge.” - Already English

(3) Numerous breeds complicate model development. - “Common beef breeds include Simmental, Angus, Charolais, Limousin, and various local breeds, with different physical and physiological characteristics across breeds and growth stages.” - Already English - “Model development requires large, accurately labeled datasets—a time-consuming, labor-intensive process with human error.” - Already English - “Currently lacking standardized datasets and evaluation criteria for various models, the disconnect between laboratory research and production practice affects model development.” - Already English - “Building standardized models suitable for various beef cattle is fundamental for promoting intelligent monitoring.” - Already English

(4) High equipment costs limit adoption. - “While dairy cattle monitoring technology is widely used in large Chinese dairy farms, China’s extensive and 粗放式 beef cattle production systems with lower technical expertise have lower adoption rates.” - Here’s the Chinese term “粗放式” that needs translation. It should be “extensive” or “extensive-style” or “extensive management style”. The phrase should be “China’s extensive beef cattle production systems” or “China’s extensive-style beef cattle production systems”. “Extensive” is the standard term in agriculture. - “Contact sensors are expensive and require individual deployment, consuming substantial labor and resources.” - Already English - “High construction and usage costs are major limiting factors.” - Already English - “Weak domestic equipment development and reliance on imported products keep prices high [101].” - Already English - “With fattening cycles around one year [97], large-scale installation of expensive cameras and sensors creates excessive production costs, while cheap equipment compromises accuracy.” - Already English - “Improving intelligent beef cattle farming requires enhanced domestic R&D, expanded utilization scale, improved technical expertise, and reduced manufacturing and usage costs.” - Already English

Wait, I need to re-read the instruction more carefully. The user says “Translate ONLY this section from Chinese to English” but then provides text that is already mostly in English with some Chinese characters mixed in. Let me look at the actual content again:

The section provided is:

3. Difficulties and Challenges in Beef Cattle Physiological Indicator Monitoring

Despite progress, practical application maturity remains insufficient, with several challenges.

(1) ****High energy consumption and damage susceptibility affect service life.**** Battery life

- (2) **Environmental interference affects accuracy.** Lighting intensity, railing occlusion,
- (3) **Numerous breeds complicate model development.** Common beef breeds include Simmental,
- (4) **High equipment costs limit adoption.** While dairy cattle monitoring technology is wide

I see that most of the text is already in English. The only Chinese characters are in the phrase “粗放式” in challenge (4). The user mentions “Chinese characters found: 粗, 放, 式” and says “These appear to be: mixed technical content and proper nouns”.

The term “粗放式” (cūfàngshì) means “extensive” or “extensive-style” in the context of agriculture, contrasting with “intensive” farming. So “extensive and 粗放式” is actually redundant - it’s saying “extensive and extensive-style”. This might be a mistake in the original text, or it’s emphasizing the point. I should translate it as “extensive” or “extensive-style” or perhaps just keep “extensive” since it’s already there.

Looking at the phrase: “China’s extensive and 粗放式 beef cattle production systems” - this seems like a case where the author wrote “extensive” in English and then added the Chinese term for clarification, or vice versa. The proper translation would be to either: 1. Remove the redundancy: “China’s extensive beef cattle production systems” 2. Keep the emphasis: “China’s extensive, extensive-style beef cattle production systems” 3. Use a more natural English phrase: “China’s extensive management-style beef cattle production systems”

Given the academic context, I think the best approach is to translate “粗放式” to its standard English equivalent and integrate it smoothly. The phrase “extensive and 粗放式” is likely a translation artifact. “Extensive management” is the standard term in agricultural science. So I could write: “China’s extensive management beef cattle production systems” or simply “China’s extensive beef cattle production systems” since “extensive” already implies the management style.

Actually, let me reconsider. The phrase might be trying to say “extensive and 粗放式” where 粗放式 ### 4. Future Development Directions for Intelligent Beef Cattle Physiological Indicator Monitoring

Future research and improvements should focus on the following aspects:

4.1 Reducing Energy Consumption and Improving Sensor Function and Lifespan At the application level, energy reduction can be achieved through lower data transmission frequency, reduced data volume, intermittent monitoring, optimized monitoring periods, and scheduled sleep modes. Solar or other wireless charging methods can extend battery life. Theoretically, energy consumption can be reduced through device chip and control structure optimization, expanded battery capacity, and improved endurance. Data transmission can focus on key valuable data, with increased gateway density to reduce sensor

transmission energy consumption. Integrating multiple sensors into single devices can reduce sensor numbers, equipment costs, and improve animal welfare.

4.2 Enhancing Multi-Parameter Data Fusion Analysis Depth and Monitoring Accuracy When reproductive, health, or stress states become abnormal, changes occur in temperature, activity, feed/water intake, behavior, and metabolism. Single sensors cannot effectively differentiate specific conditions. Integrating multi-sensor data with physiological stage characteristics for comprehensive analysis can improve detection efficiency and accuracy while reducing workload. Multi-data fusion requires monitoring multiple physiological indicators. For example, estrus is characterized by increased temperature and activity, reduced rumination, and acceptance of mounting. Automated monitoring and weighted calculation of these indicators can improve estrus detection rates and accuracy. Multi-angle health diagnosis through data fusion can safeguard cattle health.

4.3 Strengthening Non-Contact, High-Precision, Automated Analysis Technologies for Precision Intelligent Development Contact sensors on the neck, ear, tail, leg, and body interior affect cattle behavior and may cause welfare issues. Non-contact image and sound recognition technologies represent important future directions. Image-based AI technology collects body temperature and behavioral information, offering advantages for livestock health and welfare in establishing safe intelligent farms. Non-contact devices depend on high-precision, automated video/image and acoustic signal acquisition combined with emerging 3D models and deep learning for physiological monitoring. However, video signals are affected by occlusion, lighting, weather, and environment, while acoustic data is vulnerable to noise interference. Environmental impacts can be addressed at the engineering management level through improved farm environments, fly control, manure/dust management, optimized camera placement, and professional equipment maintenance. At the algorithmic level, selective capture of instantaneous animal postures can improve accuracy for non-rigid deformation issues, while incorporating environmental data in model development can enhance result accuracy.

5. Conclusion

Intelligent monitoring equipment for beef cattle physiological indicators is crucial for improving production levels. Intelligent monitoring systems acquire physiological and behavioral data, analyze them through data models or deep learning classification, and promptly monitor subtle changes in normal behavior and physiological parameters for timely detection of sick, estrus, and calving cattle. This facilitates prompt management measures, reduces personnel workload, and improves efficiency. Future development should focus on reducing contact sensor energy consumption and extending service life; improving depth of multi-parameter data fusion analysis to enhance accuracy; and strengthening

non-contact, high-precision, automated data collection and analysis technologies to reduce manual device deployment workload and equipment costs.

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