Toward Semantic Explainable AI in Livestock: MoonCAB Enrichment for O-XAI to Sheep BCS Prediction

Nourelhouda Hammouda[1][a], Mariem Mahfoudh[2][b] and Khouloud Boukadi[3][c]

[1]*University of Sfax, MIRACL Laboratory, National School of Electronics and Telecommunications, Sfax, Tunisia*

[2]*University of Sfax, MIRACL Laboratory, Institute of Computer Science and Multimedia, Sfax, Tunisia*

[3]*University of Sfax, MIRACL Laboratory, Faculty of Economics and Management, Sfax, Tunisia*

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Abstract: Body Condition Score (BCS) is a key metric for monitoring the health, productivity, and welfare of livestock, playing a crucial role in supporting farmers and experts in effective herd management. Despite advancements in BCS prediction for cows and goats, no computer vision-based methods exist for sheep due to their complex body features. This absence, coupled with the lack of interpretability in existing AI models, hinders real-world adoption in sheep farming. To address this, we propose the first interpretable AI framework for sheep BCS prediction leveraging ontology-based knowledge representation. In this paper, we enrich the ontology MoonCAB, which models livestock behavior in pasture systems, with BCS-related knowledge to prepare it for future integration into explainable AI (XAI) systems. Our methodology involves enhancing the "Herd" module of MoonCAB with domain-specific concepts and 200 SWRL rules to support logical inference. The enriched ontology is evaluated using Pellet, SPARQL, and the MoOnEV tool. As a result, MoonCAB now enables reasoning-based support for BCS-related decision-making in precision sheep farming, laying the groundwork for future developments in ontology-based explainable AI (O-XAI).

1 INTRODUCTION

The Body Condition Score (BCS) is a critical indicator used to monitor animal health, productivity, and welfare It enables both domain experts and farmers to make informed, cost-effective, and ethically sound decisions in animal management (Hamza and Bourabah, 2024).

While several studies have developed AI-based tools to predict BCS in animals such as cows and goats using computer vision techniques; deep learning (Rodríguez Alvarez et al., 2019; Çevik, 2020), machine learning algorithms (Vázquez-Martínez et al., 2023), no such work exists for sheep. This research gap is primarily due to the anatomical and visual complexities of sheep — including thick wool, variable fleece color, and less pronounced body contours — which make visual assessment and feature extraction far more challenging. As a result, BCS prediction in sheep remains a largely unexplored task, particularly in large-scale settings where regular, manual evaluations are impractical.

This lack of automation is critical, given that a sheep's BCS can vary rapidly due to nutrition management (Corner-Thomas et al., 2020). Without frequent and reliable assessments, breeders risk compromising animal health, reproductive performance, and overall productivity. Therefore, there is a pressing need for intelligent, automated, and interpretable solutions that can assess BCS in sheep at both the individual and herd levels.

Moreover, beyond prediction accuracy, explainability is crucial in agricultural settings. Farmers and domain experts require not only accurate predictions but also transparent explanations to support their decisions. In this regard, contrary to the XAI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) (Selvaraju et al., 2017) and SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017), semantic explainable AI (O-XAI) offers a promising direction by integrating symbolic knowledge through ontologies and reasoning rules, thereby making AI decisions more interpretable and actionable.

[a] https://orcid.org/0009-0005-5185-0325
[b] https://orcid.org/0000-0001-7860-8604
[c] https://orcid.org/0000-0002-6744-711X

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In this paper, we propose the first step toward building an interpretable AI framework for sheep BCS prediction. Our approach is based on the enrichment of the Modular ontology for Computational analysis of Animal Behavior (MoonCAB) (Hammouda et al., 2023), which models the behavior of livestock animals (sheep and goats) in pasture environments. MoonCAB currently comprises 154 classes, 156 properties, 234 individuals, and 14,653 axioms, structured into three main modules: M_Pasture, M_Herd, and M_Behavior.

Our contribution focuses on integrating all relevant concepts and implications of BCS into the "Herd" module, along with formal axioms and reasoning capabilities using SWRL (Semantic Web Rule Language) (Horrocks et al., 2004). Although MoonCAB already provides structured representations, it lacks inferential capacity. By embedding semantic rules, we enhance its ability to derive implicit knowledge and support informed decision-making in livestock management. In addition to structural enrichment, we define and integrate 200 SWRL rules to enable inferential reasoning about BCS conditions, behavioral patterns, and their impact on management decisions. These rules enhance the ontology's capacity to support actionable insights for precision livestock farming.

To ensure semantic consistency, structural soundness, and practical utility, a rigorous evaluation of the enriched MoonCAB ontology was conducted. We relied on several established tools, including OOPS! (Poveda-Villalón et al., 2014), Delta-T (Kondylakis et al., 2021), and XDTesting (Ciroku and Presutti, 2022), each addressing complementary aspects of ontology quality. For in-depth modular validation, we employed the MoOnEV tool, selected for its compatibility with the OMEVA framework (Gobin-Rahimbux, 2022), which encompasses 35 evaluation metrics across eight quality dimensions. Its support for modular analysis and detailed diagnostics makes it particularly suited for assessing the robustness of complex ontologies like MoonCAB.

This paper is organized as follows: Section 2 reviews related work on XAI and animal ontologies. Section 3 presents our MoonCAB-XAI framework, detailing the enrichment of the ontology with BCS-related concepts and SWRL rules. Section 4 describes the evaluation using Pellet, SPARQL, and the MoOnEV tool. Section 5 discusses the results, and Section 6 concludes with future perspectives.

2 RELATED WORK

2.1 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) seeks to enhance transparency and trust in AI systems by revealing how decisions are made, particularly in complex or black-box models (Altukhi et al., 2025).

As illustrated in Figure 1, XAI frameworks vary across multiple dimensions, including the explanation stage (ante-hoc, in-process, post-hoc), scope (local, global, system-wide), and target audience (developers, experts, or general users) (Brdnik and Šumak, 2024). XAI methods also differ depending on input type (structured, unstructured, multimodal) and produce outputs in various forms—visual, quantitative, symbolic, or linguistic (Kong et al., 2024). They incorporate different rationalization strategies (contrastive, counterfactual, extractive) and treatment models (inherently interpretable or post-hoc explanations) (Brdnik and Šumak, 2024). Evaluation metrics such as fidelity, clarity, fairness, and usefulness help assess the quality and reliability of explanations (Retzlaff et al., 2024).

To address these diverse dimensions, XAI leverages a broad range of techniques including SHAP (Lundberg and Lee, 2017), LIME (Ribeiro et al., 2016), Grad-CAM (Selvaraju et al., 2017), Anchors (Ribeiro et al., 2018), and meta-frameworks like AutoXAI (Cugny et al., 2022). These approaches are applied in critical domains such as healthcare, cybersecurity, finance, smart cities, and agriculture. Effective XAI system design is supported by structured tools like ODCM and REXAI, alongside user-centred and low-code development interfaces (Aslam et al., 2023). Increasingly, semantic approaches to XAI are being explored to incorporate ontologies and structured knowledge for deeper, more human-aligned explanations. These efforts collectively contribute to more ethical, interpretable, and reliable AI systems.

2.2 Semantic eXplainable Artificial Intelligence (S-XAI)

The integration of semantics in Explainable Artificial Intelligence (XAI) has become essential to enhance the clarity and relevance of machine-generated explanations. Traditional XAI methods often rely on attribution techniques or statistical saliency, which—though informative—lack alignment with human cognition and domain semantics. In contrast, semantic XAI leverages structured, interpretable representations such as ontologies, logical

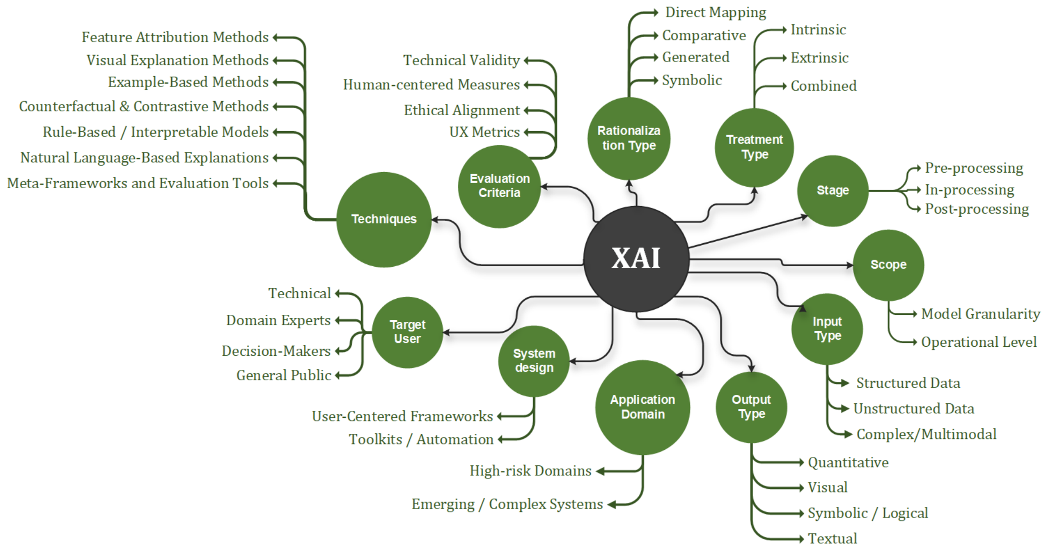

Figure 1: Overview of the key conceptual components of Explainable AI (XAI).

Table 1: Comparative overview of recent works employing semantic-based approaches in XAI.

Paper	**Scope**	**Semantic Technique**	**Stage**	**Input**	**Output**	**Evaluation Criteria**
(Dong et al., 2017)	Image classification (CNNs)	Semantic concepts + interpretable neurons	Ante-hoc	Visual images	Concept attention maps	Clarity, alignment with concepts
(Garcez et al., 2019)	Cross-domain reasoning	Neural-symbolic integration	In-process	Structured and unstructured data	Symbolic justifications + logical inference	Logical completeness, scalability
(Marcos et al., 2019)	Image recognition with explanation	Semantic Interpretable Activation Maps	Ante-hoc	CNN activations + image inputs	Tripartite semantic maps	Map interpretability, semantic decomposition
(Donadello and Dragoni, 2020)	Image classification	Ontological predicates, fuzzy logic	Ante-hoc + Post-hoc	Images, concept labels	Logical rules + fuzzy predicates	Faithfulness, interpretability
(Ngo et al., 2022)	Smart agriculture knowledge formalization	AgriComO + OAK4XAI	Post-hoc	Data mining results, concept definitions	Structured explanations (no interface)	No UI for end users, lacks feature attribution
(Dragoni and Donadello, 2022)	Generic AI decision justification	Explanation Graph	Post-hoc	Structured knowledge, logic rules	Graph-structured semantic explanation	No interaction interface, only conceptual structure
(Chhetri et al., 2023)	Cassava disease detection	Ontology + SWRL + DL	Post-hoc	Images + sensor data	Weighted decision combining CNN and SWRL rules	CNN opacity, rule-based model lacks scalability
(Sajitha et al., 2023)	Banana quality classification	Knowledge Graph + KEGCNN	Post-hoc	Banana images	Knowledge-embedded GCN output	High complexity, opaque embedding layer
(Corbucci et al., 2023)	Sequential diagnosis prediction	Ontology mapping (ICD-9 to SNOMED-CT)	Post-hoc	ICD codes, clinical notes	Ontology-linked text highlights	F1-score (text match), human validation
(Sun et al., 2024)	Image classification and OOD detection	Self-supervised concept extraction (PCA, SVD)	Post-hoc	Images	Concept prototypes and semantic labels	User trust, semantic clarity, interpretability
(Kosov et al., 2024b)	Credit risk assessment	Ontology + SWRL for tabular data	Post-hoc	Tabular records (credit attributes)	Symbolic explanation via rules	Explanation coverage, clarity
(Kosov et al., 2024a)	Images (Fashion-MNIST), generalizable	Generalized explanatory properties	In-process	Visual features	Ontology-based JSON explanation	Faithfulness, reusability
(Sharma and Jain, 2024)	Medical diagnosis (Dengue)	Ontology + SWRL + ChatGPT	Post-hoc	Clinical data	Natural language explanation	Accuracy, clarity, precision vs. ML
(Doh et al., 2025)	Face verification	Face regions + LIME/SHAP + LLMs	Post-hoc	Face image pairs	Similarity map + textual rationale	User preference, faithfulness, LLM clarity
(Chandra et al., 2025)	Disease diagnosis & treatment	BFO + PCD Ontology + SWRL + GPT	Post-hoc	Clinical data, test results (OCR)	SPARQL results + XAI suggestions	Precision, recall, batch event timing

rules, and conceptual traits to bridge the gap between model reasoning and human understanding. These elements can be applied at various stages of the AI pipeline.

Several works illustrate this semantic shift, as summarized in Table 1. Foundational contributions include (Dong et al., 2017), (Garcez et al., 2019), and (Marcos et al., 2019), which embed semantic meaning directly into neural models. (Dong et al., 2017) aligns CNN filters with semantic concepts via neuron regularization, enabling concept-level attention maps. (Garcez et al., 2019) promotes neural-symbolic integration for logic-based reasoning with deep learning. (Marcos et al., 2019) introduces the What-Where-How framework, decomposing CNN decisions into interpretable spatial and conceptual components—especially useful for image classification.

Building on these foundations, several notable contributions have proposed diverse and robust semantic XAI systems. (Donadello and Dragoni, 2020) introduced SeXAI, using fuzzy logic and ontological constraints to guide DNNs, producing rule-based explanations. (Sun et al., 2024) proposed AS-XAI, a self-supervised method that extracts concept prototypes via PCA and SVD, enabling global, annotation-free interpretation. (Doh et al., 2025) developed a semantic multimodal XAI system for face verification, combining structured face-region semantics, similarity maps, and LLM-generated explanations tailored to users.

In agriculture, where interpretability is critical for non-experts (Grati et al., 2025), (Ngo et al., 2022) used AgriComO in OAK4XAI to organize and explain model outcomes through domain knowledge. (Chhetri et al., 2023) combined CNNs with SWRL and ontology reasoning for cassava disease detection, while (Sajitha et al., 2023) used KEGCNN for banana grading by embedding graph methods based on a graph convolutional network (GCN).

In healthcare, (Corbucci et al., 2023) linked clinical notes and model predictions with SNOMED-CT via ontology-based highlights. (Sharma and Jain, 2024) introduced OntoXAI using SWRL and ChatGPT to provide human-readable explanations for dengue diagnosis. (Chandra et al., 2025) extended this with GPT-driven logic and SWRL using BFO and PCD ontologies for diagnostic support.

Other representative efforts expanded semantic XAI across domains: (Kosov et al., 2024b) proposed ontology-driven rule explanations for credit assessment, while (Kosov et al., 2024a) extended this to cross-modal reasoning with JSON-structured symbolic outputs.

These contributions mark the evolution of semantic XAI—from embedding meaning in models to developing modular frameworks combining ontological reasoning, visual and textual explanation. Ontologies are now key to structuring knowledge, ensuring traceability, and aligning AI with domain expectations. They support integration of SWRL, rule-based reasoning, and cross-domain adaptation. Yet, challenges remain in engineering, scalability, and integration with deep learning. Despite these, ontologies anchor semantic XAI as a bridge between opaque computation and intelligible, trustworthy AI.

2.3 Animal Ontologies

Ontology languages like OWL allow for the formal representation of domain knowledge, but they are limited in expressing complex logic. The Semantic Web Rule Language (SWRL) extends OWL by enabling the integration of logical rules directly into the ontology structure (Horrocks et al., 2004). They support reasoning by establishing cause-and-effect relationships, enabling the inference of new knowledge from existing facts (Amith et al., 2021). As a result, SWRL enhances ontology expressiveness, supports dynamic decision-making, and improves the semantic richness of knowledge-based systems.

In this context, several ontologies have been developed to semantically model knowledge related to animals and their environments. However, despite the potential of SWRL to enrich these ontologies, only a few of them incorporate rule-based reasoning mechanisms. MBO (Beck et al., 2009) focuses on mammalian species but does not integrate SWRL rules. NBO (Gkoutos et al., 2012) includes 23 SWRL rules to infer regulatory relationships in animal-related studies. AHSO (Dóreas et al., 2017) addresses animal health surveillance and was developed using the eXtreme Design (XD) methodology. ATOL (Golik et al., 2012) provides extensive terminology for livestock traits without implementing formal rules. GEOBIA (Gu and et al, 2017) deals with environmental concepts extracted from remote sensing and employs SWRL to enhance semantic interpretation. MoonCAB (Hammouda et al., 2023) follows the MOMo methodology to describe animals and pasture systems semantically.

Several ontology engineering methodologies focus on reusing existing ontologies and adopting modular design principles to enhance clarity and scalability. Approaches like Enterprise (Uschold and King, 1995), XD (Blomqvist et al., 2016), and MOMo (Shimizu et al., 2021) encourage creating reusable components. MOMo specifically supports systematic reuse and modularity through diagram-first modeling, pattern-based instantiation, and collaborative tools like CoModIDE (Shimizu et al., 2021).

3 MOONCAB ENRICHMENT FOR SHEEP BCS PREDICTION EXPLICATION

MoonCAB is a modular ontology designed to semantically represent knowledge about sheep and goats in pasture (Hammouda et al., 2023). It was developed in collaboration with INRAT to support smart farming through semantic annotation of observational data. The ontology adheres to the MOMo methodology (Shimizu et al., 2021), ensuring modularity, reusability, and expert validation. Existing resources like ATOL (Golik et al., 2012) and GEOBIA (Gu and et al, 2017) were reused to enhance semantic coverage. MoonCAB integrates standardized traits and environmental concepts relevant to livestock systems.

It includes 143 classes and 106 properties distributed for 3 modules: Herd, Pasture, and Production. These rules support dynamic inference and automated decision-making. Logical consistency was checked using FaCT++, and SPARQL queries validated the defined competency questions. The ontology was further assessed with the MoOnEv tool (Hammouda et al., 2024) across 36 evaluation criteria. Results confirmed its quality, modularity, and reasoning capabilities.

In this work, we apply the MOMo methodology to guide the enrichment of the MoonCAB ontology. This choice is motivated by its support for reusability and modularity, as the current extension focuses specifically on the Herd module.

3.1 Enrichment of Existing MoonCAB Modules

We contribute to the enrichment of the “Herd” module within the MoonCAB ontology by integrating structured knowledge related to the Body Condition Score (BCS) of sheep. This contribution is based on the MOMo (Modular Ontology Modeling) methodology. Evaluating the body condition in sheep is a key method for determining their overall health and nutritional status. This evaluation is based on the Body Condition Score (BCS) scale, which ranges from 1 (very thin) to 5 (obese).

To support ontology enrichment and reasoning in BCS, it is essential to formalize the process by which sheep are scored. This includes identifying the relevant anatomical parts. As illustrated in Figure 2, BCS in sheep involves evaluating three major anatomical regions.

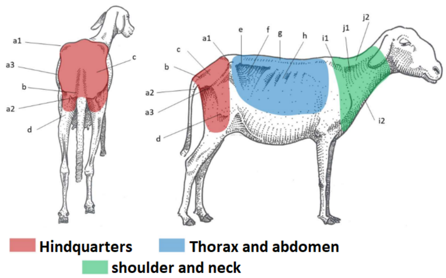

Figure 2: Main anatomical zones used for BCS in sheep (Vall, 2020).

- **Hindquarters** — shown in red: includes the iliac spines (a1), ischial spines (a2), coxo-femoral joint (a3), the base of the tail and caudal vertebrae (b), pelvic coverage (c), and the thighs (d).
- **Thorax and Abdomen** — shown in blue: covers the transverse processes of the lumbar vertebrae (e), flank depression (f), dorsal vertebrae spinous processes (g), and the ribs (h).
- **Shoulder and Neck** — shown in green: includes the scapula (i1), humerus joint (i2), neck hollow (j1), and the occiput (j2).

3.1.1 Use Cases and Data Sources

From these sources, to guide the development of our ontology according to the MOMo methodology, we describe below five representative use cases. Several use cases are proposed to guide the enrichment of the ontology, based on documents selected by the expert domain at INRAT laboratory, such as (Brugère-Picoux, 2004; Vall, 2020), which addresses the body condition scoring of sheep.

- *BCS-Based Nutritional Diagnosis.* Develop an ontology module to diagnose undernutrition in sheep by representing BCS scores alongside physiological states (e.g., gestation, lactation). The ontology should support semantic rules to flag under-conditioned individuals and generate intervention alerts. It must be extendable to integrate nutritional thresholds, herd averages, and seasonal feeding plans.
- *Reproduction Management Based on BCS.* Create an ontology module to guide mating decisions based on pre-breeding BCS scores. It will encode rules such as “BCS ≤ 3 is required for optimal conception,” and generate warnings if criteria are not met. The module should be extensible to support breed-specific thresholds, fertility indicators, and reproductive history.
- *Climate Impact on Body Condition.* Model the relationship between climate events (e.g., drought, heatwaves) and BCS trends using region-linked data. The ontology will represent BCS measurements over time, tied to environmental conditions, enabling risk alerts. It should be extendable to include pasture quality data, seasonal climate profiles, and grazing system types.
- *Maternal BCS and Lamb Survival Risk.* Design a module to assess lamb mortality risk based on maternal BCS at lambing. BCS values will be linked to birth events

and lamb outcomes to support causal inference. The model should allow extension with lamb weight, birth season, and maternal feeding data.

- *Anatomical Justification of BCS Scoring.* Build an ontology module to represent anatomical zones (e.g., spine, ribs, pelvis) used in BCS evaluation. Scoring decisions will be justified through linked observations and evaluator metadata. The module can be extended to include visual markers, and palpation techniques.

3.1.2 Competency Questions

Based on the five use cases previously mentioned, here is a table (Table 2) of competency questions aligned with each one, including the key concepts involved. Competency questions are natural language queries that define the scope and objectives of the ontology by illustrating the kinds of questions it should be able to answer once developed.

Table 2: Competency questions and key concepts for the Body Condition Score (BCS) ontology.

Competency Questions	**Key Concepts**
Which sheep currently show signs of undernutrition based on BCS?	BCS, Undernutrition Threshold, Physiological Status
Which ewes should receive additional feeding due to low BCS during lactation?	Lactation Status, Feeding Plan, BCS Trend
Which sheep have shown a significant drop in BCS during a recent climate event?	Climate Event, BCS Over Time, Region, Date
What is the lamb mortality risk based on the mother's BCS at parturition?	Maternal BCS, Lamb Survival, Parturition, Risk Factor
Which anatomical indicators justify the BCS score assigned to a specific sheep?	Hindquarters, Thorax and abdomen, Shoulder and neck, Criteria

3.1.3 Identification of Existing Ontology Design Patterns (ODPs)

We rely on the Modular Ontology Design Library (MODL) (Shimizu et al., 2019), which provides well-curated and consistently documented ODPs.

Our ontology integrates the "Identifier" pattern (see Figure 3). Additionally, the "Spatiotemporal Extent" pattern (see Figure 4) is adapted to enhance the "Herd" module.

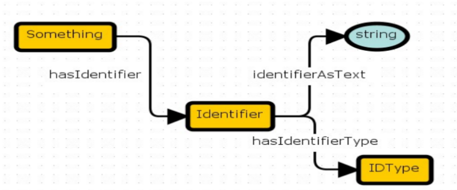

Figure 3: Schematic diagram for the MODL identifier model.

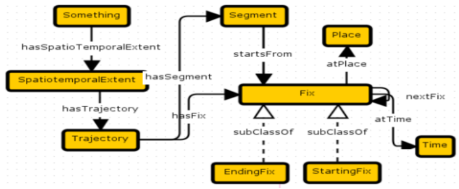

Figure 4: Schematic diagram for the MODL spatiotemporal extent model.

3.1.4 Schema Diagrams for the Enriched "Herd" Module

Figure 5 illustrates the ontological schema for the "Identifier" model, featuring three main entities: *Thorax and Abdomen, Ribs*, and *Rib Cage*. These entities are linked hierarchically: ThoraxAndAbdomen connects to Ribs via the *hasRibs* property, and Ribs connects to RibCage via *hasRibCage*. The RibCage entity includes a hasRibsCharacteristic property of type string.

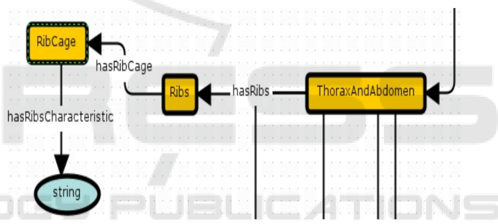

Figure 5: Schematic diagram for the identify model.

Figure 6 depicts a schema based on the "Spatiotemporal Extent" pattern, modeling the body condition assessment. The main entity, Body, must have a *BodyConditionScore*, which is associated with *PeriodBCS* instances that include hasDateBegin and *hasDateEnd* (both of type *dateTime*). This model allows tracking body condition across different periods.

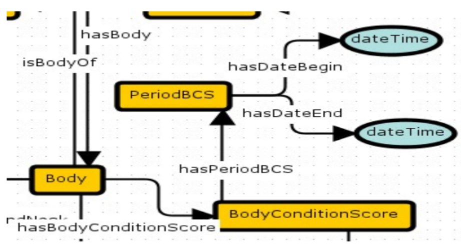

Figure 6: Schematic Diagram for the Spatio-Temporal Model.

3.1.5 Document Modules and Axioms

Documentation is a key step in ontology development, enabling communication with domain experts and facilitating the validation of knowledge models. Following MOMo guidelines, we present here the formal axioms that structure the BCS concepts.

- Animal $\sqsubseteq$ $\exists$hasBody.Body
- Body $\sqsubseteq$ ($\geq$ 1 hasBodyConditionScore.BodyConditionScore)
- PeriodBCS $\sqsubseteq$ (= 1 DateBegin :xsd:dateTime) $\sqcap$ (= 1 DateEnd :xsd:dateTime)
- Body $\sqsubseteq$ $\exists$hasHindquarters.Hindquarters $\sqcap$ $\exists$hasTailBase.TailBase $\sqcap$ $\exists$hasThoraxAndAbdomen.ThoraxAndAbdomen
- Hindquarters $\sqsubseteq$ (= 1 hasPelvicBonesAndHip.PelvicBonesAndHip) $\sqcap$ (= 1 hasBaseOfTail.TailBase) $\sqcap$ (= 1 hasPelvis.Pelvis) $\sqcap$ (= 1 hasThighs.Thighs)
- Pelvis $\sqsubseteq$ $\exists$hasPelvisCharacteristic :xsd:string
- Pelvis $\sqsubseteq$ $\exists$hasBaseOfTailCharacteristic :xsd:string

3.1.6 Create Ontology Diagram

This diagram (Figure 7) presents the enriched version of the *Herd* module, created using the CoModIDE plugin[1]. The module integrates the key concepts identified in the previous use case and competency question phases. It is now ready to be reintegrated into the global MoonCAB ontology and will serve as the foundation for the next modeling step: establishing inter-module and intra-module relations. Specifically, links will be defined between the *Herd* module and other modules such as *Pasture* and *Behavior*, enabling semantic consistency across all BCS-related components.

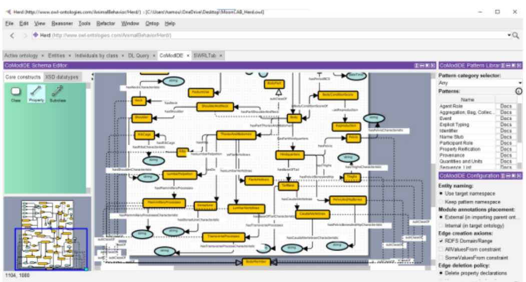

Figure 7: An enriching view of the “Herd” module, visualized using the CoModIDE plugin.

[1] CoModIDE is a Protégé plugin for ODP-based modular ontology engineering: https://comodide.com/

3.2 Enrichment of MoonCAB by SWRL Rules

To enable automated reasoning and explainable BCS classification within MoonCAB, we enriched the ontology with a set of 200 SWRL rules derived from anatomical features of the sheep body. These rules utilize previously defined structural axioms that describe the anatomical composition of an animal and enable the inference of Body Condition Score (BCS) levels from observed body part characteristics.

- **BCS = 5:** This rule identifies sheep with very convex pelvis, abundant tail base fat, invisible flank depth, and very high shoulder fat cover as over-conditioned, assigning them a BCS of 5.

  Herd:Animal(?x) ∧ Herd:hasCategory(?x,Herd:Sheep) ∧ Herd:hasBody(?x,?b) ∧ **Herd:hasPartHindquarters(?b,?hq)** ∧ Herd:hasPelvicAndHipBones(?hq,?phb) ∧ Herd:hasPelvicBonesAndHipCharacteristic(?phb, “CoveredByFat”) ∧ Herd:hasPelvis(?hq,?p) ∧ Herd:hasPelvisCharacteristic(?p,“VeryConvex”) ∧ Herd:hasThighs(?hq,?t) ∧ Herd:hasThighsCharacteristic(?t,”Bulging”) ∧ Herd:hasTailBase(?hq,?tb) ∧ Herd:hasCaudalVertebrae(?hq,?ctb) ∧ Herd:hasCaudalVertebraeCharacteristic(?ctb, “FatAccumulation”) ∧ **Herd:hasPartThoraxAndAbdomen(?b,?ta)** ∧ Herd:hasDorsalLine(?ta,?dl) ∧ Herd:hasDorsalLineCharacteristic(?dl,“Invisible”) ∧ Herd:hasFlankHollows(?ta,?fh) ∧ Herd:hasFlankHollowsCharacteristic(?fh,“Invisible”) ∧ Herd:hasLumbarPalpation(?ta,?lp) ∧ Herd:hasMammillaryProcesses(?lp,?mp) ∧ Herd:hasMammillaryProcessesCharacteristic(?mp, “BarelyPalpable”) ∧ Herd:hasLumbarVertebrae(?ta,?lv) ∧ Herd:hasVertebralAchCharacteristic(?lv, “BarelyPalpable”) ∧ Herd:hasTransverseProcesses(?ta,?tp) ∧ Herd:hasTransverseProcessCharacteristic(?tp, “CannotBeFelt”) ∧ **Herd:hasPartShoulderAndNeck(?b,?sn)** ∧ Herd:hasShoulder(?sn,?s) ∧ Herd:hasShoulderCharacteristic(?s,“ThickFatCover”) ∧ Herd:hasNeck(?sn,?n) ∧ Herd:hasNeckCharacteristic(?n,“Muscular”) ∧ Herd:hasBodyConditionScore(?b,?scoreObj) →**Herd:hasScore(?scoreObj, “Score_5”)**

- **Feed Supplementation During Lactation for Low BCS Ewes:** This rule triggers a feeding adjustment for lactating ewes whose BCS falls below 2.5, indicating the need for increased nutritional support during this energy-demanding phase.

  Herd:Animal(?x) ∧ Herd:hasCategory(?x,Herd:Sheep) ∧ Herd:hasBody(?x,?b) ∧

Herd:hasBodyConditionScore(?b,?s) ∧ Herd:hasNumericScore(?s,?scoreValue) ∧ swrlb:lessThan(?scoreValue,2.5) ∧ Herd:hasPhysiologicalStatus(?x,Herd:Lactating) → **Herd:requiresFeedingAdjustment(?x, true)**

- **Predict Lamb Mortality Risk Based on Maternal BCS:** This rule predicts a high risk of lamb mortality if the ewe's BCS at parturition is below 2.0, highlighting the importance of maternal condition in neonatal survival outcomes.

  Herd:Animal(?m) ∧ Herd:hasCategory(?m,Herd:Sheep) ∧ Herd:hasBodyConditionScore(?m,?s) ∧ Herd:hasNumericScore(?s,?scoreValue) ∧ swrlb:lessThan(?scoreValue, 2.0) ∧ Herd:hasChild(?m,?lamb) ∧ Herd:hasBirthEvent(?lamb,?b) ∧ Herd:hasBirthType(?b,"Parturition") →**Herd:hasLambMortalityRisk(?lamb,"High")**

4 EVALUATION AND VALIDATION OF NEW MOONCAB VERSION

4.1 Evaluation Using the Pellet Reasoner

To verify the consistency of the ontology and to detect any potential logical conflicts, we used the Pellet[2] reasoner, which is designed for reasoning over Description Logics (DL). It accepts OWL files as input and is capable of processing concepts, properties, and instances. In particular, it allows the verification of the ontology's coherence and the detection of logical inconsistencies. This reasoning phase was successfully completed, and no inconsistencies were detected by the reasoner.

4.2 Evaluation Using SPARQL Query Language

To verify the accuracy and the coverage of the ontology, we have used the SPARQL language by reformulating the competency questions as SPARQL queries. Table 3 shows some examples of competency questions (represented in Table 2), their corresponding SPARQL queries, and the results of the execution of these queries on our ontology.

[2]https://owl.cs.manchester.ac.uk/tools/fact

4.3 Evaluation Using MoonEv Tool

Evaluating ontology is crucial for its effectiveness in information exchange and knowledge management. This involves analyzing its clarity, structure, validity, modularity, and decision-enabling capacity. Several tools and methodologies have been developed for this purpose, such as Delta (Kondylakis et al., 2021), which evaluates specific metrics, OMEVA (Gobin-Rahimbux, 2022) for assessing ontology modules across all possible metrics (35 metrics) in eight categories, and OOPS! (Poveda-Villalón et al., 2014) for identifying 40 common ontology pitfalls. XDTesting (Ciroku and Presutti, 2022) introduces unit testing of ontology modules. MoOnEV (Hammouda et al., 2024) is a modular ontology evaluation and verification tool that stands out from other existing tools due to its comprehensive coverage of metrics. It allows for the performance testing of ontologies through use cases and provides in-depth reports of evaluation results to aid in correcting and improving ontology performance.

Figure 8 presents the evaluation of MoonCAB modules based on relatedness metrics. All modules show high independence (above 92%) and zero redundancy, confirming good modular isolation. The Herd module stands out with strong encapsulation (68) and the lowest relative intra-module distance (0.721), indicating high internal cohesion.

Figure 9 shows the results of metrics classified in the module's Quality category, including precision, recall, cohesion, coupling, and overall quality score. All modules achieve perfect precision (1.000), but recall varies, with the Herd module achieving the highest overall quality (200.700). The Behavior module has the lowest recall (0.257) and overall quality (82.500), indicating opportunities for structural improvement.

5 DISCUSSION

Compared to the ontologies presented in Section 2.3, those lacking SWRL rule integration—or incorporating only limited rule sets—remain confined to delivering explicit, surface-level information. Such ontologies are incapable of performing logical inference or capturing complex semantic relationships. In contrast, the MoonCAB ontology, after enrichment, comprises 14,653 axioms, 154 classes, 97 object properties, 62 data properties, and 234 individuals. Most importantly, it integrates 200 SWRL rules, enabling it to move beyond static representation and support advanced reasoning. This allows for the inference of

Table 3: Ontology evaluation.

<table>
<tr><th>Competency Question</th><th>SPARQL Query</th><th>Result</th></tr>
<tr><td>CQ01: Which sheep currently show signs of undernutrition based on BCS?</td><td>SELECT ?animal ?p WHERE {
?animal h:hasBody ?body.
?body h:hasBodyConditionScore ?bcs.
?bcs h:hasPeriodBCS ?bcsp.
?bcsp h:hasDateBegin ?p.
?bcs h:hasScore ?score.
FILTER(?score = "Score_1" || ?score = "Score_2") }</td><td>{ "head":{"vars":["animal","p"]}, "results":{"bindings":[{ "animal":{"type":"URI", "value":".../AnimalBehavior/Herd/H01Sh02"}, "p":{"type":"literal","datatype":"...#dateTime", "value":"2024-07-01T00:00:00"} }] } }</td></tr>
<tr><td>CQ03: Which sheep have shown a significant drop in BCS during X climate event?</td><td>SELECT ?animal ?score0 ?score1 WHERE {
?event h:hasClimateEventName "Dry Rain".
?event h:hasPeriodClimateEvent ?pe
?pe h:hasPeriodClimateEventBegin ?peB.
?pe h:hasPeriodClimateEventEnd ?peE.
?animal h:hasBody ?body1.
?body1 h:hasBodyConditionScore ?bcs1.
?bcs1 h:hasNumericScore ?score1.
?bcs1 h:hasPeriodBCS ?bcsp.
?bcsp h:hasDateBegin ?peB.
?bcsp h:hasDateEnd ?peE.
bcsp h:hasIDPeriodBCS ?id.
?animal h:hasBody ?body0.
?body0 h:hasBodyConditionScore ?bcs0.
?bcs0 h:hasPeriodBCS ?bcsp0.
?bcsp0 h:hasIDPeriodBCS ?id0.
?bcs0 h:hasNumericScore ?score0.
BIND(xsd:integer(?id) - 1 AS ?prevID).
FILTER(?score0 - ?score1 >= 1 &&
xsd:integer(?id0) = ?prevID) }</td><td>{ "head":{"vars":["animal","score0","score1"]}, "results":{"bindings":[{ "animal":{"type":"URI", "value":".../Animal-Behavior/Herd/H01Sh02"}, "score0":{"type":"literal", "datatype":"...#decimal", "value":"3.0"}, "score1":{"type":"literal", "datatype":"...#decimal", "value":"2.0"} }] } }</td></tr>
<tr><td>CQ04: Which anatomical indicators justify the BCS score assigned to a specific sheep?</td><td>SELECT ?partclass ?property ?value WHERE {
?animal h:hasBody ?body .
?body h:hasBodyConditionScore ?bcs .
?bcs h:hasScore 'Score_3' .
?body ?hasPart ?part .
FILTER(STRSTARTS(STR(?hasPart), STR(h:hasPart)))
?part rdf:type ?partclass .
FILTER(STRSTARTS(STR(?partclass), STR(h:)))
OPTIONAL {?part ?property ?rawValue .
FILTER(STRSTARTS(STR(?property), STR(h:)))
OPTIONAL {FILTER(isLiteral(?rawValue))
BIND(?rawValue AS ?value) }
OPTIONAL {FILTER(isIRI(?rawValue))
?rawValue ?subProp ?value .
FILTER(isLiteral(?value)) } } } }</td><td>{ "head":{"vars":["partclass","property", "value"]}, "results":{"bindings":[{ "partclass": {"type":"URI", "value":".../Herd/Hindquarters"}, "property": {"type":"URI", "value":".../Herd/hasPelvis"}, "value":{"type":"literal", "value":"Flat to convex"} }, ... }] }</td></tr>
</table>

Module	Inter-Module Distance	Intra-Module Distance	Relative Intra-Module Distance	Encapsulation	Redundancy	Independency
Herd	2	7.287	0.721	68	0	96.976
Pasture	2	7.408	1.448	4	0	99.389
Behavior	2	5.900	2.301	33	0	92.934

Figure 8: MoOnEV: Module' relatedness metrics results.

Module	Precision	Recall	Module Cohesion	Module Coupling (NSHR , NSNR)	Module Overall Quality
Herd	1.000	0.421	1.603	(45,2204)	200.700
Pasture	1.000	0.533	1.742	(72,583)	109.800
Behavior	1.000	0.257	1.698	(28,439)	82.500

Figure 9: MoOnEV: Module' quality metrics results.

implicit knowledge, unveiling hidden patterns and relationships within agricultural datasets—an essential feature for smart agriculture systems that require intelligent decision support and semantic awareness.

Our ongoing research aims to make a substantial contribution to the management of livestock breeding and the sustainable use of agricultural resources. This objective is grounded in the design, semantic enrichment, and quality evaluation of a domain ontology that is intended to support decision-making processes in agricultural applications. We have developed a mobile application that predicts the Body Condition Score (BCS) of sheep using deep learning models, as shown in Figure 10. The next step is to integrate the enriched MoonCAB ontology into this application, where it will serve a critical role in explaining AI-generated predictions and enhancing their interpretability.

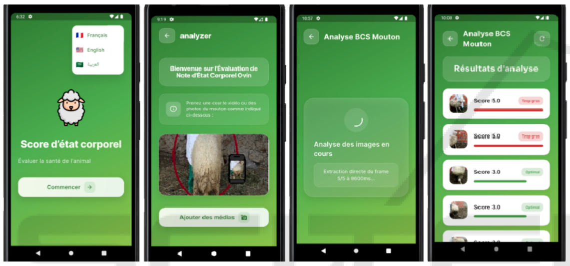

Figure 10: Mobile application interfaces for startup, video selection, and BCS classification results.

Figure 11 presents a comparative analysis of the XAI methods Grad-CAM++, Score-CAM, SHAP, LIME, and their hybrid combinations. This evaluation enabled us to identify the key body regions the model relies on for its predictions by visualizing the discriminative features involved in classifying BCS scores—features that aim to replicate the tactile assessment typically performed by human palpation under real-world conditions. These insights guided us to prioritize information and image collection on critical anatomical regions (e.g., back, rump, tail base) to enhance model accuracy. However, as no single method met all evaluation criteria, we transitioned to a semantic-based approach.

However, given that our system targets both agricultural experts and farmers—who vary in their levels of technical expertise—it is essential to provide explanations that are both semantically structured and accessible. Simple XAI methods alone are insufficient to meet these demands; therefore, we move toward adopting Ontology-based Explainable AI (O-XAI). The ontology will fulfill this role by delivering multi-level justifications: clear and intuitive for farmers, yet scientifically rigorous for domain experts.

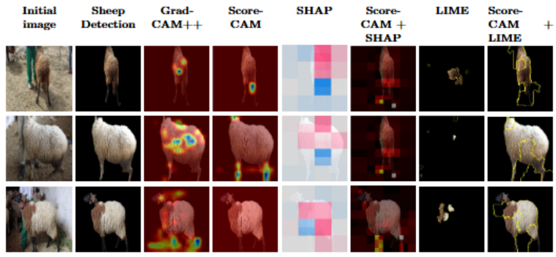

Figure 11: Attention regions generated by diverse XAI methods (Hammouda et al., 2025).

Furthermore, it will support evidence-based decision-making aligned with animal body condition assessment, thereby enhancing the efficiency, transparency, and sustainability of livestock management in smart agriculture.

6 CONCLUSION AND FUTURE WORKS

With the support of INRAT and based on expert-validated scientific documentation, we successfully enriched the MoonCAB ontology to comprehensively represent the Body Condition Score (BCS) evaluation process in sheep. The enriched ontology now contains over 14,653 axioms, 154 classes, 97 object properties, 62 data properties, and 234 individuals. Additionally, it integrates 200 SWRL rules, enabling semantic reasoning to answer complex questions related to BCS levels, their indicators, and corresponding decision-making scenarios. To ensure the quality, effectiveness, and accuracy of the ontology, a multi-method evaluation was conducted using the Pellet reasoner, SPARQL queries, and the MoOnEV tool.

This enriched version of MoonCAB is designed to enhance semantic explainability and provide deeper insights into BCS detection, both at the individual animal level and across the entire herd. This is the first work to address BCS prediction in sheep using computer vision, as no existing research has explored this specific application. This pioneering contribution opens new opportunities for automating sheep monitoring in a transparent and interpretable way.

As a future perspective, we aim to use the Ontology-based eXplainable Artificial Intelligence (O-XAI) through MoonCAB-XAI to enable transparent and interpretable BCS prediction. This leads to a broader research question: To what extent and in depth can ontology-based models like MoonCAB be integrated into computational animal behavior analysis systems (CABA) in general into smart agriculture systems?

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