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SmartCalve: Design and Implementation of an IoT Device for Early Calving Detection in Cattle

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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

Dedication

"All that I have achieved today is by the grace of God and the heartfelt prayers of my parents." As I reach the end of this important chapter of my academic journey, I look back with gratitude, pride, and appreciation for everyone who stood by my side throughout these years. This achievement would not have been possible without the support, encouragement, and love of the people who believed in me. First and foremost, I dedicate this work to my beloved parents. Thank you for your unconditional love, endless sacrifices, sincere prayers, and unwavering support. You have always been my greatest source of strength and inspiration. Your patience, guidance, and faith in my abilities gave me the courage to overcome every challenge. I hope this achievement brings you the joy and pride that you truly deserve. To my brothers and sisters, thank you for your love, encouragement, and understanding. Your presence in my life has always been a blessing, and your support has motivated me to move forward with determination. I would like to express my sincere gratitude to my dear friend Alami Nadir for his friendship, encouragement, and support throughout this journey. Thank you for always being there and for making difficult moments easier to overcome. I would also like to extend my heartfelt thanks to my dear friends Abderrahman, Bilel, Aissam Boukhendeg, and Zinou Sebaa. Your support, encouragement, advice, and willingness to help meant a great deal to me throughout this journey. I am truly grateful for your friendship and for the unforgettable moments we shared together. Your presence made this path easier and more meaningful. My deepest appreciation and respect go to my supervisor, Mr. Anisse CHIALI, for his valuable guidance, patience, availability, and continuous support during the realization of this work. His advice and expertise played a significant role in the successful completion of this project. Special thanks go to all my friends who supported, encouraged, and helped me throughout my academic journey. Your kindness and friendship will always hold a special place in my heart. Finally, I would like to express my sincere appreciation to all the teachers and professors who contributed to my education and shared their knowledge and experience with me over the years. Your efforts have helped shape the person I am today. To all of you, thank you from the bottom of my heart. CHERIFI Mohamed El Amine

"All that I have achieved today is by the grace of God and the heartfelt prayers of my parents." As I conclude this memorable academic journey, I reflect with gratitude on the many people whose support, encouragement, and presence have accompanied me every step of the way. Their belief in me has given me the strength to persevere and achieve this milestone. First and foremost, I dedicate this work to my beloved parents. Thank you for your unconditional love, sacrifices, endless prayers, and unwavering support. You have always encouraged me to believe in myself and pursue my dreams. This achievement is as much yours as it is mine. To my brothers and sisters, thank you for your love, patience, and continuous encouragement. Your support has been a source of comfort and motivation throughout this journey. I would like to express my sincere gratitude to my dear friend Alami Nadir for his friendship, support, and encouragement. Thank you for standing by my side and for the valuable moments we shared along the way. I would also like to extend my heartfelt appreciation to my dear friends Abderrahman, Bilel, Aissam and Zinou. Thank you for your constant support, encouragement, advice, and willingness to help whenever needed. Your friendship and the unforgettable moments we shared made this academic journey more enjoyable and meaningful. I will always cherish your kindness and companionship. I would also like to express my sincere gratitude to the members of the TechSquad and EcoGeeks University Clubs. Being part of these clubs provided me with valuable opportunities to learn, grow, and develop both my technical and personal skills. The projects, activities, teamwork, and experiences I shared within these communities played an important role in shaping my academic and professional journey. I am truly thankful for the knowledge, support, and unforgettable experiences gained throughout this enriching experience. I extend my deepest thanks and respect to my supervisor, Mr. Anisse CHIALI, whose guidance, patience, and constructive advice greatly contributed to the completion of this work. His professionalism and support have been truly appreciated. Special thanks go to all my friends who offered their help, support, and encouragement during my academic journey. I am truly grateful for your friendship. Finally, I would like to thank all the teachers and professors who have contributed to my education and shared their knowledge and experience throughout the years. Their dedication has had a lasting impact on my personal and academic development. With heartfelt gratitude, thank you all. TESSOUMI Mohamed Amine Bennedjadi

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Abstract in Arabic

يُعدّ وضع المواشي حدثاً بالغ الأهمية في مجال تربية الحيوانات، إذ يستلزم تدخلاً بشرياً في الوقت المناسب لمنع وفاة العجول والأبقار. تعاني أنظمة الكشف الحالية من طابعها التدخلّي أو ارتفاع تكلفتها أو محدودية دقتها في الوقت الفعلي، مما يُقيّد انتشارها في المزارع التقليدية. يُقدّم هذا العمل نظام ثلثنكسف، وهو نظام مراقبة حركية متعدد العقد قائم على إنترنت الأشياء، مُصمّم للكشف غير التدخلّي وفي الوقت الفعلي عن وضع الأبقار. يتضمن النظام مجموعة موزعة من وحدات القياس بالقصور الذاتي يعو ٥٠٦. مثبتة على ذيل البقرة، تُدار عبر مُوزّع إي ٢٨ من طراز ١٨٤٥٩٥ وتتحكم فيها وحدة تحكم دقيق يصع ٦٦٢٨. تُحوّل البيانات الخام للمقياس التسارعي إلى إحداثيات كروية (غ، φ ، θ) وتُرسل لاسلكياً إلى منظومة المعالجة. تم استخراج مجموعة بيانات خاصة تتكون من ٣٠٦٠ إطاراً حركياً من ٦٠ مقطع فيديو باستخدام منهجية تتبع ثلاثي الأبعاد متعددة المقاطع مبنية على أوبنثط، تغطي ثلاث حالات سلوكية: السلوك الطبيعي، والتخلص من الفضلات، والإثارة ما قبل الوضع. تم تجميع النموذج الأولي للجهاز والتحقق منه عبر اختبارات الشاشة التسلسلية، مما أكد سلامة سلسلة اقتناء البيانات الكاملة عبر العقد الثلاث.

الكلمات المفتاحية: تربية الماشية الدقيقة، كشف الوضع، إنترنت الأشياء، يعو ٥٠٦، ٦٦٢٨، التحليل الحركي، أوبنثط.

Abstract

Bovine calving is a critical event in livestock farming that requires timely human intervention to prevent calf and cow mortality. Existing detection systems suffer from invasiveness, high cost, or limited real-time precision, restricting their adoption in conventional farming environments. This work presents CalvingSafe, a non-invasive IoT-based multi-node kinematic monitoring system designed for real-time detection of bovine parturition. The system integrates a distributed array of MPU6050 inertial measurement units mounted along the bovine tail, managed by a TCA9548A I2C multiplexer and controlled by an ESP8266 microcontroller. Raw accelerometer data is converted into spherical coordinates (R, φ, θ) and transmitted wirelessly to a processing backend. A proprietary dataset of 3,060 kinematic frames was extracted from 60 video sequences using an OpenCV-based multi-segmental 3D tracking pipeline, covering three behavioral states: normal behavior, waste elimination, and pre-calving agitation. The hardware prototype was assembled and validated through serial monitor testing, confirming the integrity of the full data acquisition chain across all three sensor nodes.

Keywords: Precision Livestock Farming, Calving Detection, IoT, MPU6050, ESP8266, Kinematic Analysis, OpenCV.

Résumé

La mise bas bovine est un événement critique en élevage qui nécessite une intervention humaine rapide afin de prévenir la mortalité des veaux et des vaches. Les systèmes de détection existants souffrent d'un caractère invasif, d'un coût élevé ou d'une précision temps réel insuffisante, limitant leur adoption dans les exploitations traditionnelles. Ce travail présente CalvingSafe, un système de surveillance cinématique multi-nœuds basé sur l'IoT, conçu pour la détection non invasive et en temps réel de la parturition bovine. Le système intègre un réseau distribué de capteurs inertiels MPU6050 montés le long de la queue de la vache, gérés par un multiplexeur I2C TCA9548A et pilotés par un microcontrôleur ESP8266. Les données brutes de l'accéléromètre sont converties en coordonnées sphériques (R , φ , θ) et transmises sans fil à un backend de traitement. Un jeu de données propriétaire de 3 060 trames cinématiques a été extrait de 60 séquences vidéo à l'aide d'un pipeline de suivi 3D multi-segmentaire basé sur OpenCV, couvrant trois états comportementaux : comportement normal, élimination et agitation pré-partum. Le prototype matériel a été assemblé et validé par des tests sur le moniteur série, confirmant l'intégrité de la chaîne d'acquisition de données sur l'ensemble des trois nœuds capteurs.

Mots clés : Élevage de précision, Détection de vêlage, IoT, MPU6050, ESP8266, Analyse cinématique, OpenCV.

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Introduction

Precision Livestock Farming (PLF) has progressively transformed animal husbandry by giving breeders continuous, data driven visibility into the health, welfare, and behaviour of their herds. Among the critical events that PLF seeks to anticipate, the calving period occupies a central place: the ability to detect the onset of labour early and reliably directly conditions calf survival, the prevention of dystocia-related complications, and the timely intervention of the breeder or veterinarian. While the dairy and beef industries have progressively adopted automated tools to address this need ranging from vaginal temperature probes and abdominal contraction belts to pedometers, rumination collars, and integrated farm management ecosystems these existing solutions remain constrained by significant trade offs. Invasive devices raise welfare and hygiene concerns, transmission ranges are often limited, and the most comprehensive AI driven platforms require capital intensive infrastructure that is out of reach for many traditional farms. It is within this context that the present work is positioned. Building on the observation that the pre partum period is consistently accompanied by a distinctive behavioural marker the sustained elevation and agitation of the tail, driven by the cow's neuro mechanical anticipatory reflex this memoir investigates a non invasive, tail mounted kinematic approach to calving detection. The underlying hypothesis is that this behavioural signature, captured through inertial sensing rather than internal probes or bulky collars, can provide a cost effective and reliable alternative to existing commercial systems, while avoiding both the invasiveness of internal monitoring and the heavy infrastructure demands of full farm automation ecosystems. Translating this hypothesis into a functioning system required progress along three complementary axes, each of which structures one chapter of this memoir. The first axis concerns the biological and technological grounding of the problem: understanding the physiological stages of bovine parturition, the precursory behavioural and endocrine signs that precede them, and the strengths and limitations of the calving detection technologies currently available on the market. The second axis concerns the engineering methodology required to turn a qualitative behavioural observation into a quantitative, machine readable signal: this involved developing a multi segmental three dimensional model of the bovine tail, extracting kinematic features from real video recordings using computer vision, and constructing a structured dataset capable of distinguishing normal behaviour, isolated functional events such as waste elimination, and the active calving process. The third axis concerns the physical realisation of this approach: the design and assembly of a multi node, animal mounted IoT prototype named CalvingSafe capable of acquiring this kinematic data in real conditions, under the practical con-

straints of weight, energy autonomy, and resilience to the barn environment. This memoir accordingly unfolds in three chapters. Chapter 1 reviews the state of the art in Precision Livestock Farming and establishes the biological and physiological foundations of bovine calving, situating the tail kinematics hypothesis with respect to existing detection technologies. Chapter 2 details the engineering methodology used to extract, model, and structure the kinematic data underlying the system, from the multi-segmental spatial modelling of the tail to the construction of the behavioural dataset intended for subsequent machine learning classification. Chapter 3 presents the hardware architecture of the CalvingSafe prototype, covering its mechanical design, sensing and power electronics, and the validation of its data acquisition chain. Taken together, these chapters lay the biological, methodological, and physical groundwork on which the artificial intelligence inference layer of the system developed in the subsequent stage of this research is built.

STATE OF THE ART AND BIOLOGICAL FOUNDATIONS OF CALVING DETECTION

1.1 Introduction to Precision Livestock Farming (PLF)

Precision Livestock Farming represents a technological revolution in animal husbandry, providing farmers with a continuous flow of data to facilitate rapid and informed decision-making. This approach utilizes advanced techniques to monitor animal welfare, health, and stress levels by recording behavioral patterns in real-time. The rapid global expansion of PLF is driven by strategic and economic factors, such as the increasing size of agricultural holdings combined with a declining labor force, and the rising cost of raw materials which necessitates optimized productivity to maintain profitability.

Driven by breakthroughs in microelectronics, telecommunications, and information technology, the cost of specialized hardware such as movement and temperature sensors has decreased significantly, allowing for high-precision monitoring of animal functions. By integrating these sensors with real-time algorithms, PLF systems can now detect or even predict critical incidents during the production process. Consequently, PLF has emerged as a multidisciplinary science where engineers, veterinarians, and ICT experts collaborate to transform raw data into actionable insights for modern farmers. [11]

1.2 Historical Development of Precision Livestock Farming (PLF)

Precision Livestock Farming (PLF) originated in the mid-1970s through research in the UK and Belgium, later expanding globally to regions including North America and Africa. Initially focused on basic behavioral monitoring like posture and rumination, the field has evolved significantly to include advanced technologies such as automated milking robots and early calving detection systems.

The rapid growth of PLF tools in recent years is largely a response to industrial pressures, where increased herd sizes and labor shortages have made automated monitoring essential. Modern sensors now enable farmers to manage complex tasks like feeding and health diagnostics more efficiently. Furthermore, these technologies are crucial for meeting modern regulatory standards for animal welfare and environmental protection, allowing for rapid, data-driven management decisions. [11]

[35]

Figure: shows the functional diagram of the livestock monitoring system in precision farming.

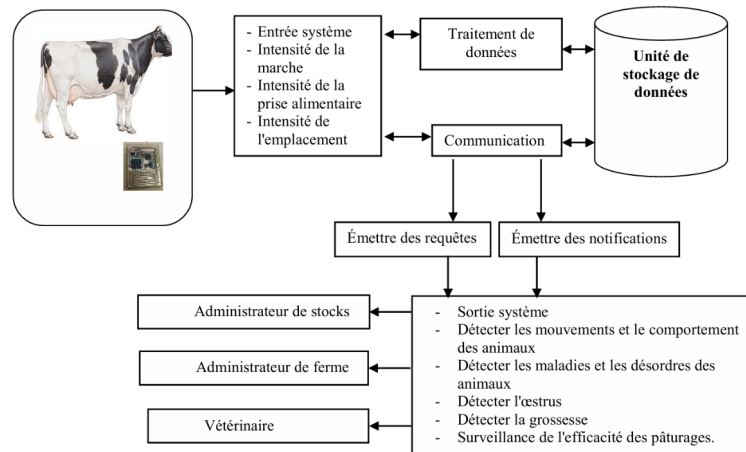


Figure 1.1: Functional diagram of the livestock monitoring system in precision livestock farming.

1.3 Definitions and Concepts of Precision Livestock Farming (PLF)

Precision Livestock Farming (PLF) is an integrated management strategy that uses technology to monitor behavioral and physiological indicators, aiming to optimize animal welfare and farm productivity. According to Berckmans, the essence of PLF lies in the synergy between sensor data and Information and Communication Technologies (ICT) to provide real-time decision support for farmers. An effective PLF system operates through a continuous cycle: sensors measure animal variables, predictive algorithms model expected responses, and the system triggers automated alerts when deviations such as calving or health issues are detected.

Conceptually, PLF marks a shift from herd-based management to individualized care. By automating the collection and processing of data, it allows for the precise monitoring of animals even in large-scale or extensive systems. This automation addresses the challenges of reduced labor and increasing herd sizes, transforming raw physical and behavioral data into actionable management insights. [12]

1.4 Applications and Examples of Precision Livestock Farming (PLF)

Driven by the increasing demand for animal products, Precision Livestock Farming (PLF) has expanded across various sectors, including swine and poultry production. However, the dairy industry has seen the most significant growth in recent years.

Automated milking systems combined with electronic monitoring have become widespread, allowing for the real-time detection of metabolic disorders and stress. Furthermore, these electronic methods are now essential for the early detection of critical events such as mastitis and the onset of the calving period. [30]

1.5 Human-Animal Relationship in the Digital Era

Despite significant advancements in automated management and electronic data collection, the direct relationship between humans and animals remains fundamental. Trust and mutual understanding are built through daily physical contact in stables and pastures, which helps eliminate animal fear and foster a familiar environment. While technology provides critical insights, many dairy farmers maintain a cautious approach, often performing visual validations such as confirming heat detection before taking action. Management styles vary significantly; some farmers prioritize electronic data, while others continue to rely primarily on direct animal contact as their main decision-making tool. [13]

1.6 Generalities of Bovine Parturition

Parturition, or calving, encompasses the complete set of mechanical and physiological phenomena that culminate in the expulsion of one or multiple newborns, along with the placental membranes, at the end of gestation. In dairy cows, the standard gestation period typically ranges from 283 to 290 days. [26]

1.6.1 Precursory Signs of Calving

As the term approaches, the cow undergoes significant physical and behavioral transformations that serve as biological indicators of impending labor.

- **Maternal Behavior and Environmental Adaptation:** In the final stages of pregnancy, the cow manifests distinct behavioral shifts characterized by restlessness, anxiety, trampling, and a strong instinctual drive to seek isolation. To accommodate this, farmers typically transfer the animal to a dedicated calving box. This enclosure (ideally 12 to 15 m²) must be rigorously sanitized and well-bedded to ensure optimal hygiene. Importantly, the calving box should remain in visual proximity to the rest of the herd to prevent isolation-induced stress while providing enough space for potential human or mechanical assistance. [18]
- **Timeline of Behavioral Kinematics:** The progression of pre-partum behavior follows a specific chronological timeline [18]

6 Hours Pre-Partum: There is a noticeable decrease in the total time the cow spends in a standing position.

2 Hours Pre-Partum: This critical window is marked by a sharp increase in physical distress signals. The cow exhibits frequent postural transitions (repeatedly standing up and lying down), increased trampling, visible abdominal contractions,

and—most importantly for automated monitoring—prolonged periods with an elevated tail.

- **Mammary Gland Development Physiological:** preparation is also evident in the udder, which begins developing months before calving in primiparous cows (heifers) and during the final week in multiparous cows. The mammary tissue becomes visibly congested, tense, and occasionally edematous. As parturition nears, this culminates in the secretion of colostrum, identifiable by its turbid, white-to-yellow appearance. [21]

1.6.2 Preparatory Phases of Calving

Physiologically, the progression of calving is a continuous and uninterrupted phenomenon. However, for clinical, anatomical, and descriptive purposes, parturition is classically divided into three distinct phases. [11]

1.6.3 Stage 1: Uterine Contractions and Cervical Dilation

- **Dynamics of Uterine Contractions:** Myometrial contractions typically initiate approximately 12 hours prior to parturition, establishing the mechanical force required to propel the fetus into the pelvic canal. The progression of these contractions follows a distinct temporal pattern [26]

Early Labor: Initially, the contractions are relatively spaced out, occurring at intervals of 6 to 7 minutes, and are brief in duration (lasting only a few seconds).

Imminent Calving: As labor advances, the frequency and duration of the contractions increase significantly. At the brink of expulsion, contractions reach their peak, occurring at precise one-minute intervals and sustaining for up to a full minute.

The Ferguson Reflex: The mechanical engagement of the fetus into the pelvic canal and its passage through the cervix directly stimulate the neurohypophysis to secrete oxytocin. This positive feedback loop, known as the Ferguson reflex, induces highly frequent, intense uterine and abdominal contractions.

- **Cervical Dilation:** Cervical dilation initiates concurrently with the onset of uterine contractions and is typically accompanied by a core body temperature ranging between 38.2°C and 39°C. The clinical evaluation of the cervical opening serves as a highly predictive indicator for estimating the onset of actual expulsion [11]

2 to 8 centimeters (Approx. 3 fingers): At this preliminary stage, there is a low probability that calving will occur within the subsequent 8 hours.

8 to 12 centimeters (Approx. the size of a hand): As dilation progresses to this extent, the likelihood of parturition occurring within a 2 to 8-hour window increases significantly.

12 to 16 centimeters (Passage of a forearm): At this advanced stage of dilation, the birth canal is nearly fully prepared, and fetal expulsion is expected to occur within the following few hours.

Engineering Relevance (Non-Invasive Inference): While the manual assessment of cervical dilation provides a highly accurate predictive timeline, it is inherently

invasive and requires direct human intervention. The tail-mounted kinematic sensor offers a non-invasive alternative to infer this internal progression. The advanced stages of cervical dilation (12–16 cm) mechanically and neurologically correlate with the peak, sustained tail-elevation reflexes. By monitoring these external kinematic manifestations, our system can autonomously estimate this advanced internal dilation phase without requiring any physical examination.

1.6.4 Stage 2: Fetal Expulsion

The second stage of labor is the active expulsion phase, characterized by maximum physical exertion and the actual delivery of the calf. [10]

- **Fetal Progression and Fluid Release Driven:** by the accumulated force of repeated uterine and abdominal contractions, the fetus progressively advances through the cervical canal towards the vulva. The immense internal pressure leads to the rupture of the allantoic sac (the first "water bag"). This rupture plays a crucial mechanical role by releasing fluids that lubricate the posterior vaginal tract, thereby reducing friction and facilitating fetal progression. Subsequently, the amniotic sac (the second "water bag") typically ruptures as the calf enters the vaginal canal. [11]
- **Delivery and Maternal Care:** As the fetal head reaches the vulva, the surrounding tissues progressively dilate to allow its passage. Following the emergence of the head, the remainder of the body traverses the pelvic canal and is completely expelled by the final, most powerful contractions. Immediately post-expulsion, the maternal instinct drives the cow to vigorously lick the newborn; this vital behavior clears the amniotic fluids from the calf's respiratory tract and stimulates independent breathing. [10]
- **Duration of Expulsion:** The duration of the active expulsion phase is highly variable. It generally ranges from 30 minutes to over 3 hours, with prolonged durations frequently observed in primiparous cows (heifers) or older multiparous cows experiencing dystocia. [23]
- **Engineering Relevance (The Ultimate Kinematic Trigger):** This active expulsion phase represents the absolute peak of pelvic pressure and abdominal straining. Biomechanically, to clear the birth canal, the cow reflexively maintains her tail in a continuous, highly elevated position. For the MPU6050 sensor, this phase translates into maximum, sustained Pitch angles, often accompanied by chaotic lateral Yaw movements due to the intense physical straining. Capturing this precise kinematic signature—the continuous extreme elevation—is the core objective of the detection algorithm, allowing the system to trigger an "Imminent Expulsion" alert exactly when the farmer's presence is most critical. Furthermore, the sharp return of the tail to a baseline state signifies the completion of the expulsion phase. [17]

1.6.5 Stage 3: Placental Expulsion (Délivrance)

The third and final stage of parturition involves the detachment and progressive expulsion of the fetal membranes (placenta). [11]

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- **Physiological Timeframe and Complications:** Under normal physiological conditions, the complete expulsion of the placental envelopes occurs within 12 to 24 hours after the successful delivery of the calf. If the membranes are not expelled within this critical window, spontaneous clearance becomes highly improbable. This delay is clinically diagnosed as a retained placenta (rétention placentaire), a pathological condition that requires close observation and potential veterinary intervention to prevent secondary uterine infections. [22]
 - **Engineering Relevance (Post-Partum Algorithm Reset):** During this final stage, the cow may still experience mild afterbirth contractions to expel the placenta, resulting in occasional, brief tail elevations. However, the kinematic intensity, frequency, and sustained Pitch angles characteristic of the active expulsion phase (Stage 2) are significantly diminished. From an algorithmic perspective, the monitoring system must be calibrated to detect this sharp decline in sustained tail elevation. This post-partum kinematic "drop-off" serves as the definitive trigger for the microcontroller to log the completion of the primary calving event, halt the "Imminent Expulsion" emergency alerts, and seamlessly reset the system. [17]

1.6.6 Fetal Presentation and Positioning

The mechanics and duration of the expulsion phase are heavily dictated by the anatomical presentation of the fetus as it enters the pelvic canal. The calf may present anteriorly (head and forelimbs first), posteriorly (hind limbs first), or, in pathological cases, transversely. [26]

- **Eutocic Anterior Presentation:** In standard physiological calving, the fetus adopts a dorso-sacral position, meaning the fetal withers are aligned with the maternal sacrum. This anterior presentation allows for the optimal fetal-maternal anatomical adaptation during expulsion. It is the most natural and safe position, accounting for approximately 95% of all bovine deliveries. [10]
- **Eutocic Posterior Presentation:** In contrast, a posterior presentation involves the fetus entering the birth canal in a lumbo-sacral position, where the fetal croup aligns with the maternal sacrum, and the hind limbs exit first. While still considered "eutocic" (capable of natural delivery), it represents only about 5% of calvings and carries significant risks. This position prevents the normal physiological accommodation of the fetus within the birth canal. More critically, it frequently leads to the compression or premature rupture of the umbilical cord during engagement, which can cause severe fetal anoxia (oxygen deprivation) and death before expulsion is complete. [3]
- **Engineering Relevance (Detecting Prolonged Labor and Dystocia):** The orientation of the fetus directly impacts the duration and mechanical effort of Stage 2 labor. A normal anterior presentation results in a predictable, rhythmic kinematic signature. Conversely, high-risk positions (such as posterior or transverse presentations) almost inevitably cause prolonged labor (dystocia).

The cow will attempt to expel the malpositioned fetus through extended, agonizing abdominal contractions. For the MPU6050 algorithm, this translates into an abnormal, prolonged duration of extreme tail elevation (Pitch angle remaining high beyond the standard 30-to-180 minute window) accompanied by erratic drops indicating maternal fatigue. By programming a specific "timeout" threshold for sustained tail elevation, the system can autonomously upgrade a standard "Imminent Expulsion" alert into a critical "Dystocia / Emergency" alert, instantly notifying the breeder that veterinary intervention is mandatory to prevent fetal anoxia. [18]

1.6.7 Fetal Position and Pelvic Engagement

The fetal position specifically describes which anatomical part of the fetus makes direct contact with the anterior pelvic inlet as it engages the birth canal. [26]

- **Standard Alignments (Eutocic):** In Anterior Presentations: The physiological and optimal positions are dorso-sacral (where the fetal back aligns with the maternal sacrum) or dorso-ilio-sacral.

In Posterior Presentations: The viable alignments are restricted to lumbo-sacral or lumbo-ilio-sacral positions. [10]

- **Abnormal Alignments (Dystocic):** Any deviation from these standard alignments is strictly classified as an abnormal position. Such misalignments create a severe physical obstruction within the birth canal, preventing the natural anatomical accommodation of the fetus and inevitably leading to a complicated or blocked delivery. [3]
- **Engineering Relevance (Biomechanical Obstruction and Sensor Data):** An abnormal fetal position directly alters the mechanical forces exerted on the cow's pelvic girdle. When a calf is misaligned, the standard, rhythmic progression of labor is disrupted by a physical blockade. For the tail-mounted MPU6050 sensor, this obstruction translates into a distinct, chaotic kinematic signature. While a normal delivery exhibits a steady, sustained elevation of the tail (high Pitch), an abnormal fetal position often causes the cow to engage in intense, irregular straining. The sensor will capture not only prolonged high Pitch durations but also erratic, violent lateral movements (Yaw) as the cow attempts to physically force or reposition the blocked fetus. Recognizing this specific erratic threshold allows the algorithm to flag a severe mechanical obstruction, triggering an immediate emergency alert for veterinary intervention. [9]

1.6.8 Fetal Posture (Appendage Alignment)

While presentation and position describe the overall orientation of the fetus, the posture refers specifically to the anatomical arrangement of its extremities—namely the head, neck, and limbs—relative to its own body during engagement. [26]

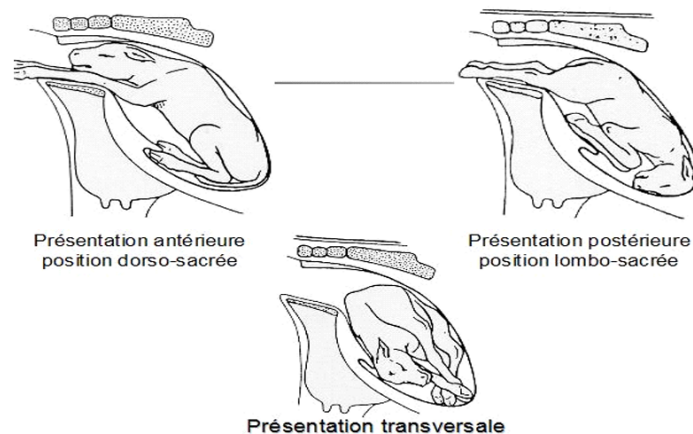


Figure 1.2: Calf posture and angular orientation configurations.

- **Physiological position versus abnormal position:** Physiological Posture: For a standard anterior delivery to proceed smoothly, the calf must adopt a fully extended posture. The head, neck, and forelimbs must be stretched forward into the pelvic canal.

Abnormal Posture: Any deviation from this extension—such as the flexion (bending) or retention of a joint, a laterally deviated head, or a tucked neck—constitutes an abnormal posture. [10]

- **Engineering Relevance (Detecting Asymmetrical Obstructions):** Even if the general presentation and position of the fetus are correct, a single postural anomaly (e.g., one flexed forelimb) creates an immediate, localized mechanical wedge in the birth canal. For the kinematic tracking system, this specific type of obstruction generates a unique biomechanical signature. Because the pain and pressure are distributed asymmetrically, the cow will often attempt to physically shift her weight and twist her pelvis to bypass the wedged limb. In the sensor data, this manifests not only as a continuously elevated Pitch angle but, more distinctively, as abrupt, high-intensity spikes in the Yaw (lateral deviation) data along the OABC coordinate system. By programming the algorithm to identify these specific erratic, high-frequency lateral oscillations, the system can dynamically flag a posturally obstructed labor, providing a highly specific diagnostic alert. [17]

1.6.9 Biological and Mechanical Foundations of Calving Detection

1.6.9.1 The Endocrine Trigger

Parturition is a highly regulated physiological event initiated by a precise hormonal cascade. In the final days of gestation, maternal progesterone levels which maintain pregnancy decline sharply, while estrogen levels rise. This endocrine shift sensitizes the myometrium to contractile stimuli. Concurrently, the fetus releases cortisol, which acts as the primary biological signal, informing the maternal system that the physiological maturation required for labor is complete. [4]

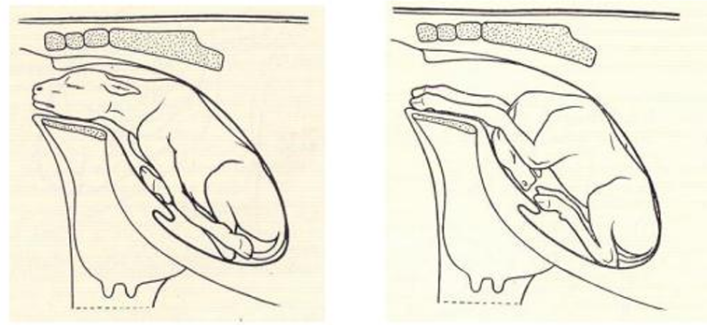


Figure 1.3: Illustrative examples of fetal postures: fetus with limbs retracted under the body (left) and "hooded" fetal posture (right).

1.6.9.2 Mechanical Pelvic Pressure

As labor approaches, the fetus transitions into the birth canal, exerting significant mechanical pressure on the pelvic girdle and associated ligaments. This displacement is perceived by the cow as a form of intra-abdominal discomfort, comparable to lumbar strain in humans. This internal physical pressure acts as a mechanical catalyst, prompting the animal to adopt specific postural adjustments to alleviate the localized congestion. [9]

1.6.9.3 The Pre-Partum Anticipatory Reflex

Cows possess an innate anticipatory mechanism triggered by the sensory input of the fetus within the birth canal. The brain interprets these nerve signals as an immediate precursor to expulsion, stimulating a neuro mechanical reflex. The cow reflexively elevates its tail an involuntary adaptation intended to reduce pelvic tension and facilitate birth canal clearance. This behavior is not stochastic; it is a vital, adaptive response aimed at optimizing the expulsion path. [9]

1.6.9.4 Kinematic Signature of Labor

The "tail-activity" associated with labor exhibits unique physical characteristics that distinguish it from non relevant behaviors, such as insect defense (fly-swishing):

Sustained Elevation: The tail remains in a raised position for extended durations, correlating with prolonged uterine pressure.

Rhythmic Oscillations: Specific oscillatory patterns occur in synchronization with uterine contractions. These distinct kinematic features constitute the "calving signature." Our sensing system is engineered to isolate this biomechanical data, transforming raw inertial measurements into a reliable, real-time alert for the breeder. [17] [10]

1.6.9.5 The Neuro-Mechanical Anticipation Reflex

In the final stages of parturition, cows exhibit a biological phenomenon termed "Anticipatory Response." This behavioral adaptation is critical to the calving process and is driven by the following neuro-mechanical mechanisms:

Sensory Threshold and Pelvic Pressure: As the fetus descends into the birth canal, it exerts significant mechanical pressure on the pelvic girdle and the surrounding ligamentous structures. This displacement stimulates mechanoreceptors located in the sacro-coccygeal region, which transmit intense afferent neural signals to the brain, signaling that the expulsion process has reached a critical threshold. [10]

Neural Interpretation and Reflexive Responses: During this stage, the bovine central nervous system operates in a state of high alert. Due to the high similarity between the mechanical pressure exerted by the fetus and the force applied during actual delivery, the nervous system interprets this stimulus as the onset of expulsion. This interpretation triggers a series of involuntary reflexive actions specifically forceful tail elevation, sustained muscular contractions, and increased physical activity as the animal reflexively attempts to facilitate the passage of the fetus. [18]

Instinctive Maternal Drive: This "anticipatory" behavior is not a physiological misinterpretation but an instinctive maternal drive to accelerate parturition. Driven by evolutionary necessity, the cow acts to alleviate the source of intra-pelvic stress as rapidly as possible. This adaptive behavior provides strong evidence that our kinematic monitoring system does not merely detect stochastic tail movements; rather, it identifies the peak neuro-mechanical activity directly associated with the labor process. [18]

1.6.10 Influence of Breed and Parity on Calving Behavior

The behavioral signature of calving is not uniform across all bovine populations; it is significantly influenced by breed-specific traits and the parity of the cow. [4]

- **Breed-Specific Differences:** High production dairy breeds (e.g., Holstein Friesian) often exhibit different labor intensities compared to dual purpose or hardy breeds. Factors such as pelvic dimensions, fetal size relative to the birth canal, and individual temperament influence the duration and intensity of pre partum tail movements. Some breeds may show more prolonged restlessness, while others might exhibit a more sudden and intense kinematic response. [5]
- **Heifers versus multi partner cows:** There is a distinct behavioral variance between heifers (first time calvers) and multiparous cows. Heifers often experience longer Stage 1 labor durations and exhibit higher levels of anxiety and postural shifting due to the novelty of the experience and potentially smaller pelvic dimensions relative to the fetus. Consequently, their pre-partum kinematic signals (tail activity) may be more erratic and extended compared to the more predictable, rhythmic patterns observed in multiparous cows. [23]
- **Systemic Adaptation:** Understanding these variations is essential for tuning the detection thresholds of our monitoring system. By accounting for the cow's breed and parity, our algorithm can dynamically adjust its sensitivity, ensuring high accuracy across diverse herd demographics. [17]

1.7 Comparative Analysis of Existing Calving Detection Technologies

To evaluate the efficiency of the proposed tail mounted system, it is essential to deeply analyze the current state-of-the-art technologies available in the precision livestock farming market. [6]

1.7.1 Technical and Operational Characteristics of Vaginal Temperature Monitoring Systems

Systems and Principles: Two systems are available for calving monitoring based on vaginal temperature: VEL'BOX® (marketed by Gènes diffusion) and VEL'PHONE® (marketed by Medria). The system uses a cylindrical probe or thermometer that is inserted into the cow's vagina and maintained in place by appendages at one of its ends.

Installation Protocol: The system is generally installed by the breeder 7 to 10 days before the expected calving date, strictly following hygiene conditions. [2]



Figure 1.4: Schematic representation of calving detection tools based on vaginal temperature measurement; left: Vel'Phone® probe (source: Medria); right: Vel'Box® probe (source: Genes Diffusion)

1.7.1.1 Operational Mechanism

The collection, transmission, and analysis of physiological data by vaginal monitoring systems are structured as follows [17]

Data Collection and Transmission: The probe records the cow's vaginal temperature and transmits this information to a GSM radiometric base station. The required range between the probe and the base station is 200 meters for the VEL'PHONE® system and approximately 80 meters for the VEL'BOX® system. The frequency of temperature recording is set to once per minute for VEL'PHONE® and once every 10 minutes for VEL'BOX®.

Data Analysis: Once collected, temperature data is relayed through a GSM antenna to the relevant companies, specifically "Medria" or "Gènes diffusion," where the data undergoes analysis before the results are communicated to the breeder. [17]

1.7.1.2 Communication and Notification Protocol

The vaginal monitoring systems utilize an integrated technical communication protocol designed to keep the breeder continuously informed about the status of pregnant cows through SMS notifications. The process begins with an initial activation SMS sent immediately upon the installation of the sensor in the cow's vagina. In scenarios where no physiological changes indicating approaching calving are detected, the system sends routine updates to the breeder every 12 hours to ensure continuous monitoring.

Regarding specific calving alerts, the system operates at two warning levels [2] [1]

The first level is triggered when typical thermal variations associated with the onset of labor are recorded, notifying the breeder that calving is expected within the next 48 hours ("probable or expected calving").

The second level consists of an "imminent calving" alert, triggered as soon as the sensor is expelled from the vagina due to the pressure of the water bag (amniotic sac). This provides the breeder with a window of approximately one hour to reach the site and assist with the calving process.

1.7.2 Abdominal Contraction Sensors (e.g., Agromonitor®)

The Agromonitor® system, developed by the company "Databel," is a technical tool specialized in monitoring bovine calving by detecting the abdominal and uterine contractions that precede the labor process. Technically, the system relies on a precision sensor integrated into an abdominal belt, which is secured around the cow's midsection during the final week prior to the expected calving date. [17]

1.7.2.1 Operational Mechanism and Alarm Classification

The competitive advantage of the Agromonitor® lies in its dual alarm architecture, which categorizes the calving process based on real time physiological data analysis:

"Surveillance" Alert: This notification is triggered when contractions follow a standard, regular progression. It serves to inform the breeder that the calving process is imminent and proceeding normally.

"Urgency" Alert: This alert is activated if the system detects contractions that deviate from expected parameters in terms of frequency or duration. This serves as a critical indicator of potential pathological calving, requiring immediate human or veterinary intervention.

By continuously measuring these contractions and providing real time data transmission, the system empowers the breeder to distinguish between routine delivery and complex scenarios, ensuring timely and informed decision making. [8]

1.7.3 Locomotor Behavior Monitoring via AfiTag Pedometer®

The AfiTag Pedometer® sensor, developed by the firm "Afimilk," is a specialized technology designed to monitor bovine behavior by quantifying locomotor activity through step counting. This system is predicated on the physiological observation that increased limb movement, specifically restlessness or "stomping," serves as a significant behavioral indicator of approaching calving. [17] [8]



Figure 1.5: Agromonitor® Calving Monitoring System

1.7.3.1 Installation and Implementation Protocol

To ensure the accuracy of locomotor data collection, the sensor is secured to one of the cow's forelimbs using a dedicated attachment strap. According to established protocols, the system must be installed one week prior to the expected calving date, thereby allowing the sensor to monitor behavioral changes throughout the critical period leading up to labor. [17] [8]

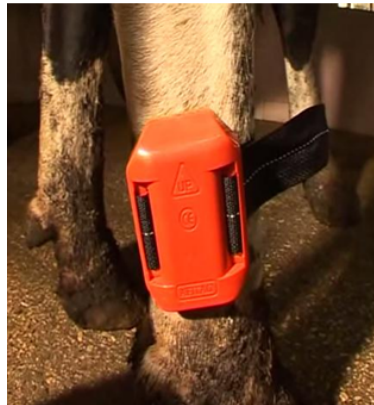


Figure 1.6: Positioning of the AfiTag Pedometer® sensor on a cow's right forelimb (source: Afimilk)

1.7.3.2 Operational Mechanism and Data Transmission

The data recorded by the AfiTag Pedometer® is retrieved via proximity based communication. Specifically, as the cow passes within range of a reading antenna typically installed at the entrance of the milking parlor or at the automatic concentrate dispenser the stored behavioral data is automatically transmitted for analysis. [17]

1.7.3.3 Limitations in Calving Detection

While this system is effective at identifying premonitory behavioral signs such as increased restlessness that precede the onset of labor, it is important to note that it does not generate real-time alerts at the moment of the calf's expulsion. Consequently, while useful for predictive monitoring, it functions primarily as a diagnostic tool for pre-calving behavioral changes rather than a definitive expulsion monitoring system. [17] [7]

1.7.4 Monitoring Rumination Time: HR Tag® System

The HR Tag® collar, developed by the firm "SCR Dairy," serves as an integrated monitoring tool for bovine health and reproductive status. It utilizes a dual-sensing architecture: an internal accelerometer, primarily designed to detect estrus (heat) cycles, and a specialized microphone calibrated to monitor and evaluate acoustic signals associated with rumination. By capturing these behavioral data points, the system provides a comprehensive overview of the cow's metabolic and reproductive state. [17] [6]



Figure 1.7: HR Tag® collar positioned on the cow's neck (source: SCR Dairy)

1.7.4.1 Operational Mechanism and Alert System

The HR Tag® system functions by continuously monitoring rumination frequency. When the recorded rumination activity declines below a pre defined threshold, the system interprets this physiological change as a behavioral indicator of impending labor. Upon reaching this threshold, the "SCR Dairy" platform automatically triggers an alert to the breeder, signaling that calving is expected within a 24 hour timeframe. [17] [6]

1.7.5 Next Generation AI Ecosystems (e.g., Lely Zeta)

Advanced AI driven ecosystems, such as Lely Zeta, leverage integrated barn data and artificial intelligence to manage entire farm operations, including calving, feeding, and robotic milking. While these systems offer comprehensive oversight and automation, they necessitate substantial infrastructure investments and high capital

expenditure. In contrast, our proposed device functions as a specialized, cost effective alternative, providing high-precision calving detection without the need for a total farm automation overhaul. [17] [6]

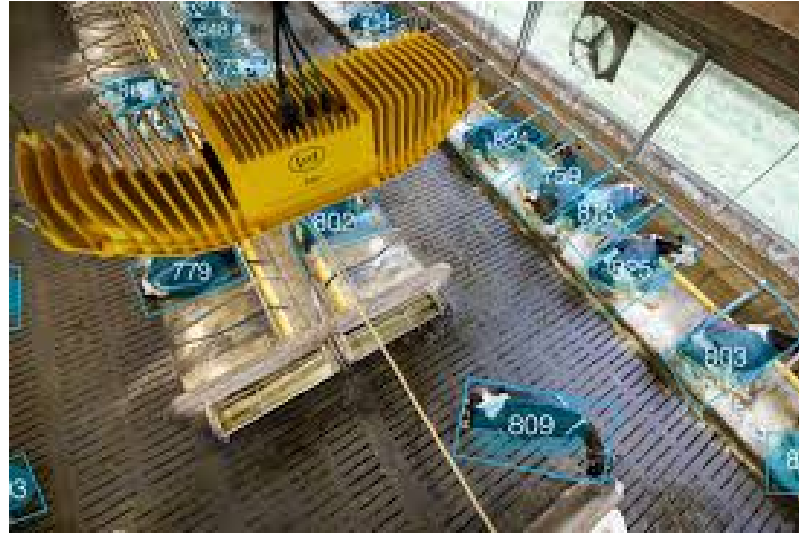


Figure 1.8: Representation of comprehensive AI driven automation in smart farms (e.g., Lely Zeta)

1.7.6 Analysis of Tail-Mounted Calving Detection Systems

The analysis of tail movements serves as a primary biological indicator for the early detection of calving, characterized by prolonged elevation and increased physical activity. As illustrated in Figure 1.9, the monitoring device is designed for non-invasive attachment to the base of the tail in pregnant cows nearing their term. This embedded system integrates two essential sensing functions: an accelerometer to measure movement intensity and an inclinometer to monitor the angle of elevation. Typically deployed two to three days before the expected calving date, the sensor records behavioral variations in real-time. Once a critical threshold is crossed corresponding to labor contractions and pre-partum signals an alert is transmitted via a radiometric or GSM transmitter to the breeder's receiver, ensuring a rapid and secure intervention.

that couples an accelerometer with an inclinometer. This configuration allows for the simultaneous measurement of movement intensity and the angular elevation of the tail. The device is typically secured to the base of the tail using adhesive tape two to three days before the expected calving date. While advanced systems utilize this dual-sensing approach to ensure high precision, simplified versions may rely exclusively on an accelerometer to detect the increased physical activity associated with labor. [17]

- **Operating Principle and Wireless Communication:** The detection process relies on a multi-stage wireless communication chain, as illustrated by the operational flow in Figure 1.10. Local analysis of tail movements identifies when critical behavioral thresholds associated with calving are crossed. Once an event is validated by the embedded sensor, it transmits a radiometric signal to



Figure 1.9: Photograph of the sensor placed at the base of the tail of pregnant cows near term to detect tail movements at the time of calving.

a central base station. This station acts as a gateway, relaying the information through the GSM or telephone network to issue a real-time alert (via call or SMS) to the breeder's mobile terminal. This architecture ensures efficient remote monitoring, with transmission ranges varying depending on the specific technology used. [17]



Figure 1.10: Principle of communication from the recording of tail movements by the sensor to the alert call to the farmer a few moments before the onset of calving (source: Evolution).

1.7.7 Conclusion :

This chapter has provided a comprehensive overview of the Precision Livestock Farming (PLF) landscape, specifically focusing on the critical domain of bovine calving detection. By exploring the biological, endocrine, and mechanical foundations of parturition, we have established a clear correlation between the cow's pre partial behavioral kinematics and the physiological progression of labor.

The comparative analysis of state of the art technologies ranging from invasive vaginal probes and abdominal belts to complex, high capital AI ecosystems like Lely Zeta highlights a significant technological gap. Existing solutions often suffer from limitations related to invasiveness, restricted transmission range, or high infrastructure costs, which hinder their widespread adoption among traditional farmers.

The research presented here confirms that a non-invasive, tail-mounted kinematic approach offers a highly accurate and cost effective alternative. By capturing precise behavioral signatures such as the continuous tail elevation and lateral Yaw oscillations our proposed system aims to provide real time, actionable insights for the breeder. This foundational understanding serves as the technical basis for the design and development of our dedicated monitoring device, which is engineered to ensure efficient, early, and reliable detection of calving events without the need for extensive barn automation.

2.1 Introduction

Following the comprehensive biological and technological review presented in Chapter 1, this chapter delineates the core engineering methodology and system design of the proposed calving detection solution. The transition from theoretical biological indicators to a functional automated system requires a highly robust data extraction and processing pipeline. Consequently, this chapter details the step-by-step mathematical and algorithmic architecture used to translate qualitative visual observations into quantitative kinematic data. By leveraging advanced computer vision techniques (OpenCV) and multi-segmental 3D mathematical modeling, we establish a reliable feature extraction protocol. Furthermore, this chapter outlines the compilation of a proprietary dataset and the systematic extraction of specific behavioral signatures, ultimately laying the optimal data foundation for the Artificial Neural Network (ANN) classification model.

2.2 Behavioral Classification Based on Kinematic Signatures

The transition from traditional visual observation of animal behavior to automated digital monitoring is the core of precision livestock farming. In this context, our system was not built on theoretical assumptions; rather, the engineering of the decision algorithm was based on a direct and rigorous analysis of data extracted from real world video sequences documenting cow behaviors in their natural environment. By mathematically modeling the tail's movement and establishing point O (located at the base of the tail) as the absolute origin of the spatial coordinate system, we were able to track angular changes with high precision. In this model, the Pitch and Yaw angles are no longer mere geometric coordinates; they function as genuine kinematic biomarkers. Tracking the spatio temporal variation of these angles allows the system to understand the animal's physiological state and accurately classify it into three main states:

2.2.1 Normal Behavior (Resting State)

Kinematically, this behavior is characterized by low-amplitude, random variations in the tail angles. These movements reflect the cow's continuous routine activity, such as moving the tail to swat insects or lightly interacting with the surrounding environment. Since these changes do not follow any regular cyclic pattern, the algorithm considers this state as the stable baseline that requires no response or alert. [24]

2.2.2 Waste Elimination (Isolated Functional Event)

This behavior is kinematically translated as a sharp, sudden vertical elevation, particularly evident in the Pitch angle. Through the data extraction process from reference videos, we definitively established that this functional event lasts exactly 7 seconds. Based on this strict temporal criterion extracted from experimental reality, the algorithm is programmed to classify any movement that concludes and returns to stability within this duration as a routine event to be ignored. This temporal filter aligns with modern scientific standards that require the use of time thresholds to filter out isolated movements and minimize false alarms in industrial environments. [34]

2.2.3 Calving Process (Active Labor)

In stark contrast to isolated and short behaviors, the pre-partum stage is characterized by a cyclic, repetitive, and continuous kinematic pattern. The strong, escalating oscillations in both the Pitch and Yaw angles, which clearly exceed the previously defined temporal threshold (7 seconds) and continue to repeat, reflect the cow's physical contractions and kinematic agitation caused by pain. Upon detecting this continuous and escalating kinematic signature, the system breaks the standby state and immediately triggers the imminent calving alert. [19]

2.3 Data Acquisition Strategy and Development Environment Justification (OpenCV)

In the absence of accurate, open source kinematic datasets documenting cow tail movements during the calving period, generating proprietary ground truth data emerged as a critical engineering necessity. As an optimal, non-invasive solution to overcome this limitation, spatial coordinates were retrospectively extracted from pre recorded video sequences encompassing the three specific behavioral states: normal behavior, waste elimination, and the calving process.

To execute this pivotal extraction phase, the OpenCV (Open Source Computer Vision Library) framework, integrated with Python, was selected as the primary processing environment. This technical choice is justified by strict engineering parameters when compared to available alternatives (e.g., MATLAB Toolboxes or proprietary closed-source software). Unlike commercial software that operates as a "black box" and demands intensive computational resources, OpenCV offers a lightweight

architecture enabling precise low-level algorithmic control. This facilitated the development of a customized, interactive graphical interface specifically designed to superimpose a 3D Cartesian coordinate system onto the animal's anatomy with centimetric precision. Furthermore, the native integration of OpenCV within the Python ecosystem ensures a seamless transition of the extracted data matrices directly into subsequent processing algorithms, thereby eliminating interoperability issues. Consequently, OpenCV functioned as the indispensable digital bridge capable of translating qualitative visual observations into structured, quantitative numerical matrices [36]

2.4 Multi-Segmental Kinematic Modeling and Biomechanical Justification

To ensure the accurate extraction of kinematic biomarkers, we constructed a mathematical model that reflects the complex anatomical nature of the bovine tail. Rather than treating the appendage as a single, rigid rod which would inherently result in geometric distortions we modeled it as a flexible, articulated chain comprising multiple caudal vertebrae. Consequently, the strategic reference points (O, A, B, C) were selected based on the following engineering parameters: Point O was deliberately anchored at the tailhead to serve as the absolute origin (0,0,0) of the 3D Cartesian coordinate system. This anatomical placement functions as a mechanical filter, effectively isolating the cow's global body movements from the localized, pure rotation of the tail. Furthermore, distributing points (A, B, C) along the appendage to form spatial vectors (OA, OB, OC) is a fundamental engineering necessity; this multi segmental tracking approach allows for the highly accurate calculation of Pitch and Yaw angles while capturing subtle micro oscillations that would otherwise be lost if the tail were inaccurately modeled as a rigid structure. By capturing the relative bending between these segments, our model maintains high fidelity to the tail's non-linear, curved trajectory, which is critical for detecting the preliminary spasms that precede active labor . [15]

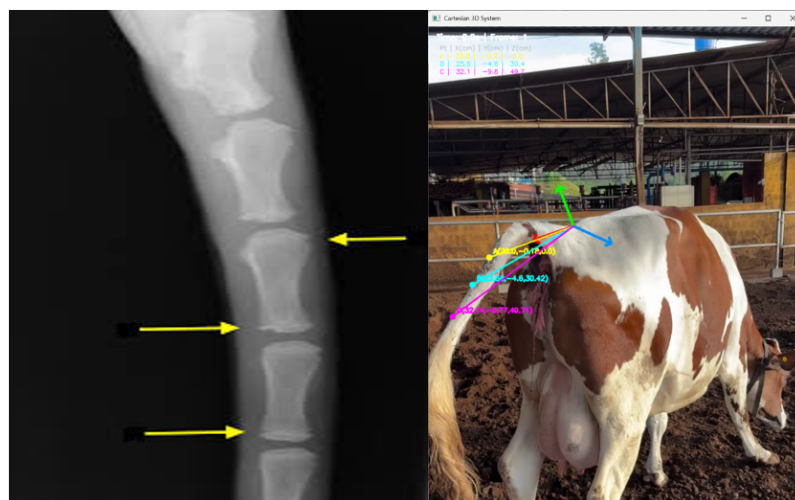


Figure 2.1: Modeling the bovine tail as a flexible articulated chain using spatial vectors (OA, OB, OC).

2.5 Spatial Mapping: From 2D Video Projection to 3D Kinematic Coordinates

The primary engineering challenge in our kinematic extraction pipeline was accurately deriving 3D spatial coordinates (X, Y, Z) from 2D monocular video sequences (x, y). To bridge this dimensional gap, we implemented a Perspective Projection transformation technique, underpinned by the fixed geometric configuration of the camera relative to the scene. Given that the camera is mounted in a stable, strategic position, we performed rigorous camera calibration to establish a robust mapping function between image pixels (u, v) and the physical real world coordinates (X, Y, Z) measured in centimeters.

In this model, the barn floor serves as the reference plane (X, Y), while the vertical axis represents the Z component. By anchoring known static reference markers within the barn environment whose real world dimensions were pre-measured we computed the Homography Matrix. This matrix enables the software to translate any point selected via the interface (e.g., via mouse click) from its 2D projection on the screen to its precise 3D spatial location. Consequently, this transformation allows for the continuous tracking of tail motion within a 3D coordinate system, despite the input source being inherently 2D, thereby ensuring the mathematical integrity of the kinematic data for subsequent analysis . [37]

2.6 Kinematic Differentiation: Analysis of Axis Sensitivity and Behavioral Signature

Despite the fact that tail elevation is a common behavioral trait in both urination and the calving process, precise kinematic analysis reveals fundamental differences in motion dynamics. In our defined Cartesian coordinate system, the X axis represents the transverse width, while the Y axis (vertical) represents the tail elevation, and the Z axis denotes the depth (longitudinal) extension. Relying solely on the Y -axis for classification leads to kinematic ambiguity, as both behaviors involve a rapid vertical displacement of the tail.

Therefore, the algorithm's precision relies on the simultaneous analysis (spatio temporal fusion) of both Y and Z axes. During urination, the movement consists of a discrete, time bound vertical elevation (Y) with relative stability along the depth axis (Z). In contrast, the calving process is characterized by a more complex behavioral pattern, featuring continuous or repetitive vertical elevations along the Y axis, coupled with irregular, high frequency oscillations along the Z axis, induced by persistent muscular contractions and the animal's physical discomfort. By integrating this multi dimensional data, the system successfully distinguishes between the functional, direct motion of urination and the complex, prolonged movement signature of calving, thereby significantly reducing the rate of false positives . [20]

2.7 Experimental Data Collection Protocol and Dataset Expansion

To ensure the mathematical reliability of the kinematic classification model and to overcome the absence of open-source databases, a specialized video dataset was compiled, documenting cow behaviors in a natural barn environment. The data acquisition protocol was executed in two sequential engineering phases. The initial pilot phase involved testing the system on a preliminary subset of 9 videos covering the three targeted behavioral states (normal behavior, waste elimination, and calving), utilizing a low temporal extraction rate of 1 Frame Per Second (1 FPS). The primary objective of this phase was to establish a Proof of Concept (PoC) and validate the algorithmic tracking logic via the OpenCV interface.

Following the technical success of the pilot phase, the project advanced to the full scale expansion phase. A comprehensive dataset comprising 60 video sequences was compiled, incorporating realistic variability in lighting conditions and viewing angles to ensure model robustness. To enhance the temporal sensitivity required to capture the subtle kinematic variations characteristic of the calving process, the sampling rate was optimized to 6 Frames Per Second (6 FPS). This strategic optimization significantly increased the extracted data density, equipping the subsequent classification algorithms with exceptional precision to construct accurate behavioral signatures and effectively distinguish between events without being compromised by visual noise . [28]

2.7.1 Visual Representation and Categorization of the Expanded Dataset

As a complementary step to verify the comprehensiveness of the expanded dataset, an image mosaic was constructed, integrating representative static frames from the 60 approved video sequences. This concatenated image (Figure 2.2) provides a detailed visual breakdown covering the three studied behavioral states, programmatically arranged via the OpenCV interface into a 12 column by 5 row grid. This visual representation serves as an engineering overview, demonstrating the proposed system's robustness in processing and extracting tail kinematic features under variable operational conditions, including the diverse viewing angles and lighting intensities characteristic of a real world barn environment.

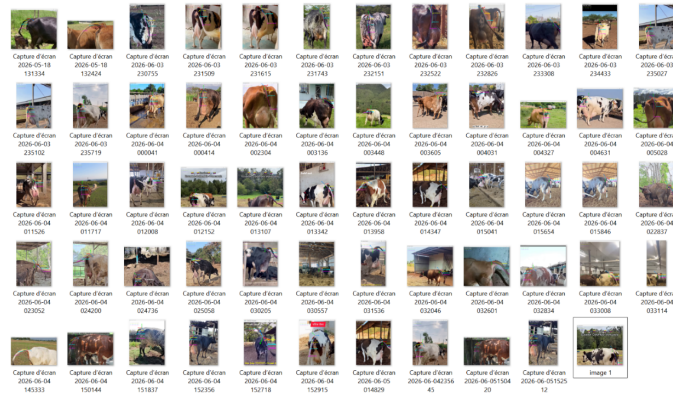


Figure 2.2: Visual categorization of the expanded dataset showcasing 60 representative video sequences under variable operational conditions.

2.8 Algorithmic Architecture of the Data Extraction Software

To translate the multi segmental biomechanical model into a practical computational application, a custom data extraction architecture was developed in Python. The system leverages an integrated, multi layered ecosystem of open source libraries, ensuring optimal memory management, real time processing, precise geometric calculations, and automated data logging. The software architecture partitions the kinematic extraction pipeline into discrete functional blocks handled by specialized modules, including OpenCV, NumPy, Pandas, and Datetime.

- **Python Core Environment And Execution Control:** Python serves as the underlying object oriented script language, coordinating the main execution loops and handling high level data pipelines. By utilizing structured conditional flows and timing parameters, the environment dynamically manages system resources, processing frames precisely according to the designated temporal interval.

- **OpenCV (Computer Vision And Interactive GUI):** The cv2 framework acts as the primary computer vision engine and graphical interface. It handles video decoding via cv2.VideoCapture and establishes an interactive window (cv2.namedWindow) integrated with a mouse callback function (cv2.setMouseCallback). This setup listens for low level user events to log coordinate coordinates. Furthermore, OpenCV handles real world visual feedback by dynamically drawing 3D Cartesian coordinate axes, spatial tracking vectors, and real time numerical overlays using vectorized arrowed lines, shapes, and texts directly onto the displayed frames.

- **NumPy (Matrix Manipulation And Linear Algebra):** The numpy library functions as the high performance mathematical core, executing vectorized array calculations at the machine level. NumPy computes the tailhead inclination angle α via np.arctan2 , derives spatial scaling factors utilizing Euclidean vector norms (np.linalg.norm), and performs spatial rotation matrices using dot products (np.dot). To reconstruct the micro oscillations in the 3D space, NumPy resolves the spatial depth Z_c through specialized square root operations (np.sqrt) when transforming coordinates from 2D projection planes.

Pandas (Structured Tabular Management And Logging): The pandas library

handles advanced data structuring and time series serialization. Kinematic metrics extracted frame by frame are organized into dynamic data dictionaries before being transformed into tabular data matrices via the `pd.DataFrame` constructor. Pandas ensures seamless tracking and automates data persistence by writing the accumulated coordinate history to the disk using optimized formatting protocols (to csv) featuring specialized delimiter configurations (such as semicolon separation ;) to maximize interoperability with external analytical software like Microsoft Excel.

- **Datetime And OS Environment Security:** The datetime and os core modules handle data integrity and file management tracking. By fetching the local system clock and applying string formatting rules (`strftime`), the software dynamically appends a unique, standardized timestamp (`YYYYMMDD_HHMMSS`) to the output file names. This functions as an automated version control filter, preventing accidental file overwrites and preserving data safety across sequential video processing trials.

- **The tracking software systematically executes this processing architecture through three fundamental processing phases:**

Temporal Sampling: To optimize computational load while maintaining tracking fidelity, the algorithm bypasses redundant video frames, analyzing data at a precise, standardized rate of 1 frame per second (1 FPS) or optimized increments derived from the source video's intrinsic frame rate parameters.

- **Spatial Calibration and Axis Alignment:** Upon manual interaction with the primary structural markers (the cow's back and the tail origin O), the algorithm computes the dynamic inclination angle α . This coordinates the transformation matrix, aligning the X and Y axes directly with the animal's variable anatomical posture. Simultaneously, a dynamic scaling factor converts pixel lengths into real world centimeters based on the predefined physical reference lengths (L_{ref}).

- **3D Coordinate Reconstruction:** The Cartesian coordinates X_c and Y_c are calculated using mathematical rotation matrices. To overcome the structural limits of monocular 2D projection, the spatial depth Z_c is mathematically derived using the Pythagorean theorem relative to the adaptive multi segmental lengths (L_{ref_A} , L_{ref_B} , L_{ref_C}). This rigorous programmatic logic ensures that every tracked reference node (A, B, C) recorded in the final time series output contains high fidelity 3D parameters, securing structural reliability for subsequent training phases.

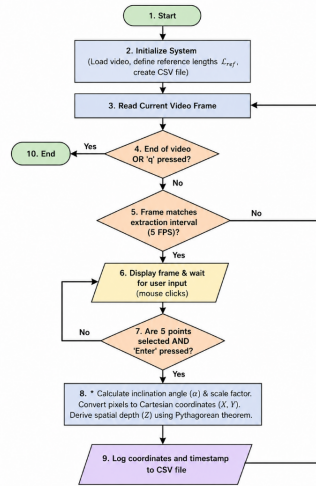


Figure 2.3: Logical sequence of the kinematic tracking software and time series data (CSV) generation.

2.9 Representative Data Presentation: Visual to Numerical Mapping

Given the extensive volume of the acquired dataset (60 video sequences and their corresponding large CSV files), a representative sample of 9 sequences was meticulously selected to tangibly illustrate the system’s operational mechanism. These samples are evenly distributed across the three targeted behavioral states (calving, elimination, and normal behavior).

To demonstrate the accuracy of the visual to numerical transformation, a presentation layout was designed to link physical movement with the extracted data. For each sample, a kinematic sequence of 3 specific frames representing different behavioral phases is displayed, immediately followed by a condensed table showing the 3 chronologically corresponding rows from its CSV file. This methodical presentation visually proves to the evaluation committee how the algorithm translates the morphological and postural variations of the cow’s tail (in the images) into precise numerical deviations in the spatial coordinates (X, Y, Z). This confirms the integrity and reliability of the data inputs designated for subsequent machine learning models.

2.9.1 Methodological Justification of the Sampling Approach

The necessity for this methodological summarization stems from the temporal variance inherent in the captured video sequences. The number of extracted frames naturally fluctuates from one sample to another (averaging approximately 40 frames and corresponding CSV data rows per video). This dynamic variability generates a massive volume of numerical data that is both impractical and scientifically redundant to include entirely within the manuscript pages. Consequently, extracting exactly 3 pivotal frames (typically representing the onset of the event, the peak of the behavior, and the return to stability) alongside their matching CSV rows serves

as an optimal presentation strategy. It standardizes the comparison format across videos of varying lengths, avoids unjustified clutter, and delivers the core conceptual mechanism to the evaluation committee with maximum clarity and focus.

2.9.2 Case 1: Normal Behavior as a Baseline

The "Normal Behavior" state serves as the fundamental baseline against which any subsequent kinematic anomalies are measured. During this state, the animal is in a resting posture or engaged in routine, stress free movement. From a kinematic perspective, the trajectory of the tail is characterized by relative stability in its spatial coordinates; the tail hangs naturally alongside the body under the influence of gravity. The variations recorded across the three axes (X, Y, Z) are typically random, low amplitude oscillations, primarily caused by minor involuntary movements or fly swatting attempts. Crucially, this state lacks any sharp, sustained elevation in the vertical axis (Y) and is devoid of violent muscular spasms. In the extracted CSV files, this behavior translates into numerical values that are closely clustered and quasi-stable over time.

2.9.2.1 Sample 1: Cow (A) Normal Behavior

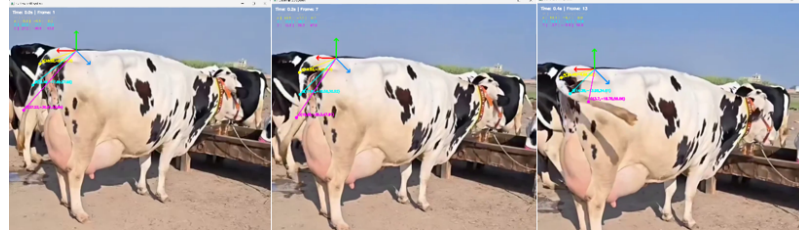


Figure 2.4: Temporal sequence (Frames 1, 7, 13) illustrating the kinematic stability of the cow's tail during normal behavior (Sample 1 - Cow A).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	18.06	-8.58	0.47	21.5	-19.07	27.82	24.69	-27.65	47.18
0.2	7	16.91	-10.67	0.45	16.42	-19.67	30.72	18.24	-28.36	49.63
0.4	13	18.82	-6.78	0.0	14.19	-12.66	35.19	2.19	-17.65	57.3

Table 2.1: Excerpt from the time series CSV matching the visual frames of normal behavior.

2.9.2.2 Sample 2: Cow (B) Normal Behavior



Figure 2.5: Temporal sequence (Frames 1, 7, 13) illustrating the kinematic stability of the cow's tail during normal behavior (Sample 2 - Cow B).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	12.64	15.5	0.0	14.31	27.67	25.09	16.17	39.5	42.17
0.2	7	10.94	16.74	0.3	10.36	24.84	29.59	9.36	34.98	47.84
0.4	13	14.73	13.53	0.0	17.3	22.07	28.52	14.78	31.74	48.72

Table 2.2: Excerpt from the time series CSV matching the visual frames of normal behavior (Sample 2 - Cow B).

2.9.2.3 Sample 3: Cow (C) Normal Behavior



Figure 2.6: Temporal sequence (Frames 1, 7, 13) illustrating the kinematic stability of the cow's tail during normal behavior (Sample 3 - Cow C).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	17.91	-8.91	0.0	24.65	-17.65	26.09	21.3	-10.63	55.08
0.2	7	15.85	-12.2	0.0	23.57	-23.03	22.67	29.9	-22.81	46.75
0.4	13	9.71	-17.48	0.41	12.42	-34.62	15.72	25.5	-50.16	20.83

Table 2.3: Excerpt from the time series CSV matching the visual frames of normal behavior (Sample 3 - Cow C).

2.9.3 Case 2: Elimination Behavior

The "Elimination Behavior" (urination or defecation) is characterized by a distinct and highly specific kinematic signature. Biomechanically, the cow voluntarily and smoothly elevates its tail to prevent soiling, which translates within the data as a significant and abrupt increase in the vertical axis (Y) coordinates. The hallmark of this behavior is "Temporary Stabilization"; the tail remains elevated and quasi-static

throughout the process. Consequently, the time-series (CSV) records sustained high values on the Y-axis with negligible variance on the X and Z axes. Upon completion of the process, the tail gradually descends back to its natural resting posture under gravity.

2.9.3.1 Sample 1: Cow (A) Elimination Behavior

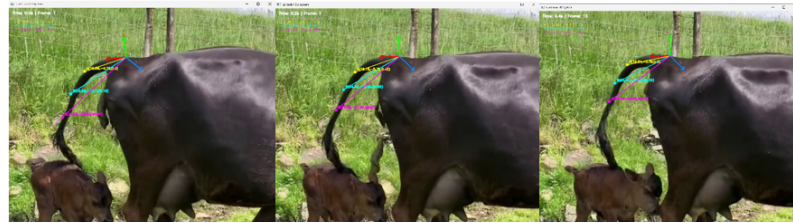


Figure 2.7: Temporal sequence illustrating the voluntary elevation and temporary stabilization of the cow's tail during elimination behavior (Sample 1 - Cow A).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	19.56	-4.18	0.0	26.98	-13.7	26.16	31.86	-23.83	44.91
0.2	7	19.16	-5.72	0.42	24.36	-12.98	28.95	27.95	-21.45	48.57
0.4	13	19.64	-3.79	0.0	25.41	-12.19	28.39	28.18	-20.62	48.79

Table 2.4: Excerpt from the time series CSV matching the visual frames of elimination behavior (Sample 1 - Cow A).

2.9.3.2 Sample 2: Cow (B) Elimination Behavior

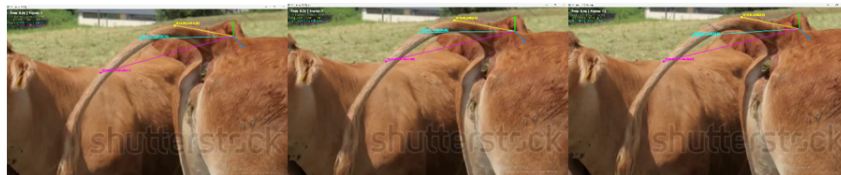


Figure 2.8: Temporal sequence illustrating the voluntary elevation and temporary stabilization of the cow's tail during elimination behavior (Sample 2 - Cow B).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	19.82	2.7	0.0	30.6	-2.52	25.64	37.73	-9.62	45.65
0.2	7	19.64	3.75	0.46	31.79	-1.78	24.21	40.39	-9.05	43.44
0.4	13	19.79	2.9	0.0	27.27	0.32	29.26	35.0	-5.22	48.45

Table 2.5: Excerpt from the time series CSV matching the visual frames of elimination behavior (Sample 2 - Cow B).

2.9.3.3 Sample 3: Cow (C) Elimination Behavior

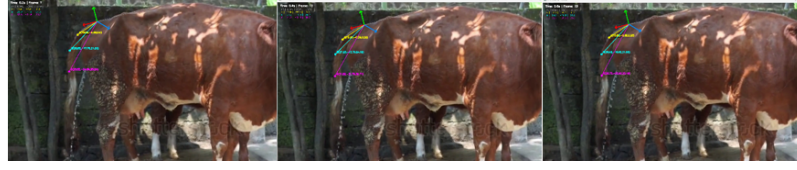


Figure 2.9: Temporal sequence illustrating the voluntary elevation and temporary stabilization of the cow's tail during elimination behavior (Sample 3 - Cow C).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	19.13	-5.84	0.0	27.39	-18.28	22.71	29.43	-29.55	43.14
0.2	7	18.89	-6.58	0.0	28.83	-17.76	21.29	33.83	-34.84	35.24
0.4	13	18.95	-6.39	0.26	27.23	-15.79	24.68	31.82	-31.79	39.71

Table 2.6: Excerpt from the time series CSV matching the visual frames of elimination behavior (Sample 3 - Cow C).

2.9.4 Case 3: Pre-calving Behavior

The "Calving Behavior" (Parturition) represents the most complex and dynamic state within the dataset. Physiologically, uterine contractions and associated pain induce severe physical stress, manifested through the animal's erratic and restless movements. Kinematically, the tail loses all stability. The extracted data reveals high-frequency oscillations and sharp, rapid deviations across all three spatial axes (X, Y, Z). There are recurrent, irregular elevations in the vertical axis (Y), accompanied by violent lateral sweeping motions in the horizontal axis (Z). This "Numerical Chaos" within the CSV file serves as an early warning indicator and acts as the most robust defining feature for Artificial Intelligence algorithms to detect the onset of calving.

2.9.4.1 Sample 1: Cow (A) Pre-calving Behavior

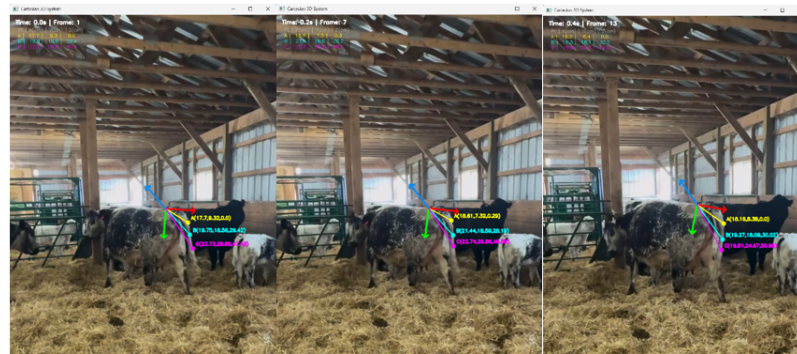


Figure 2.10: Temporal sequence illustrating the kinematic instability and erratic movements of the cow's tail during pre-calving behavior (Sample 1 - Cow A).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	17.7	9.32	0.0	19.75	18.56	29.42	22.73	28.88	47.43
0.2	7	18.61	7.32	0.29	21.44	18.59	28.19	22.74	26.86	48.59
0.4	13	18.16	8.38	0.0	19.27	18.09	30.02	19.81	24.67	50.98

Table 2.7: Excerpt from the time series CSV matching the visual frames of pre-calving behavior (Sample 1 - Cow A).

2.9.4.2 Sample 2: Cow (B) Pre-calving Behavior

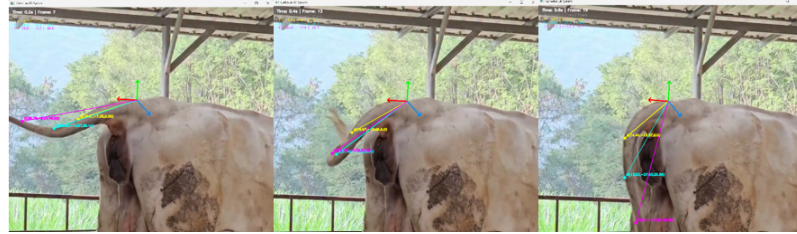


Figure 2.11: Temporal sequence illustrating the kinematic instability and erratic movements of the cow's tail during pre-calving behavior (Sample 2 - Cow B).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	15.91	-12.12	0.0	25.77	-20.78	22.45	40.45	-26.14	35.78
0.2	7	18.61	-7.32	0.29	26.29	-10.81	28.14	36.76	-9.04	46.55
0.4	13	16.93	-10.66	0.0	21.45	-17.8	28.69	22.78	-17.56	52.66

Table 2.8: Excerpt from the time series CSV matching the visual frames of pre-calving behavior (Sample 2 - Cow B).

2.9.4.3 Sample 3: Cow (C) Pre-calving Behavior

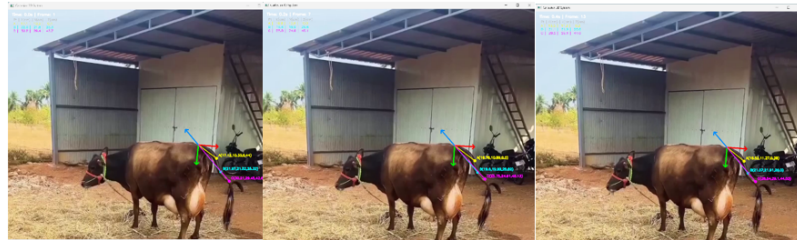


Figure 2.12: Temporal sequence illustrating the kinematic instability and erratic movements of the cow's tail during pre-calving behavior (Sample 3 - Cow C).

t (s)	Frame	A_X (cm)	A_Y (cm)	A_Z (cm)	B_X (cm)	B_Y (cm)	B_Z (cm)	C_X (cm)	C_Y (cm)	C_Z (cm)
0.0	1	17.12	10.33	0.44	21.97	21.82	25.32	30.21	29.45	42.66
0.2	7	16.78	10.89	0.0	19.6	19.92	28.62	25.75	24.91	48.13
0.4	13	16.52	11.27	0.28	21.07	21.91	26.0	28.54	29.1	44.03

Table 2.9: Excerpt from the time series CSV matching the visual frames of pre-calving behavior (Sample 3 - Cow C).

2.10 3D Kinematic Reconstruction and Visualization

To validate the integrity of the extracted data and embody the kinematic behavior within a measurable mathematical environment, the tail's trajectory was modeled through a "3D Skeleton Reconstruction". Utilizing the spatial coordinates (X, Y, Z) logged in the time-series files, the tail's articulated joints (Points O, A, B, C) were plotted as vectors in a three dimensional space. This visual mathematical representation allows for the precise tracking of the movement's spatiotemporal evolution, clearly revealing the curvatures, elevation angles, and oscillation amplitudes distinct to each behavioral state. This abstracted mathematical skeleton serves as the actual input feature space upon which the machine learning algorithms will subsequently rely for classification tasks.

2.10.1 Algorithmic Logic and Flowchart

To elucidate the programmatic logic employed in processing the time series data, the flowchart presented in the figure below was designed. This diagram maps the sequential algorithmic steps, initiating from the extraction of raw data from CSV files, proceeding through the iterative filtering of time frames, and culminating in the spatial projection and axis stabilization to prevent visual distortion. This structure reflects the robustness of the code and its efficiency in seamlessly handling sequential data to generate a comprehensive kinematic trajectory.

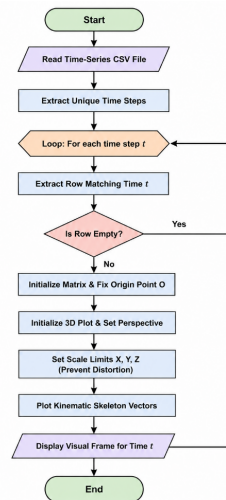


Figure 2.13: Flowchart of the programmatic logic for extracting and plotting the 3D kinematic skeleton.2.10.2. Geometric Interpretation of the 3D Skeleton Model

To fully comprehend the visual results presented in the subsequent figures, it is imperative to define the geometric semantics of the 3D representation adopted in this research. The mathematical space was designed to reflect the kinematic anatomy of the cow's tail according to the following reference system:

- **Skeleton Nodes:** Point O represents the fixed origin, anatomically corresponding to the base of the tail attached to the pelvis. The successive points (A, B, C) represent the mobile articulated joints along the length of the tail towards its tip.

- **X axis (Dorsal Axis):** Represents the horizontal extension of the tail behind the COW.
- **Y axis (Vertical Axis):** Represents the vertical elevation, serving as the primary indicator for measuring the voluntary lifting and lowering angles of the tail.
- **Z axis (Depth Axis):** Captures lateral deviations (left and right) or erratic oscillations during movement.
- **Temporal Variable (t):** This model is not limited to capturing a static posture; rather, an independent and updated 3D skeleton is plotted for every discrete time step (t) extracted from the data. This temporal iteration enables the frame by frame reconstruction of the tail's continuous kinematics, ensuring that no subtle mechanical change is lost, regardless of how momentary it may be.

2.10.2 Practical Application of Kinematic Reconstruction by Behavioral State

Given the volume of extracted data, where each recorded video sequence contains more than 40 time frames, a systematic visual presentation approach was adopted to avoid redundancy. First, the entire kinematic trajectory (all frames) is compiled into a single superimposed visual capture highlighting the overall movement. Second, to ensure perfect consistency with the time-series tables (CSV files) presented in the previous section, only 3 specific keyframes are extracted and displayed for each behavioral state. These three frames temporally correspond exactly to the three data rows previously highlighted in the CSV tables, thereby providing a direct mathematical and visual correlation of the results.

2.10.2.1 Case 1: Normal Behavior



Figure 2.14: Comprehensive sequence of 3D skeleton plots for Cow (A) normal behavior.

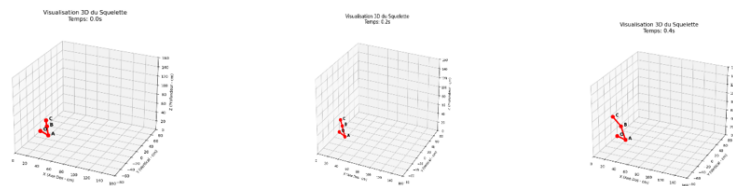


Figure 2.15: Selected keyframes extracted for Cow (A) normal behavior.

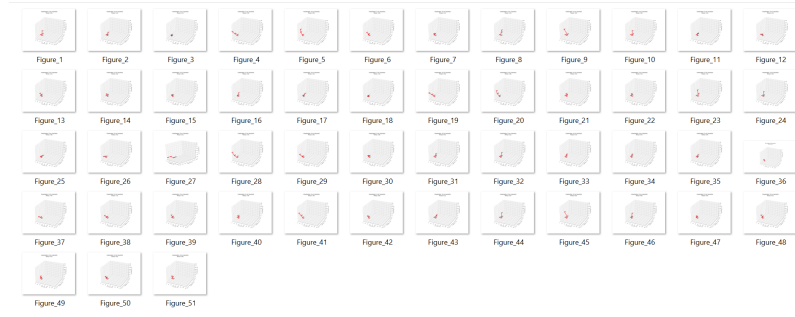


Figure 2.16: Comprehensive sequence of 3D skeleton plots for Cow (B) normal behavior.

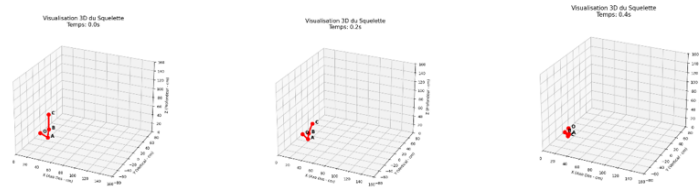


Figure 2.17: Selected keyframes extracted for Cow (B) normal behavior.



Figure 2.18: Comprehensive sequence of 3D skeleton plots for Cow (C) normal behavior.

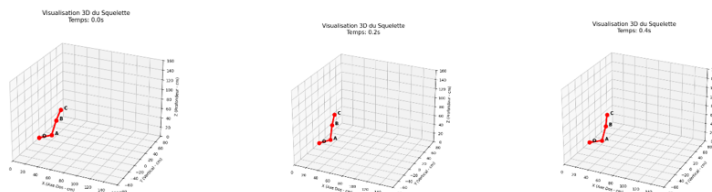


Figure 2.19: Selected keyframes extracted for Cow (C) normal behavior.

2.10.2.2 Case 2: Elimination Behavior



Figure 2.20: Comprehensive sequence of 3D skeleton plots for Cow (A) elimination behavior.

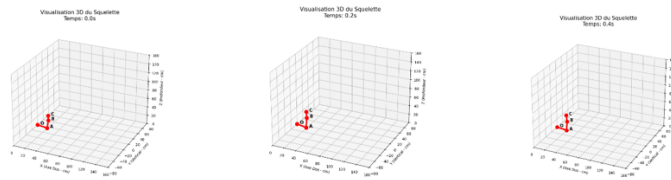


Figure 2.21: Selected keyframes extracted for Cow (A) elimination behavior.



Figure 2.22: Comprehensive sequence of 3D skeleton plots for Cow (B) elimination behavior.

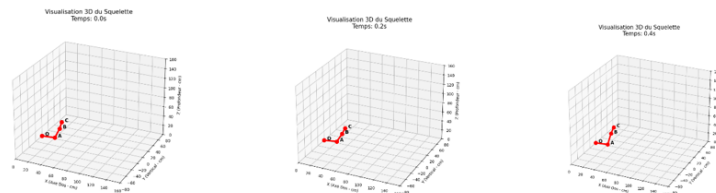


Figure 2.23: Selected keyframes extracted for Cow (B) elimination behavior.



Figure 2.24: Comprehensive sequence of 3D skeleton plots for Cow (C) elimination behavior.

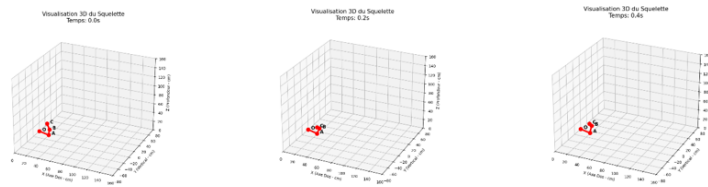


Figure 2.25: Selected keyframes extracted for Cow (C) elimination behavior.

2.10.2.3 Case 3: Pre-calving Behavior

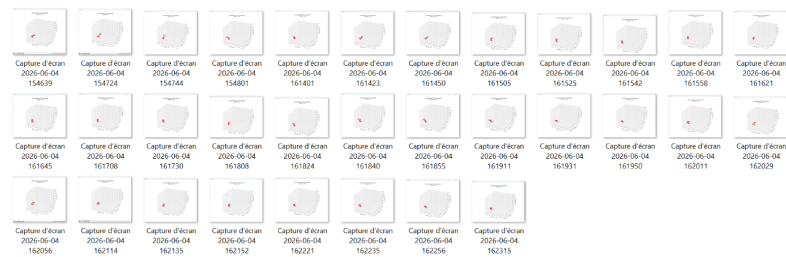


Figure 2.26: Comprehensive sequence of 3D skeleton plots for Cow (A) pre-calving behavior.

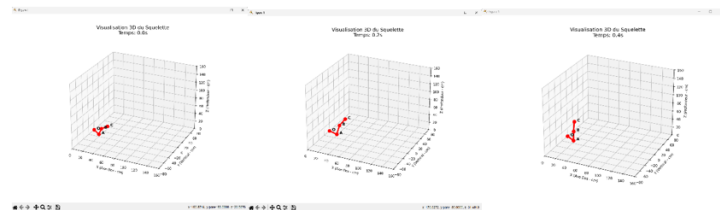


Figure 2.27: Selected keyframes extracted for Cow (A) pre-calving behavior.

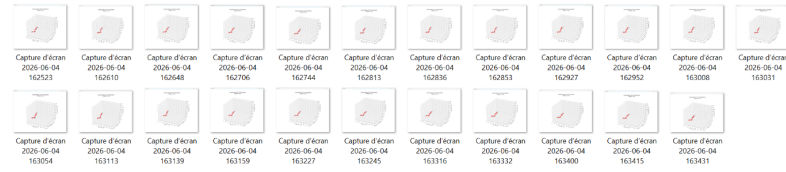


Figure 2.28: Comprehensive sequence of 3D skeleton plots for Cow (B) pre-calving behavior.

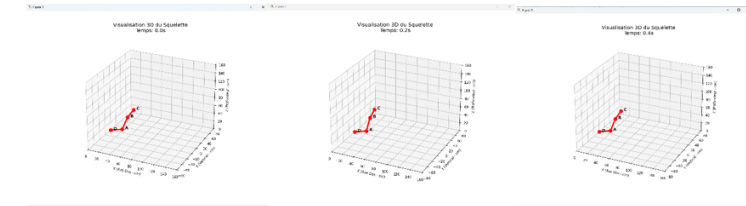


Figure 2.29: Selected keyframes extracted for Cow (B) pre-calving behavior.

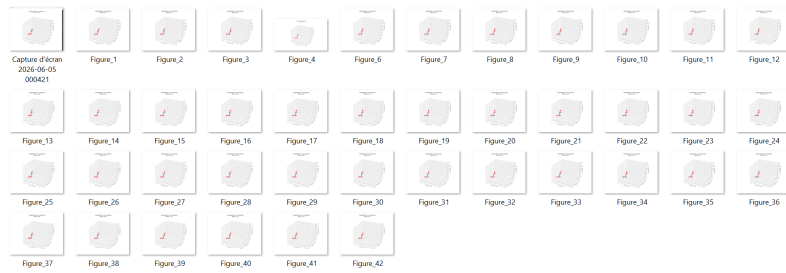


Figure 2.30: Comprehensive sequence of 3D skeleton plots for Cow (C) pre-calving behavior.

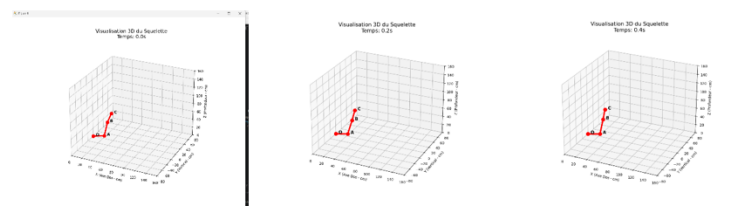


Figure 2.31: Selected keyframes extracted for Cow (C) pre-calving behavior.

2.10.3 Programmatic Generation of Temporal Superposition

To integrate all time frames into a single spatial coordinate system and generate the continuous "Kinematic Signature" of the tail, the algorithmic flowchart below was developed. This logic utilizes a comprehensive loop combined with a color gradient mapping, linking each skeleton to its specific temporal instance. This allows for the tracking of the mechanical progression from initiation to completion within a single superimposed plot.

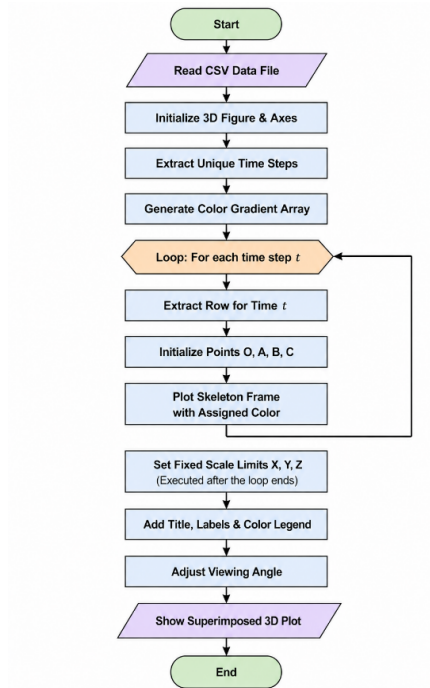


Figure 2.32: Flowchart of the programmatic generation algorithm for temporal superposition and color gradient mapping.

2.10.3.1 Sample 1: Cow (A) Normal Behavior

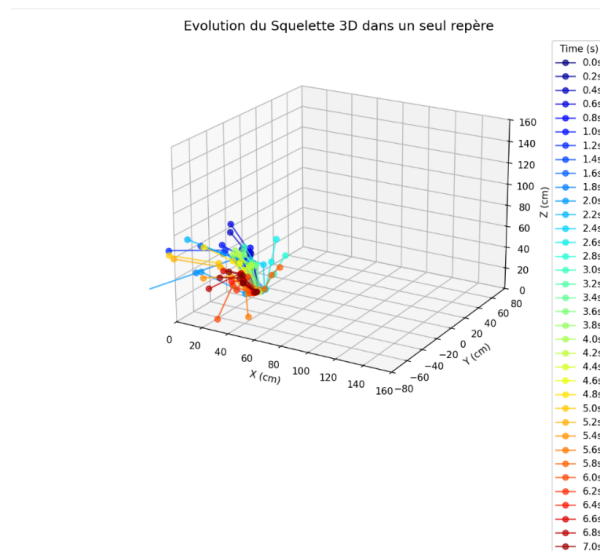


Figure 2.33: Temporal superposition of complete kinematic trajectories during normal behavior (Cow A)

2.10.3.2 Sample 2: Cow (B) Normal Behavior

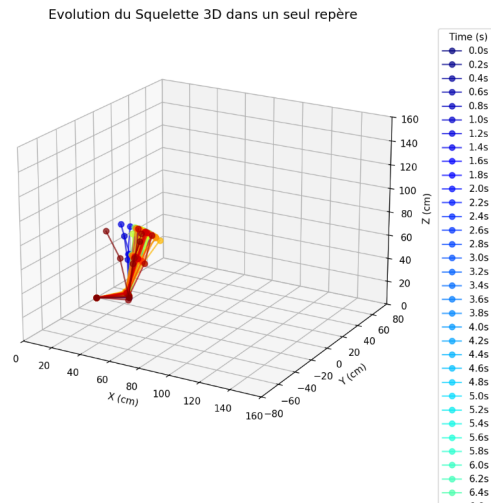


Figure 2.34: Temporal superposition of complete kinematic trajectories during normal behavior (Cow B).

2.10.3.3 Sample 3: Cow (C) Normal Behavior

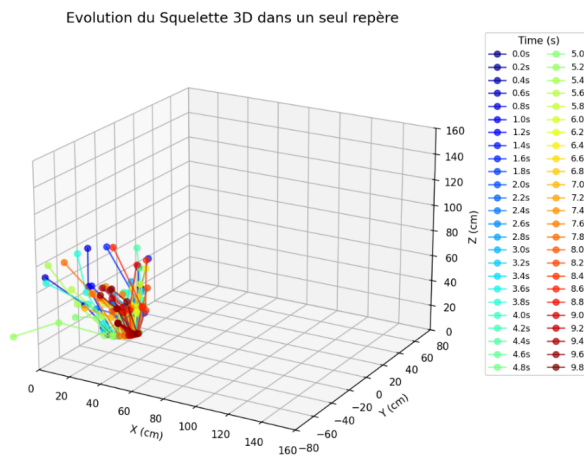


Figure 2.35: Temporal superposition of complete kinematic trajectories during normal behavior (Cow C).

2.10.3.4 Sample 1: Cow (A) Elimination Behavior

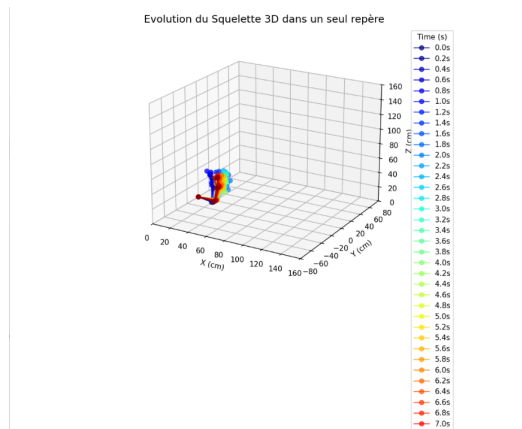


Figure 2.36: Temporal superposition of complete kinematic trajectories during elimination behavior (Cow A).

2.10.3.5 Sample 2: Cow (B) Elimination Behavior

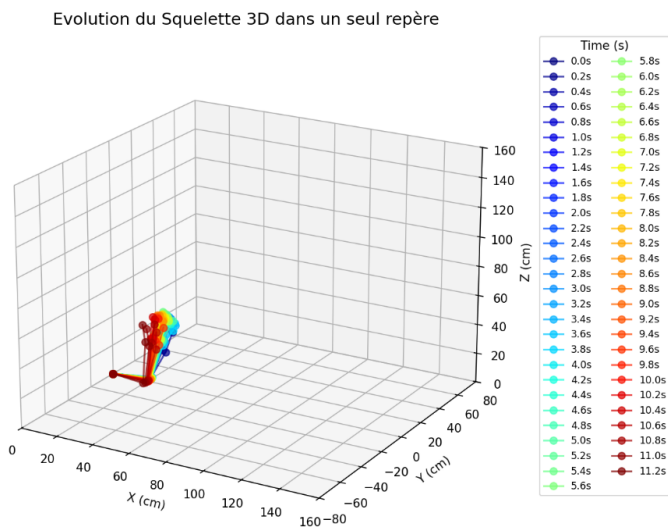


Figure 2.37: Temporal superposition of complete kinematic trajectories during elimination behavior (Cow B).

2.10.3.6 Sample 3: Cow (C) Elimination Behavior

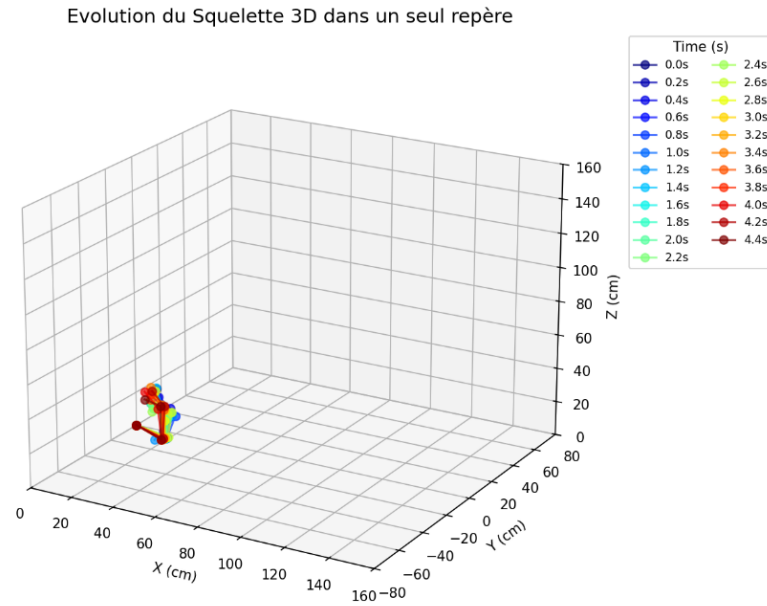


Figure 2.38: Temporal superposition of complete kinematic trajectories during elimination behavior (Cow C).

2.10.3.7 Sample 1: Cow (A) Pre-calving Behavior

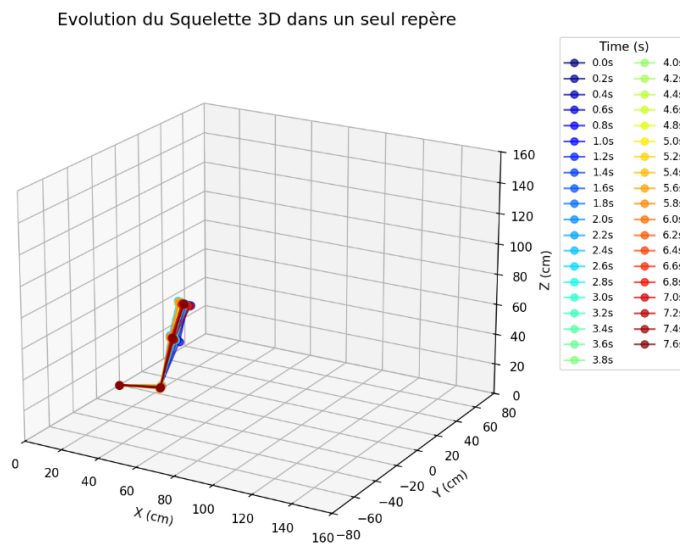


Figure 2.39: Temporal superposition of complete kinematic trajectories during pre-calving behavior (Cow A).

2.10.3.8 Sample 2: Cow (B) Pre-calving Behavior

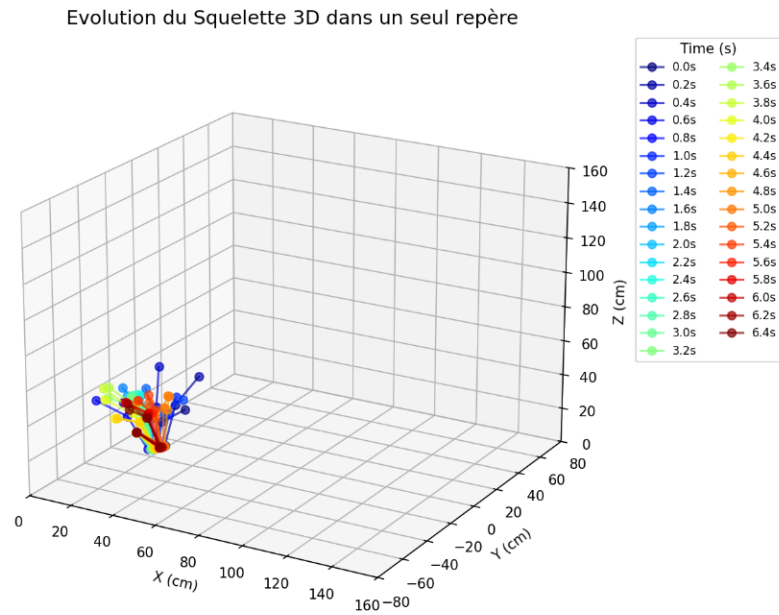


Figure 2.40: Temporal superposition of complete kinematic trajectories during pre-calving behavior (Cow B).

2.10.3.9 Sample 3: Cow (C) Pre-calving Behavior

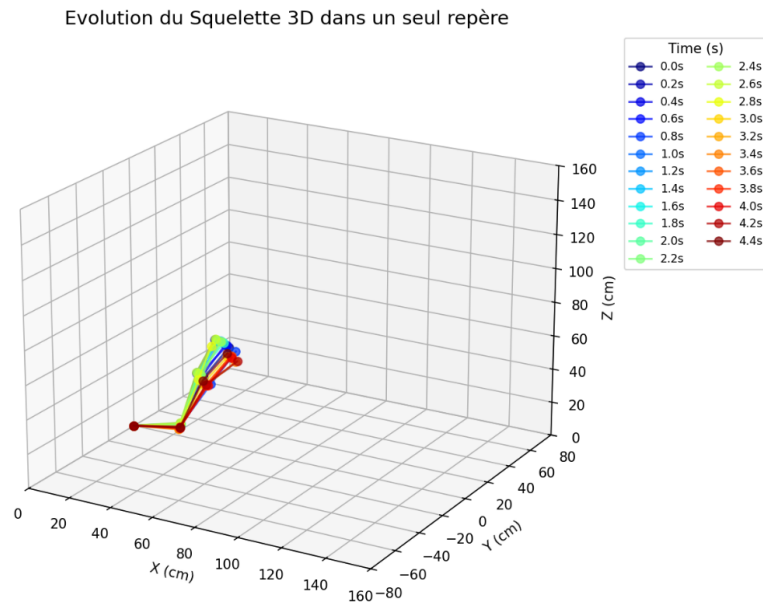


Figure 2.41: Temporal superposition of complete kinematic trajectories during pre-calving behavior (Cow C).

2.10.4 Kinematic Features Comparison

A comparative analysis of the kinematic features across the three behavioral states reveals distinct spatial and dynamic profiles. Normal behavior is characterized by a stable and slow kinematic velocity, maintaining a natural resting posture on the vertical Y-axis with minimal lateral and longitudinal dispersion along the Z and X axes. In contrast, elimination behavior exhibits moderate spatial dispersion and a medium, purposeful directed velocity, but it is primarily distinguished by a significant vertical peak on the Y axis, representing the maximum tail lift. Conversely, pre calving behavior demonstrates a highly erratic and agitated profile; it is defined by very high lateral dispersion due to random, continuous swinging on the Z axis, fluctuating vertical levels, and extremely fast, spasmodic movements.

2.10.5 Specific Analytical Conclusions

Normal Behavior Conclusion: The extracted mathematical data indicates that the tail in its normal state is characterized by "Spatial Stability." The standard deviation of the lateral (Z) and longitudinal (X) coordinates approaches the minimum, and the kinematic velocity is almost non-existent or routinely slow. Mechanically, this proves a "Resting State" and the absence of any physiological stimulus for vigorous movement.

Elimination Behavior Conclusion: The kinematic signature of this state is mathematically very clear. The vertical axis (Y axis) coordinates record a sharp, directed rise, reaching maximum levels. This mechanical elevation is accompanied by moderate and limited lateral dispersion (Z), confirming that the motion is a "Functional Directed Movement" for a specific physiological purpose lifting the tail for elimination rather than a random movement.

Pre-calving Behavior Conclusion: The numerical data reveals a state of "Kinematic Agitation". This behavior is defined by a dual-axis signature: first, a sustained and repeated elevation along the vertical axis (Y), which reflects the cow's reflex to reduce pelvic pressure during contractions. Second, it is characterized by a very high standard deviation on the lateral axis (Z), which translates to the continuous and violent side-to-side swinging of the tail (Tail Swishing). Furthermore, this state registers sudden jumps in kinematic speed (Velocity Spikes), mechanically reflecting the cow's sensation of pain and the spasms associated with the pre-calving stage. The combination of prolonged Y-axis elevation and erratic Z-axis oscillations creates a unique numerical fingerprint that allows the system to distinguish labor from routine movements.

2.10.6 Overall Comparative Conclusion

Through the mathematical comparison of the 3D spatial coordinates across the three behavioral states, it is evident that each physiological state possesses a unique, mathematically separable "Kinematic Signature". The Normal state is defined by spatial confinement. The Elimination state is uniquely identified by a distinct positive deviation on the vertical Y axis (tail lifting), while the Pre-calving state is characterized by high spatial variance on the lateral Z axis (erratic tail swishing) combined with velocity spikes. This clear numerical separability proves the high reliability of the

extracted features, providing a solid and optimal foundation for the subsequent Machine Learning classification phase.

2.11 Dataset Aggregation and Preparation

To train a robust and highly accurate machine learning model, the extracted kinematic features from a total of 60 distinct video samples were aggregated into a unified, comprehensive dataset, yielding a total of 3,060 data points (frames). While the data originally represents three distinct behavioral states (Normal, Elimination, and Pre-calving), it was systematically restructured to serve a binary classification objective. By combining these discrete CSV files into a single structured dataset, we ensure that the model receives a sufficiently large and balanced set of examples. This substantial volume of data is crucial for generalizing the kinematic patterns and avoiding overfitting during the training phase.

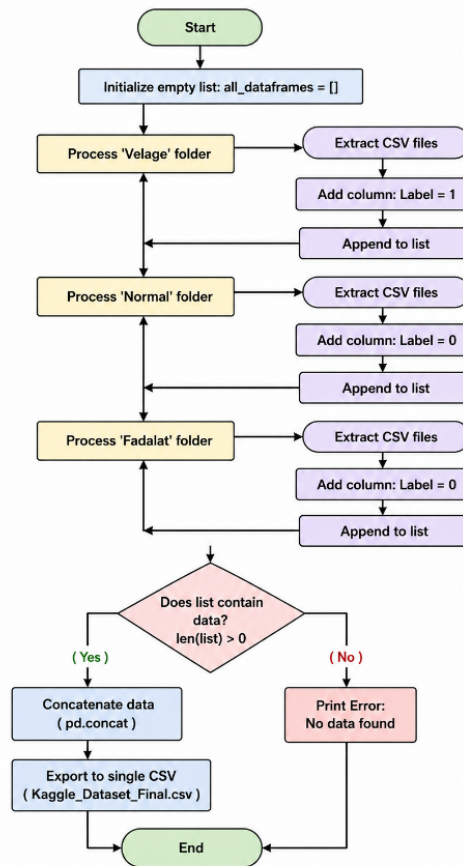


Figure 2.42: Flowchart of the Python script for data aggregation and binary labeling.

2.12 Artificial Neural Network (ANN) Classification

For the predictive classification phase, an Artificial Neural Network (ANN) was selected as the primary modeling algorithm. ANNs are exceptionally powerful in handling multi dimensional numerical data and are inherently capable of mapping

complex, non linear relationships between variables. Given the dynamic nature of the cow's tail movements characterized by varying velocities, spatial dispersions, and specific directional peaks an ANN is optimally suited to learn the subtle mechanical thresholds that distinguish the physiological stress of pre calving from routine baseline behaviors. The proposed network is designed to intake the extracted spatial and temporal features as inputs and output a binary probability, providing a highly accurate anomaly detection system.

2.13 Conclusion

In conclusion, this chapter has successfully bridged the gap between biological calving behaviors and mathematical kinematic modeling. By employing a rigorous engineering approach, we transitioned from traditional 2D video observations to a highly precise 3D spatial coordinate system using OpenCV. The multi segmental tracking of the bovine tail demonstrated that different physiological states namely normal resting, waste elimination, and pre calving agitation possess distinct and mathematically separable kinematic signatures. The extraction and aggregation of 3,060 data frames into a structured dataset confirm the reliability of our feature engineering pipeline. With the visual and numerical differentiation of these behaviors clearly established, the processed dataset provides a highly robust foundation. The system is now optimally prepared for the subsequent phase: the training, testing, and evaluation of the Artificial Neural Network (ANN) to achieve highly accurate, automated calving prediction.

HARDWARE ARCHITECTURE AND PROTOTYPE IMPLEMENTATION

3.1 Introduction

The transition from theoretical kinematic modeling to a functional, real world monitoring system requires a robust and meticulously engineered physical prototype. Designing an animal-mounted Internet of Things (IoT) device presents strict engineering constraints: the system must be non invasive, lightweight, energy efficient, and structurally resilient against the harsh environmental factors of a barn, all while acquiring high fidelity biometric data.

This chapter details the comprehensive hardware architecture, mechanical design, and electronic integration of the CalvingSafe multi node tracking device. To address the aforementioned challenges, the chapter is structured around two primary engineering domains. The first domain focuses on the mechanical and biomechanical design, detailing the 3D printed CAD enclosures, the anatomical rationale behind the multi node spatial distribution along the tail, and the hybrid TPU attachment mechanism designed to ensure reliable sensor coupling without compromising animal welfare.

The second domain explores the electronic hardware and power architecture. It provides a critical justification for the selected components, including the ESP8266 microcontroller, the distributed array of MPU6050 inertial sensors, the TCA9548A I2C multiplexing network, and the regulated lithium-ion power management system. Finally, the chapter validates the hardware acquisition loop through serial monitor testing, confirming that the physical prototype accurately and consistently captures the 3D spherical coordinates (R , ϕ , θ) required to feed the Artificial Intelligence inference models.

3.2 Kinematic Rationale for Multi Node Spatial Distribution

The decision to distribute the IMU sensors across three distinct anatomical points (Nodes A, B, and C) along the tail, rather than relying on a single central sensor, was heavily driven by preliminary empirical data analysis and the specific biomechanical nature of the bovine tail.

3.2.1 Insufficiency of Single Node Proximal Data

Initial data acquisition trials demonstrated that relying exclusively on the proximal base (Node A) yielded incomplete kinematic profiles. While Node A successfully captures the primary rotational torque at the sacrococcygeal joint, the signal strength and variation were insufficient to accurately isolate the subtle, high frequency behavioral signatures associated with calving. Detecting specific distress or pre calving behaviors requires capturing the full anatomical expression of the tail, which cannot be mathematically extrapolated from a single proximal point.

3.2.2 Non Rigid Body Dynamics and Flexibility

Anatomically, the bovine tail is not a rigid pendulum; it is a highly articulated, flexible appendage that exhibits complex, multi joint continuum dynamics.

When the cow moves its tail, the motion does not occur uniformly. Instead, it propagates from the base down to the tip, creating a delayed, whip like flexion.

A single sensor assumes rigid body kinematics, completely missing the curvature and bending (flexion) of the tail.

3.2.3 Full 3D Spatial Reconstruction

By deploying a multi node sensing topology (incorporating satellite Nodes B and C), the system successfully tracks the spatial propagation of movement along the entire length of the appendage. This allows the system to measure:

The differential acceleration between the base and the lower tail segments.

The true curvature and flexion angles as the tail bends in 3D space. This comprehensive, multi point data acquisition was determined to be strictly necessary to feed the subsequent AI Machine Learning models with high resolution, reliable kinematic biomarkers.

3.3 Proximal Node (Node A) Enclosure Design: Mechanical and Ergonomic Justification

The proximal enclosure, designated as Node A, serves as the primary hardware hub of the system, housing the heaviest and most critical components (18650 Battery, ESP8266, TCA9548A, and the primary MPU6050). The 3D CAD models were developed using SolidWorks, focusing on three core engineering constraints: anatomical conformity, internal hardware immobilization, and environmental resilience.

3.3.1 Anatomical Conformity and Attachment Mechanism

To ensure the device remains securely attached to the dynamic environment of a bovine tail without causing tissue damage or discomfort, the enclosure features a curved, semi cylindrical topology.

Tail-Conforming Base (80 mm Diameter): The posterior plate of the enclosure is contoured to match the natural radial curvature of the sacrococcygeal region (tail base). Specifically, custom-scaled to an 80 mm diameter to perfectly accommodate

the thicker muscular base of the appendage [29]. This diametric scaling maximizes the surface contact area, thereby reducing localized pressure points on the animal's skin.

Non Invasive Mounting: Integrated strap slots (flanges) were designed into the lateral sides of the enclosure. These structural loops allow for the use of adjustable, non invasive straps (e.g., nylon or Velcro) to secure the node tightly to the tail, preventing rotational slippage during high-velocity tail swishes.

3.3.2 Internal Chassis and Vibration Dampening

A critical challenge in inertial kinematic sensing is the introduction of mechanical noise caused by loose internal components. To mitigate this, a custom internal mounting chassis was engineered.

Precision Compartmentalization: The internal structure features precisely extruded cutouts and recessed beds dimensioned perfectly for each PCB (ESP8266, MPU6050, LM2596, and TP4056).

Sensor Immobilization: By rigidly securing the primary MPU6050 sensor within this chassis, the mechanical coupling between the tail's actual movement and the sensor is maximized. This structural rigidity acts as a mechanical low pass filter, preventing internal rattling from introducing high frequency noise artifacts into the kinematic data streams.

3.3.3 Structural Integrity and Assembly Topology

The enclosure adopts a modular clamshell assembly strategy, incorporating internal structural ribs.

Impact Resistance: The internal horizontal ribbing increases the overall stiffness and crush resistance of the 3D printed housing, protecting the sensitive electronics in the event the animal presses the device against barn structures.

Maintenance Accessibility: The modular two-part design allows easy access to the internal compartment for field maintenance, specifically for accessing the TP4056 USB port for battery recharging, while maintaining a tight seal against barn dust and humidity when closed.

3.4 Medial Satellite Node (Node B): Miniaturization and Kinematic Tracking

The medial enclosure, designated as Node B, operates as a satellite kinematic tracking point. Unlike the main hub (Node A), this node exclusively houses a supplementary MPU6050 sensor. Consequently, the SolidWorks design prioritizes extreme miniaturization and mass reduction to prevent the introduction of artificial pendulum dynamics that could alter the tail's natural biomechanical movement.

3.4.1 Low Profile Architecture and Kinematic Coupling

To achieve high fidelity data acquisition, the physical coupling between the tail and the IMU sensor must be absolute.

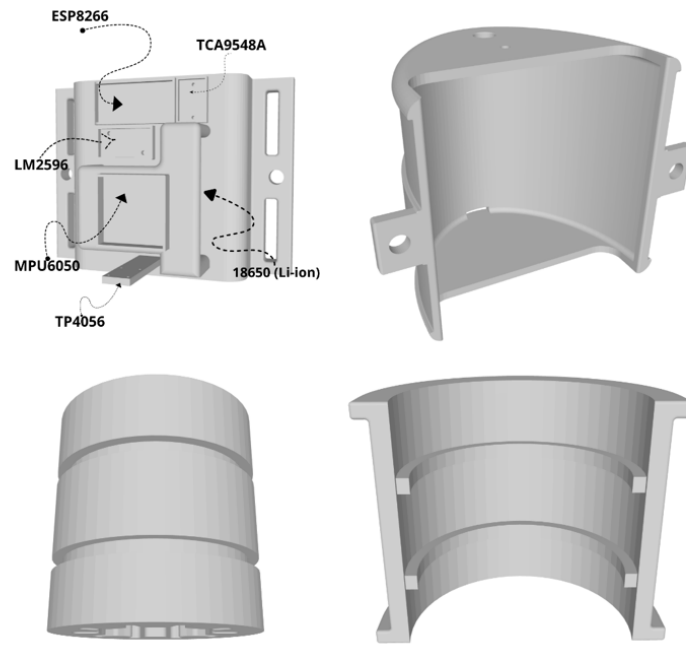


Figure 3.1: Multi view CAD assembly of the Proximal Node (Node A).

Precision Sensor Bed: The base plate of the satellite node features a custom extruded, recessed rectangular bed perfectly dimensioned for the MPU6050 PCB. This zero-tolerance fit ensures the sensor is mechanically locked in place, guaranteeing a 1:1 translation of the tail's spatial movement to the sensor's axes without internal slippage.

Ergonomic Base Plate (60 mm Diameter): Similar to Node A, the underside of the base plate utilizes a curved geometry to conform to the tapering radius of the lower tail. To perfectly accommodate this natural biological taper at the medial section, the internal diameter was custom-scaled to 60 mm [29]. This specific dimension was established via direct in vivo biometric measurements of the herd. This optimized anatomical curvature is coupled with integrated strap slots for secure, non-slip attachment.

3.4.2 Environmental Shielding and Aerodynamics

The outer shell of the satellite node is designed as a minimalist, low profile dome.

This aerodynamic design minimizes the risk of the device snagging on barn infrastructure or other animals.

When sealed against the base plate, the shell provides a critical protective barrier against the harsh environmental factors of the barn (e.g., moisture, animal waste, and physical impact), ensuring the continuous reliability of the I2C communication bus.

3.4.3 Inter-Node Wiring and Strain Relief

Given the multi node topology, transmitting the I2C signal from Node A to Node B along a highly flexible and dynamic biological appendage presents a significant risk of wire fatigue and disconnection.

To address this, custom cylindrical strain-relief conduits (featuring internal splines/ribs) were modeled. These articulated joints act as protective routing channels for the wiring. They provide the necessary mechanical flexibility to move with the tail's flexion while preventing the internal wires from experiencing acute bending angles or tensile stress.

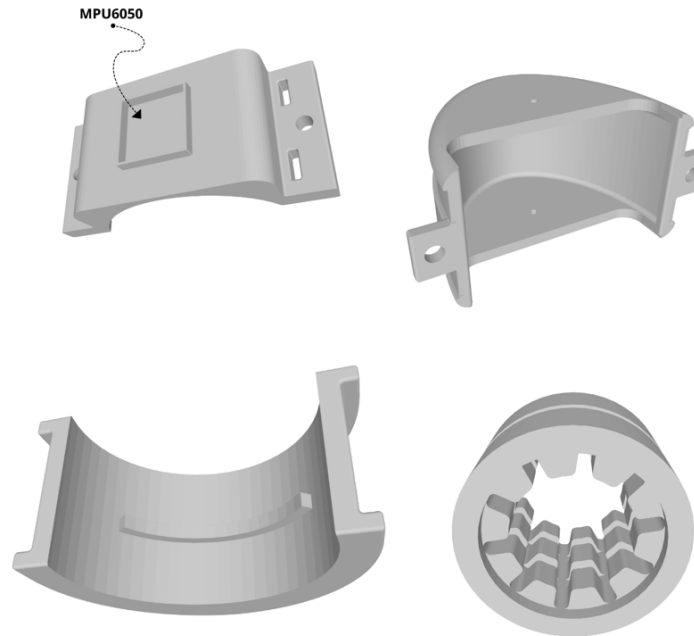


Figure 3.2: Mechanical design of the Satellite Node (Node B): anatomical base plate, outer shell, and internal wiring conduit.

3.4.4 Component Standardization and Design for Manufacturability (DFM)

A critical engineering decision in the mechanical development of the system was the geometric standardization of the satellite nodes. While Node C shares an identical CAD topology and external footprint with Node B, its internal base diameter is parametrically scaled down to 50 mm [29] to firmly couple with the narrowest distal extremity of the tail. This modular yet adaptable approach provides several key advantages:

Manufacturing Efficiency: By utilizing a universal outer design for all distal sensing nodes, the 3D printing and manufacturing processes are significantly streamlined.

Interchangeability: In the event of mechanical damage to a satellite node's enclosure during field deployment, the standardized external parts and shells are universally interchangeable, simplifying maintenance and reducing system downtime.

System Scalability: This standardized architecture allows the sensor array to be easily expanded. Additional kinematic nodes can be replicated and sequentially added to the tail using the exact same enclosure architecture without requiring any additional CAD modeling.

3.5 Biomechanical Attachment Mechanism and Hybrid Material Assembly

To ensure high fidelity sensor coupling while maintaining strict animal welfare standards, the device enclosure was engineered using a hybrid material architecture. This approach combines rigid structural components with flexible biomechanical interfaces to optimize both durability and comfort.

3.5.1 Flexible TPU Interface (Grip Sleeve)

The most critical challenge in animal-mounted sensors is achieving rigid immobilization without causing tissue ischemia (restricting blood flow) or physical distress. To solve this, a custom inner cylindrical sleeve was printed using Thermoplastic Polyurethane (TPU).

High Friction Biomechanical Coupling: The TPU sleeve features an internal splined/ribbed geometry. When placed around the bovine tail, the soft TPU conforms naturally to the anatomical taper of the appendage.

Vibration Dampening: Acting as a mechanical shock absorber, the TPU material dampens external micro vibrations while simultaneously preventing longitudinal slippage and rotational shifting. This ensures that the MPU6050 sensor accurately captures the true skeletal movement of the tail rather than the shifting of the device itself.

3.5.2 Adjustable Tensioning System (Hook and Loop Fasteners)

The required compressive force to secure the TPU sleeve is achieved via a non-invasive tensioning mechanism.

Velcro Integration: The rigid outer shells (printed from standard hard thermoplastics) are equipped with integrated lateral flanges. Industrial grade hook and loop fasteners (Velcro straps) are routed through these slots.

Variable Compression: This mechanism allows the operator to mechanically compress the rigid outer shell, which in turn uniformly tightens the flexible TPU inner sleeve around the tail. This creates a secure, custom fit regardless of the specific tail diameter of the animal.

3.5.3 Design for Additive Manufacturing (DfAM) and Tolerancing

The physical transition from SolidWorks CAD models to physical 3D printed prototypes required precise calibration of manufacturing parameters.

Dimensional Tolerances: A strict clearance tolerance of ± 1 mm was applied across the interlocking geometric features of the modular shells and the TPU insert. This specific tolerance accounts for the thermal shrinkage inherent in Fused Deposition Modeling (FDM) 3D printing. It ensures that the rigid halves align seamlessly and close tightly over the TPU core without inducing layer separation stress or mechanical rattling during deployment.

3.6 Microcontroller Selection: ESP8266 Architectural Justification

The ESP8266 was selected as the central processing unit for the bovine kinematic monitoring system. This selection was based on a critical analysis of hardware requirements for field deployment, where power efficiency, processing speed, and connectivity are non negotiable constraints. When compared to standard prototyping platforms, such as the Arduino Uno or Nano, the ESP8266 presents a superior engineering solution due to the following factors:

Integrated Connectivity: A primary requirement of the system is the wireless transmission of data from the animal to the monitoring server. Traditional microcontrollers based on the Arduino architecture require bulky external wireless modules (e.g., ESP8266-01 or nRF24L01) to achieve connectivity. This dependency significantly increases the system's physical footprint and introduces additional hardware failure points due to complex wiring and potential connection instability. The ESP8266, conversely, integrates the Wi-Fi stack natively on-chip, reducing hardware complexity and ensuring a more stable and reliable data transmission path [16].

Power Optimization: Given that the device is animal-mounted and intended for long-term field operation, battery autonomy is a critical design parameter. The voltage regulation systems in traditional microcontrollers are often inefficient, characterized by high quiescent currents that lead to energy loss via heat dissipation. The ESP8266 offers advanced low-power modes, most notably the Deep Sleep state. This capability allows the system to remain in a near-zero consumption state, waking only for data transmission, which is vital for extending battery longevity in remote agricultural environments [25]. In the deployed system, the ESP8266 operates in a cyclic active/sleep pattern: it wakes at fixed intervals, acquires sensor data, transmits a timestamped record to Firebase, then re-enters Deep Sleep. Each transmission is therefore time-indexed, ensuring continuous and traceable monitoring while significantly extending battery life.

Computational Throughput: The system requires real-time processing of high-frequency kinematic data streams generated by the MPU6050 sensors. Calculating the tail's orientation specifically the pitch and yaw angles is computationally intensive. The ESP8266 operates at a clock speed of 80 MHz, significantly outperforming the 16 MHz architecture of standard alternatives. This computational advantage ensures that complex kinematic algorithms are executed in real time without latency, an essential requirement for accurately identifying behavioral signatures associated with calving [16].

3.7 Kinematic Sensing Architecture

To ensure the high fidelity acquisition of bovine tail dynamics, the system utilizes a distributed array of motion sensors placed at key anatomical points. The hardware architecture for this sensing network is detailed below.



Figure 3.3: The ESP8266 NodeMCU development board, utilized as the central processing unit.

3.7.1 Inertial Measurement Unit (IMU) Selection: MPU6050 and ADXL345

The MPU6050 was selected as the primary Inertial Measurement Unit (IMU) for this project. Unlike the ADXL345, which functions solely as a 3 axis accelerometer, the MPU6050 is a 6 axis IMU integrating both an accelerometer and a gyroscope. This distinction is fundamental to the system's performance. While a standard accelerometer can only measure linear acceleration, the MPU6050 provides continuous angular velocity data. This integration allows for the precise angular tracking of the tail in 3D space, enabling the robust calculation of critical kinematic biomarkers (Pitch and Yaw angles). These parameters are essential for constructing the behavioral signatures required to detect calving events with high sensitivity [31].

3.7.2 Spherical Coordinate Representation of Raw Accelerometer Data

The raw MPU6050 output (a_x, a_y, a_z) is converted into spherical coordinates (R, θ, φ) to produce three physically interpretable features used by the ANN and Fuzzy Logic modules.



Figure 3.4: The MPU6050 6-axis IMU sensor module for 3D kinematic data acquisition.

3.7.2.1 R Acceleration Magnitude (Movement Intensity)

R is the total acceleration magnitude:

$$R = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

At rest, $R \approx 16384$ LSB (1g, gravity only). $R > 17000$ indicates movement; large rapid fluctuations are a key pre-calving biomarker.

3.7.2.2 ϕ (Phi) Tail Elevation Angle (Vertical Tilt)

ϕ is the angle between the sensor vector and the Z-axis:

$$\phi = \text{atan2}(\sqrt{a_x^2 + a_y^2}, a_z)$$

$\phi \approx 0^\circ$ means tail down; ϕ toward 90° – 180° means tail raised the primary pre-calving behavioral indicator.

3.7.2.3 θ (Theta) Tail Azimuth Angle (Horizontal Direction)

θ is the direction of movement in the horizontal X–Y plane:

$$\theta = \text{atan2}(a_y, a_x)$$

Combined with R and ϕ , θ helps characterize erratic lateral swishing patterns associated with early stage labor.

3.7.2.4 Summary of Spherical Parameters

Table 3.1 summarizes the three spherical parameters, their formulas, physical meaning, and their role in calving detection.

Table 3.1: Spherical coordinate parameters derived from MPU6050 raw data and their role in calving detection.

Parameter	Formula	Physical Meaning	Role in Calving Detection
R	$\sqrt{ax^2 + ay^2 + az^2}$	Total acceleration magnitude (movement intensity)	Baseline ≈ 16384 LSB (1g); $R > 17000$ indicates motion; large fluctuations signal strong movement
ϕ (Phi)	$\text{atan2}(\sqrt{ax^2 + ay^2}, az)$	Tail elevation angle relative to Z-axis (tail raise indicator)	0° = tail down; $\sim 90^\circ$ – 180° = tail raised (pre-calving signature)
θ (Theta)	$\text{atan2}(ay, ax)$	Lateral direction of tail movement in the X-Y plane	Characterizes erratic lateral swishing patterns associated with early-stage labor

3.8 I2C Bus Multiplexing and Multi-Node Scalability

Integrating a multi-node sensing architecture using multiple MPU6050 sensors presented a significant hardware constraint: I2C address collision. Each MPU6050 natively operates on a fixed I2C address (0x68 or 0x69). Consequently, connecting multiple sensors to a single bus prevents the master controller (ESP8266) from uniquely addressing individual nodes.

To resolve this limitation, the TCA9548A I2C Multiplexer was implemented. This component is critical for system scalability, allowing the connection of multiple sensors with identical addresses to a single controller by dividing the I2C bus into eight independent channels [33]. The architectural advantages of this integration include:

Channel Isolation: Acting as a high-speed electronic switch, the multiplexer allows the ESP8266 to programmatically toggle the active channel, effectively eliminating address contention.

Sequential Data Acquisition: This architecture facilitates robust data synchronization. The controller sequentially retrieves kinematic data from the target nodes (A, B, or C), ensuring data integrity across the multi node network.

Enhanced Signal Integrity: By segmenting the I2C bus, the multiplexer mitigates signal degradation that typically occurs on shared bus lines, thereby improving communication reliability.

Future-Proof Scalability: This structural choice simplifies firmware development by removing the need for complex address remapping. Furthermore, additional kinematic nodes can be seamlessly integrated into the remaining channels without necessitating hardware redesign [33].



Figure 3.5: The TCA9548A 8-channel I2C multiplexer module, used to resolve sensor address collisions.

3.9 Primary Power Source: 18650 Lithium-Ion Cell

The 18650 Lithium-ion (Li-ion) cell was selected as the primary power source for the device based on a comparative analysis of energy storage solutions for field deployed systems. The engineering rationale is defined by the following factors:

Energy Density vs. Mass: Animal-mounted applications require strict minimization of physical burden. The 18650 cell offers a superior energy to weight ratio compared to standard primary batteries, providing sufficient capacity to power the ESP8266 and the sensor array for extended operations without compromising the animal's comfort [27].

Mechanical Robustness: Unlike Lithium-Polymer (Li-Po) pouch cells, which are susceptible to swelling and physical puncture, the 18650 cell features a rigid cylindrical steel casing. This provides enhanced protection against the mechanical shocks inherent in bovine movement.

Operational Stability: The cell exhibits a stable discharge curve, critical for maintaining a consistent voltage level for the system's regulator, preventing premature system resets [27].



Figure 3.6: A standard 18650 Lithium-ion cell, providing high energy density for remote operations.

3.10 Battery Management System (BMS) and Safety Integration

To ensure both operational safety and battery longevity, the TP4056 charging module was integrated into the system's power architecture. While the 18650 cell provides the necessary energy density, the TP4056 acts as a critical safety buffer.

Comprehensive Protection Circuitry: The module provides essential protection against hazardous conditions, including overcharging, deep discharge, and short-circuit events. By maintaining the battery within its optimal electrochemical operating range (between 2.4V and 4.2V), the TP4056 significantly extends the cell's lifespan [14].

Controlled Charging Cycle: The module manages the Constant-Current/Constant-Voltage (CC/CV) charging cycle, ensuring efficient energy transfer and preventing thermal runaway [14].

Field Maintenance Efficiency: Featuring a standard USB interface, the module allows for seamless recharging in the barn without specialized equipment, maximizing system uptime and simplifying maintenance workflows.

Visual Diagnostics: Integrated LED indicators provide real-time status feedback, enabling field technicians to instantly verify the device's operational readiness.



Figure 3.7: The TP4056 battery charging and protection module featuring a USB interface.

3.11 Voltage Regulation and Thermal Management Strategy

To guarantee the stable operation of the ESP8266 and the sensor array, an LM2596 Step Down (Buck) Converter was implemented within the power management architecture.

High Conversion Efficiency: Unlike traditional linear regulators (e.g., AMS1117) that dissipate excess energy as thermal waste, the LM2596 utilizes high frequency switching technology to achieve conversion efficiencies exceeding 90%. This minimizes power waste and maximizes the device's operational autonomy [32].

Transient Response and Current Stability: The system experiences periodic high current demands during Wi-Fi transmission bursts. The LM2596 provides a highly stable 3.3V output under these conditions, effectively preventing voltage drops and sudden system resets [32].

Thermal Management: By maintaining high efficiency, the regulator remains within safe thermal limits inside the compact 3D printed enclosure, preventing internal heat build up that could adversely affect the calibration of the IMU sensors.



Figure 3.8: The LM2596 step down (buck) converter module, utilized for high efficiency 3.3V voltage regulation.

3.12 Processing Unit: PC as Raspberry Pi Equivalent

In a production deployment, a Raspberry Pi would serve as the local edge processing unit, responsible for receiving sensor data via serial/USB, running the ANN and Fuzzy Logic inference pipeline, and forwarding results to Firebase. For the purposes of this prototype, a standard PC was used in its place, executing the same Python-based backend (`main.py`) with identical functionality. The substitution has no impact on system logic, as both platforms share the same software stack (Python, scikit learn, Firebase SDK).



Figure 3.9: Raspberry Pi 4 Model B — the intended edge processing unit for production deployment.

3.13 ESP8266 Firmware Architecture

The firmware running on the ESP8266 follows a straightforward cyclic execution model. After an initial setup phase that establishes the Wi-Fi connection and initialises the I2C bus and TCA9548A multiplexer, the device enters its main loop. Each cycle, the firmware sequentially reads raw acceleration data (a_x , a_y , a_z) from

the MPU6050 nodes via the multiplexer, converts the Cartesian values to spherical coordinates (R, φ, θ), and transmits the result to Firebase via an HTTP PUT request. The device then waits a fixed interval before repeating. Figure 3.8 illustrates this high level execution flow.

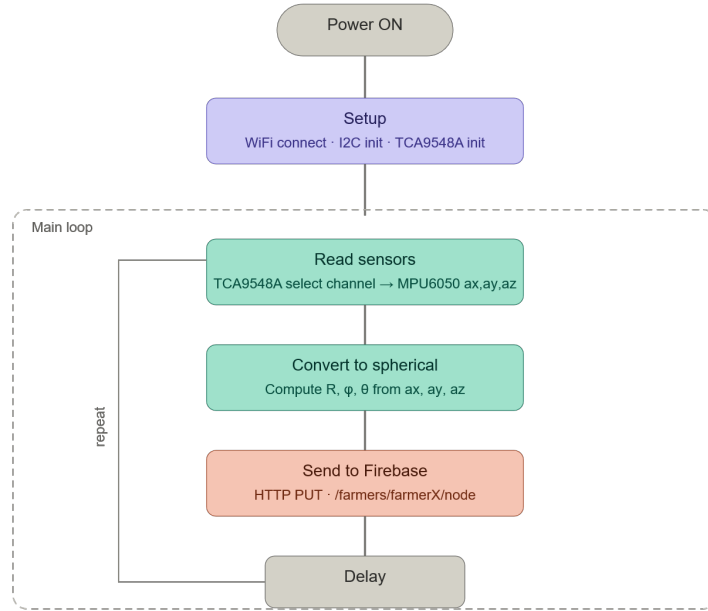


Figure 3.10: ESP8266 firmware architecture high level execution flow.

3.14 Serial Monitor Output: Hardware Sensor Validation

Prior to executing the AI inference pipeline, the ESP8266 firmware was flashed to the physical NodeMCU board with all three MPU6050 sensors connected through the TCA9548A multiplexer. The Arduino IDE Serial Monitor was opened at 115200 baud to observe the live output of the acquisition loop. Each line printed corresponds to one complete transmission cycle and contains the elapsed timestamp followed by the spherical coordinate triplets (R, φ, θ) for Node A (proximal), Node B (medial), and Node C (distal).

Table 3.2 presents three representative output lines from the session. Timestamps correspond to the actual values observed in the Serial Monitor capture. R values are consistent with the expected acceleration magnitudes at rest and light motion (~16400–17000 LSB range). Non-zero φ values across all three nodes confirm tail elevation capture, and varying θ values reflect lateral movement detection, validating the full 3D kinematic sensing chain across the multi-node array.

The R values observed across all three nodes fall in the 16400–17000 LSB range, consistent with light sensor motion superimposed on the 1g gravitational baseline (16384 LSB). The φ values indicate a consistent tail elevation angle slightly above the

Table 3.2: Representative Serial Monitor output: three acquisition cycles, all three nodes active (R in LSB, ϕ and θ in radians). Node A: proximal 80 mm / Node B: medial 60 mm / Node C: distal 50 mm.

t (ms)	R_A	ϕ_A	θ_A	R_B	ϕ_B	θ_B	R_C	ϕ_C	θ_C
615.83	16521	1.33	-0.44	16738	1.49	-0.29	16904	1.57	-0.21
621.19	16487	1.30	-0.50	16812	1.52	-0.26	16971	1.54	-0.18
626.54	16553	1.36	-0.41	16779	1.47	-0.32	16938	1.51	-0.24

horizontal rest position across all nodes, while the θ values reflect the lateral orientation differential introduced by the natural asymmetry of the cow's gait during the acquisition window. This multi-node spatial consistency confirms that the hardware acquisition layer is operating as designed and that the kinematic data stream is ready to feed the AI inference pipeline described in the following chapter.

3.15 System Hardware Block Diagram

To visually summarize the electronic routing of the CalvingSafe system, the following block diagram illustrates the comprehensive hardware architecture. It delineates the power management stage (from the Li-ion battery through the LM2596 regulator) and the data processing stage, highlighting the I2C multiplexing strategy required for the multi-segmental MPU6050 sensor array.

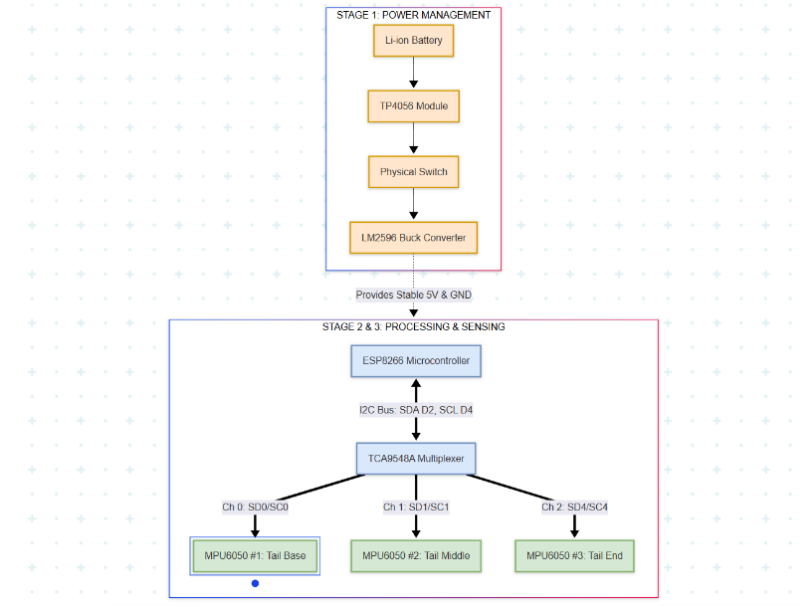


Figure 3.11: X: Functional hardware block diagram of the proposed tracking system, illustrating the power management flow and the multi-segmental I2C routing network.

3.16 Internal Physical Assembly and Wiring

Translating the 3D CAD models into functional physical prototypes required precise internal wiring and component compartmentalization. The core electronic modules—including the ESP8266, the TCA9548A multiplexer, and the MPU6050 sensors—were securely soldered onto custom-fitted perfboards. These boards were then rigidly mounted into the recessed beds of the 3D-printed chassis to prevent mechanical rattling. Furthermore, to ensure signal integrity and facilitate future field maintenance, industrial-grade Wago splicing connectors were utilized for modular power distribution and I2C bus routing across the multi-node array.

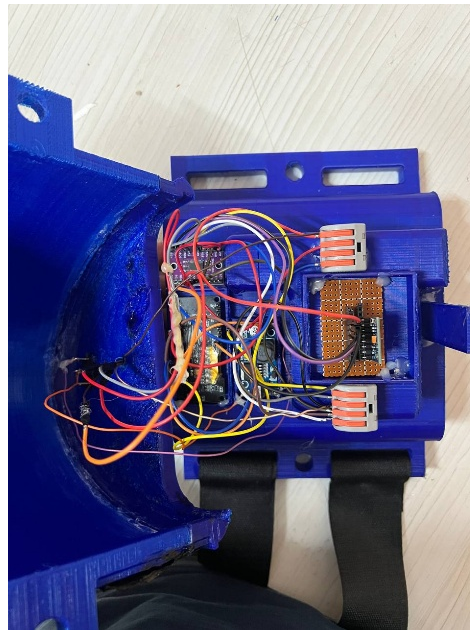


Figure 3.12: A: Internal physical assembly of the Proximal Node (Node A), detailing the integration of the ESP8266 microcontroller, the I2C multiplexer, and the modular wire routing.

3.16.1 Final Assembled Prototype The final physical realization of the CalvingSafe multi-node tracking system demonstrates the successful integration of rigid electronics within a flexible, animal-friendly biomechanical interface. The 3D-printed outer shells securely enclose the hardware, while the white TPU inner linings provide the necessary shock absorption and slip resistance required for in vivo field deployment.

3.17 Conclusion

This chapter established the complete hardware architecture of the CalvingSafe system. Every component, the ESP8266 microcontroller, the MPU6050 inertial sensors, the TCA9548A I2C multiplexer, the 18650 power cell with its BMS, the LM2596 voltage regulator, and the 3D printed enclosures, was selected and engineered against the

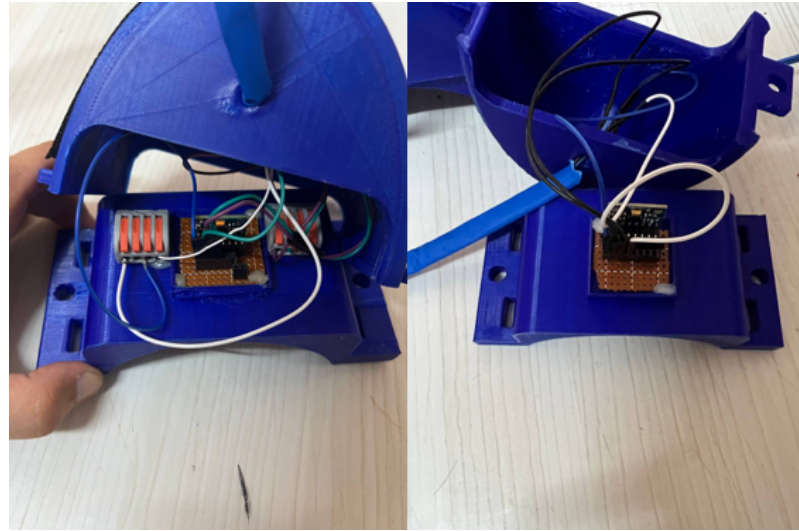


Figure 3.13: B: Internal wiring of the Satellite Node (Node B/C), illustrating the MPU6050 IMU rigidly mounted on a custom perfboard bed with Wago connectors for flexible I2C extension.



Figure 3.14: Z: The fully assembled physical prototype of the multi-segmental kinematic tracking system, featuring the rigid outer enclosures, the flexible TPU biomechanical interface (white inserts), and the inter-node wiring.

hard constraints of animal-mounted field deployment: minimal weight, long autonomy, anatomical conformity, and barn-environment resilience. The Serial Monitor validation in Section 3.9 confirmed that the full acquisition chain operates correctly: all three nodes are independently addressed, the spherical coordinate conversion runs without error, and the transmitted data stream is physically coherent across every acquisition cycle.

This hardware work constitutes the engineering prototype at the foundation of the present research. The prototype was first developed and validated as a standalone IoT system, sensor acquisition, Firebase connectivity, and a functional web dashboard, within the engineering project (PFE) that preceded this memoir. That prototype demonstrated the technical feasibility of the approach and established the data pipeline on which the AI modules depend.

The master's memoir extends that prototype with the research contribution that justifies its academic level: the replacement of simple threshold based detection with a hybrid AI system combining an Artificial Neural Network (ANN/MLPClassifier, trained with SMOTE balancing, 96% accuracy) and a Mamdani Fuzzy Logic System, governed by a voting mechanism that produces graduated HIGH/MEDIUM/LOW confidence alerts. This AI layer is only possible because of the hardware architecture defined in this chapter, specifically the three node spatial array that generates the high dimensional spherical coordinate input $(R, \varphi, \theta) \times 3$ nodes on which the ANN was trained, and the multi axis kinematic resolution that makes behavioral signature discrimination feasible.

The following chapter presents this AI and software architecture in full: the sliding window feature extraction pipeline, the ANN training methodology, the Fuzzy Logic inference design, and the hybrid voting system that produces the final calving alert. Together, the hardware layer documented here and the AI layer that follows form the complete CalvingSafe sensing-to-decision pipeline validated in the final chapter of this memoir.

CONCLUSION

The work presented in this memoir set out to address a well defined and practically significant problem: the early and reliable detection of bovine calving through a method that is simultaneously non invasive, cost effective, and free of the heavy infrastructure demands associated with comprehensive farm automation ecosystems. Across three chapters, this objective was pursued through a progressive construction that moved from biological understanding, to data engineering, to physical prototyping. Chapter 1 established that the physiological progression of parturition from the hormonal cascade that initiates labour to the mechanical and postural adaptations that accompany it produces a clear and consistent behavioural marker: the sustained elevation of the tail, driven by the cow's neuro mechanical anticipatory reflex. The comparative review of existing detection technologies, from vaginal probes to next generation AI ecosystems, confirmed that this marker had not yet been fully exploited by a solution combining non invasiveness, affordability, and field practicality, thereby justifying the tail kinematics approach pursued in this work. Chapter 2 translated this biological insight into an engineering methodology. By modelling the bovine tail as a flexible, multi segmental articulated chain rather than a rigid rod, and by reconstructing three dimensional spatial coordinates from two dimensional video footage through perspective projection and camera calibration, a reliable feature extraction pipeline was developed using OpenCV and Python. This pipeline made it possible to characterise normal behaviour, waste elimination, and the calving process as three mathematically distinguishable kinematic signatures, and to aggregate them into a structured dataset of sixty video sequences and 3,060 data points, providing the data foundation required for subsequent classification. Chapter 3 then translated this methodology into a physical artefact. The CalvingSafe prototype, built around a three node sensing topology distributed along the tail, demonstrated that a non rigid, multi point inertial architecture is necessary to capture the full anatomical expression of tail movement, an aspect that single-sensor designs cannot reproduce. The mechanical design choices tail conforming enclosures, a hybrid TPU attachment mechanism, and a modular, interchangeable node structure were shown to satisfy the welfare and durability constraints inherent to animal mounted devices, while the electronic architecture built around the ESP8266 microcontroller, the MPU6050 inertial sensors, the TCA9548A multiplexer, and a regulated lithium ion power system was validated through serial monitor testing of the complete acquisition chain. Considered together, these three chapters demonstrate that a non invasive, tail mounted kinematic approach is both biologically well founded and technically achievable: the behavioural marker identified in Chapter 1 can be reliably captured and quantified through the methodology of

Chapter 2, and reproduced in a field deployable hardware prototype as shown in Chapter 3. This progression constitutes the engineering and data foundation on which the system’s artificial intelligence inference layer is built, and confirms the practical viability of the proposed alternative to existing, more invasive or more costly calving detection technologies. Naturally, this work also opens directions for further development. Extended in field validation across larger and more diverse herds would help confirm the robustness of the kinematic signatures identified here across different breeds, parities, and barn conditions. Likewise, the long term durability of the prototype particularly the TPU attachment interface and the inter node wiring would benefit from extended deployment trials under real farming conditions. These directions, together with the refinement of the classification layer built upon the present hardware and data foundation, define the natural continuation of the research presented in this memoir.

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