FEDERATED TEMPORAL GRAPH, CAUSAL DIGITAL TWIN AND CONTROL MODELS FOR PRECISION LIVESTOCK

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Abstract. *Heterogeneous monitoring of animals, environment and governance within precision livestock farming (PLF) requires interpretation, energy efficiency and auditability. To go beyond the classical CNN-LSTM based monitoring system, we extend the model suite to BIoTa-X, consisting of an extended federated temporal graph model (Fed-TGAT), a welfare risk estimating causal digital twin (CausalTwin) and a safe multi-objective control model (Safe-MORL) for a cattle smart-barn from Romania. The Fed-TGAT model represents all entities of interest, cow, barn, sensor and management events over time as a dynamic graph and learns their dependencies without export of farm raw data. CausalTwin enables the modeling of counterfactual scenarios to distinguish between intervention and correlation effects of time, animal identity, feed schedule and housing configuration. Safe-MORL is a constrained multi-objective reinforcement learning and predictive control model that recommends the best actions for ventilation, misting, shading and feeding to improve animal welfare, while being constrained by energy, and water. The data-governance layer of BIoTa-X consists of conformal uncertainty, explainable AI, federated model cards and blockchain. BIoTa-X is a solution for a transparent, adaptive and certifiable smart-barn intelligence system.*

Keywords: precision livestock farming, graph attention networks, causal digital twin, blockchain, animal welfare

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1. Introduction

As dairy production becomes a cyber-physical activity during the latest period of Agriculture 4.0, the biological processes on the farm, the environment and the digital services provided on the farm interact continuously and produce large

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amounts of data in barns [1]. According to the International Committee for Animal Recording (ICAR), big amounts of data from cow collars, cameras, microphones and environmental sensors such as temperature and humidity probes, gas sensors for CO_2, ammonia and methane as well as feeding and milking systems and farm management software first must be transformed into stable, meaningful and feasible decisions for animal welfare [2].

Most behavioral models like CNN-Bi-LSTM [3], hidden Markov models (Support Vector Machine, Random Forest, and XGBoost) [4], vision-based multiview tracking [5], fully convolutional networks and sequential time-series [6], treat individual animals within a group as independent behavioral sequences. However, the welfare of animals is a relational process, as animals interact socially with each other, occupy the same local environment, compete for feed and resources, experience local ventilation and noise [7]. Monitoring systems primarily focus on correlation rather than intervention [8]. While models can be developed to predict co-occurrence of increased temperature-humidity index (THI) and decreased rumination, there is also great value in knowing what to expect to change for animal welfare when increasing ventilation, adding misting, or changing from free access feeding to fixed time feeding [9]. Blockchain and auditability have been introduced for dairy farm welfare records [10]. However, welfare records are primarily stored on the blockchain as additional welfare records, with little connection to the model's uncertainty, lack of explanation, model versions, and certification logic [11, 12].

Dairy production is turning into a cyber physical activity, where the biological processes of cows, environmental parameters and services delivered by IT systems interact on a continuous basis. In modern barns, high frequency data is collected by collars, cameras, microphones, temperature and humidity probes, gas sensors, feeders, milking robots and farm management software [13]. However, the data collected has value only to the extent that it is possible to transform it into reliable, interpretable and actionable welfare decisions. Most current models treat each animal as independent sequences of behavior, whereas welfare risk is relational, as cows interact socially, they share microclimatic zones, compete for resources; and are exposed to the same local ventilation conditions and to noise, while being affected by the same management decisions [14]. Furthermore, most current systems for monitoring animals focus on correlation rather than on intervention, like in the case when a model may learn to predict the co-occurrence of THI and low rumination, but a decision support system (DSS) for a farm needs to predict the effects of changing the ventilation, of switching on misting and of altering the feeding schedule [15]. Most current systems for auditability and for tracking the origin of data treat the blockchain as an additional layer on top of the models, and on top of the intervention space, whereas the blockchain and the welfare record validation should be integral components of the model, intervention space, versioning and certification [16].

In our previous work, a solution called BIoTa was developed [17, 18, 19], which integrates IoT sensing, deep learning for behavioral interpretation and blockchain for welfare record validation. In the current work, a CNN-LSTM model is used for synchronized online monitoring of behavioral and environmental parameters of dairy cow welfare using accelerometry, video and microclimate data streams. Furthermore, the BIoTa-X solution is presented, which includes 4 new models. Firstly, a federated temporal graph attention transformer model is used for temporal multimodal relational inference. Secondly, a digital twin for a welfare-enabled dairy farm is applied, with focus on causal welfare-related counterfactuals. Moreover, a safe multi-objective control model for intervention planning is applied, with welfare-related competing objectives. Lastly, a trustworthy AI data governance model is included, supporting auditability and cross-farm learning. These models were developed and validated using multimodal data acquired from a single dairy farm with 42 animals monitored over a period of 30 days, while each animal was monitored using a set of corresponding multi-sensor data streams, including temperature, humidity, gas concentration, noise, video frames and animal accelerometry signals. The remainder of this paper is structured as follows. Section 2 presents the proposed BIoTa-X architecture. Section 3 introduces the proposed models, including Fed-TGAT, CausalTwin, Safe-MORL, and the trustworthy AI governance framework. Section 4 describes the experimental design, validation protocol, and performance evaluation. Finally, Section 5 concludes the paper and outlines future research directions.

2. BIoTa-X System Architecture

In the architecture of the BIoTa-X system, data acquisition and preprocessing, AI prediction, decision support, and governance are realized as separate services. The perception layer consists of environmental sensors and the ones that are put on animals. In the edge layer, the perception layer is processed in high frequency. Received data are normalized, synchronized and validated. The normalized data are then sent to the AI layer where the proposed models are implemented. In the governance layer, smart-contract hash and certified welfare events are stored.

Raw images and high frequency data from sensors are stored in cloud data repositories according to data policies (camera images are stored for a certain time in a public cloud, while high frequency sensor data is stored on a private cloud). The blockchain layer includes the hash values, the event metadata, the model version identifiers, the audit information (activated welfare events). A high-volume ledger is not a data warehouse and incurs too many costs for storing the various decision records for welfare alerts, model updates and control recommendations. Simple provenance information is sufficient for the welfare alerts, model updates and control recommendations.

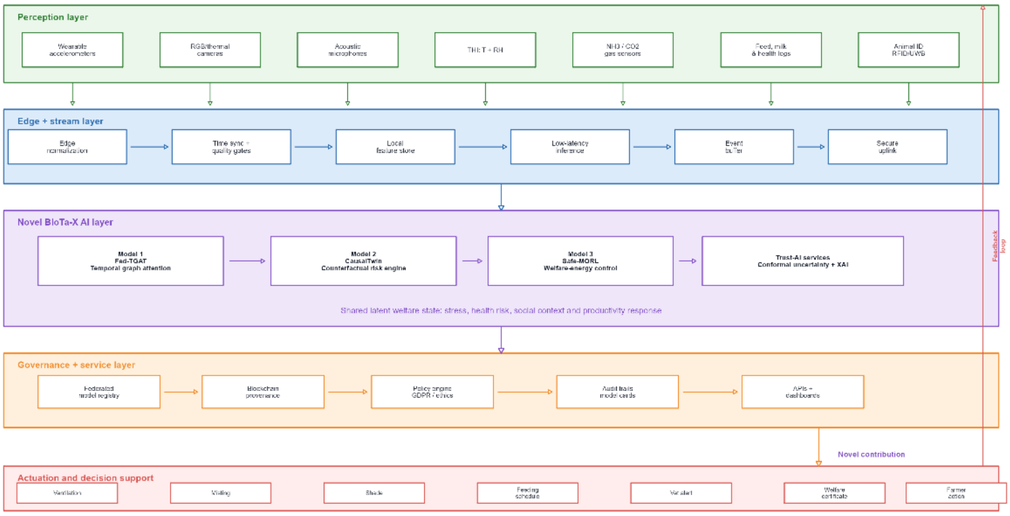

Fig. 1. BIoTa-X architecture based on multimodal sensing, trustworthy AI and adaptive control

Figure 1 illustrates the BIoTa-X smart-barns architecture consisting of a graph-relational, causal counterfactual, and constrained control, as opposed to traditional CNN-LSTM-based smart-barns architecture for behavior recognition. The BIoTa-X platform was decomposed into service families, as in Table 1.

Table 1. BIoTa-X microservices and main responsibilities.

Service	*Inputs*	*Processing responsability*	*Outputs*
Sensor Gateway	Wearables, cameras, microclimate sensors	Protocol translation, local buffering, time synchronization	Normalized sensor packets and availability state
Data Quality	Raw and normalized packets	Range checks, drift alerts, missing-data imputation flags	Quality-controlled streams and confidence flags
Feature Store	Sensor windows, event logs	Window aggregation, feature engineering, graph construction	Animal-zone features and dynamic graph snapshots
Fed-TGAT Inference	Graph snapshots, sequence windows	Relational temporal inference, uncertainty estimation	Behavior class, risk score, embeddings, conformal interval
CausalTwin	Risk forecasts, context, interventions	Counterfactual and causal-effect estimation	Action effect estimates, causal confidence, safety recommendation

Safe-MORL	CausalTwin outputs, constraints, actuator states	Multi-objective action planning and model predictive control	Ventilation/misting/shadin g/feed recommendations
Blockchain	Event metadata, hashes, model IDs	Immutable timestamping and audit trail creation	Verifiable welfare and model-governance records
Dashboard	Predictions, explanations, records	Role-specific visualization and decision support	Alerts, reports, certificates and exports

Each Service has a scope and is scaled independently. There is different hardware requirements based on load for camera analytics, transformer inference (GPU or edge-hardware accelerated), blockchain validation and dashboard. Design choices were guided by biological traceability, for every prediction that is made by the system it is possible to trace back to the used information, such as sensor window, animal, zone, used model, prediction uncertainty, used feature for prediction explanation and finally the actuator used for the recommended action.

3. BIoTa Data Management and Processing

3.1. Federated Temporal Graph Attention Transformer Model

The first proposed model is a dynamic heterogeneous graph, where a barn is modeled as a graph consisting of cow, zone, sensor and event nodes. The edges connecting the nodes are time varying and represent social relationships, competition for resources, camera zones, areas with shared microclimates, as well as influence of actuator nodes. The input features, for each animal i at time t, are collected in a vector $x\_i,t \in R^n$ where n is the number of features for each animal at time t. The wearable sensors and the visual behavior of animals (eating, resting) are among the input features, as well as the microclimate of the zone where animals are located, time-of-day, last management events for animals and data-quality features. The graph attention in the TGAT model learns about relevant neighboring animals, zones and sensors for the behavior of the animal i at time t, and the temporal transformer layer in the model learns about long-time spans (an animals' rumination can decline gradually over time, an animal can be exposed to noise repeatedly, the thermal load on an animal can add up over time).

Our proposed model, Fed-TGAT, allows a farm to train local updates on its own data without having to transfer data. Cross-farm learning then happens by secure aggregation of local model updates. Model cards, which contain information about a models' knowledge of local data, sensors, as well as a models' performance on a local validation set, are also used in cross-farm learning. The Fed-TGAT model is trained using a multi-task learning framework, consisting of behavioral classification and welfare-risk forecasting, graph-structure reconstruction, and model calibration. The following loss function is used to train the model:

$$L = L\_behavior + \lambda\_r\, L\_risk + \lambda\_c\, L\_calibration + \lambda\_g\, L\_graph + \lambda\_f\, L\_federated \quad (1)$$

where L_behavior is cross-entropy over behavioral classes, L_risk is a multi-horizon risk forecasting loss, L_calibration penalizes unreliable probabilities, L_graph regularizes relational embeddings and L_federated controls divergence between local farm models and the global model.

There are three types of splits to evaluate Fed-TGAT, namely a random, a temporal and an animal-wise split, where the latter is the most challenging for generalization. The behavior classification loss is cross-entropy between predicted distributions and true labels for all animals in a batch. The risk forecasting loss is multi-horizon, being for all time-steps for all animals in a batch, as in Figure 2. The calibration loss penalizes a model for reporting unreliable confidence. The graph loss penalizes the relational embeddings for violating constraints on the relations between nodes. The federated loss penalizes the local models of all farms in the federation for drifting too far from the global model.

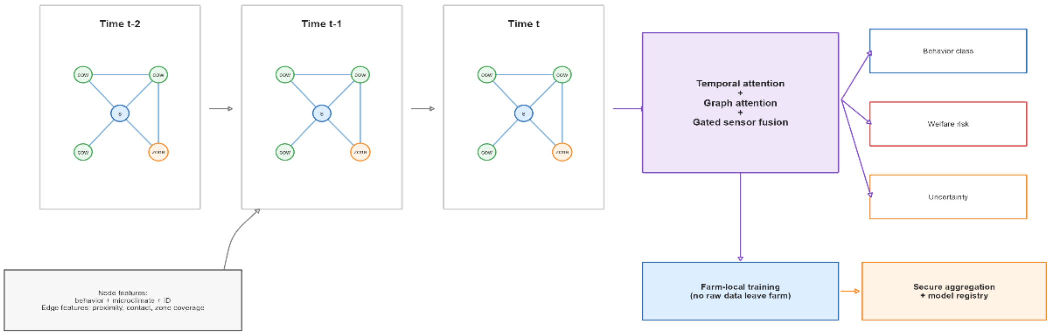

Fig. 2. Fed-TGAT model design. Dynamic temporal graph snapshots connect cows, sensors and barn zones. Graph attention, temporal attention and gated sensor fusion generate behavior classes, welfare-risk forecasts and uncertainty estimates. Federated training enables multi-farm learning without raw data transfer.

3.2 CausalTwin for Counterfactual Welfare Risk

A smart barn must provide more than predictions with high accuracy. The management recommendations give an estimation of intervention effect on the welfare risk and not only be correlated with it. To achieve this goal, CausalTwin models the latent stress caused by the environmental stressors as a function of the environmental context, management and actuator decisions of the farmer. Thus, the platform not only predicts the effects of the users' observed actions but also the effects of all other possible actions. The structural graph of a causal nature digital twin is used to build up the model, as in Figure 3.

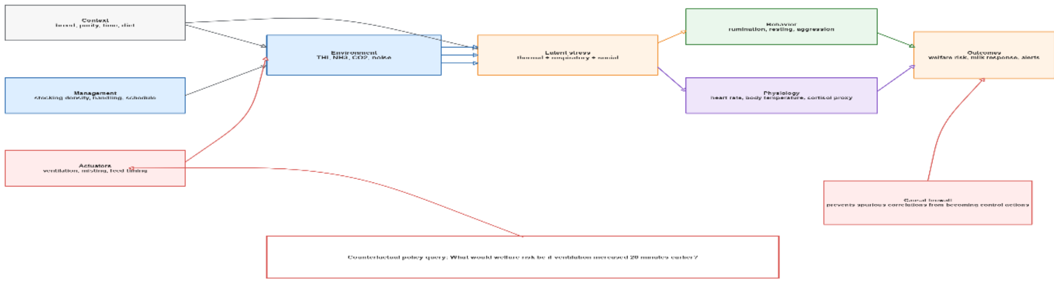

Fig. 3. CausalTwin model. Digital twin separates prediction from intervention. Correlations trigger diagnostics, control actions are filtered through counterfactual safety evidence and causal assumptions.

In the graph, environmental stressors determine the level of latent stress. The level of latent stress determines the behavioral and physiological indicators of an animal. The management context and the identity of an animal are confounders for this model. The actuator's decisions determine the interventions on an animal, as in Table 2. In this way, the platform can ask questions such as what is the probability of reduced rumination when the ventilation intensity is increased before THI reaches a certain value or what is the expected welfare gain by redistributing the feeding space under high stocking density.

Table 2. Causal variables, interventions, and measurable proxies.

Construct	*Variables*	*Intervention examples*	*Potential confounders*
Environmental exposure	THI, NH_3, CO_2, noise, air velocity, light, particulate matter	Ventilation, misting, shading, bedding, and cleaning	Season, barn zone, sensor drift, time of day
Latent stress	Unobserved stress state inferred from behavior, physiology and environment	Indirectly reduced through climate and management actions	Breed, parity, lactation stage, baseline health
Behavioral response	Rumination duration, inactivity, aggression, vocalization, lying/standing transitions	Resource redistribution, handling adjustment, enrichment	Feeding schedule, milking time, social hierarchy
Physiological response	Body temperature, heart rate, respiration proxy, cortisol proxy where available	Veterinary examination, cooling, hydration support	Disease status, pregnancy, medication
Production outcome	Milk yield, milk quality, feed intake, health events	Preventive intervention before productivity loss	Diet, milking robot traffic, herd management
Governance output	Audited event, model version, uncertainty, and explanation	Certification, compliance report, human override	Data ownership, access rights, annotation policy

3.3 Safe Multi-Objective Reinforcement Learning and Predictive Control

Safe-MORL adds a layer of functionality on top of welfare-risk forecasts and causal analysis of the expected intervention effect. Smart barns do not only perform, but they also control. The objective of a controller is to keep the welfare risk within a bound area, while trying to minimize other risks (the risk of using water, electricity, other system instabilities). The safe operation of a barn is a constrained multi-objective problem, as in Figure 4 and Table 3. An objective for Safe-MORL is to minimize expected barn welfare risk, expected energy, water, and instability, while trying to keep all interventions within a set of hard constraints that relate to the risk of animal welfare loss and that limit the interventions in terms of THI exposure, concentration of NH_3 in the air, noise exposure, actuator limits, human in the loop approval limits, and safety margins for animal welfare. Model predictive control is used for the near real-time barn control, and Reinforcement Learning improves the controller's policy by validation and learning from several interventions. For uncertain situations such as interventions with low causal confidence or even poor-quality data, Safe-MORL produces a recommendation for actions, instead of performing irreversible actions. When data has not been collected for expensive interventions, required data may not even exist. In such cases, Safe-MORL prompts an intervention by an operator or a veterinarian, boosting system control.

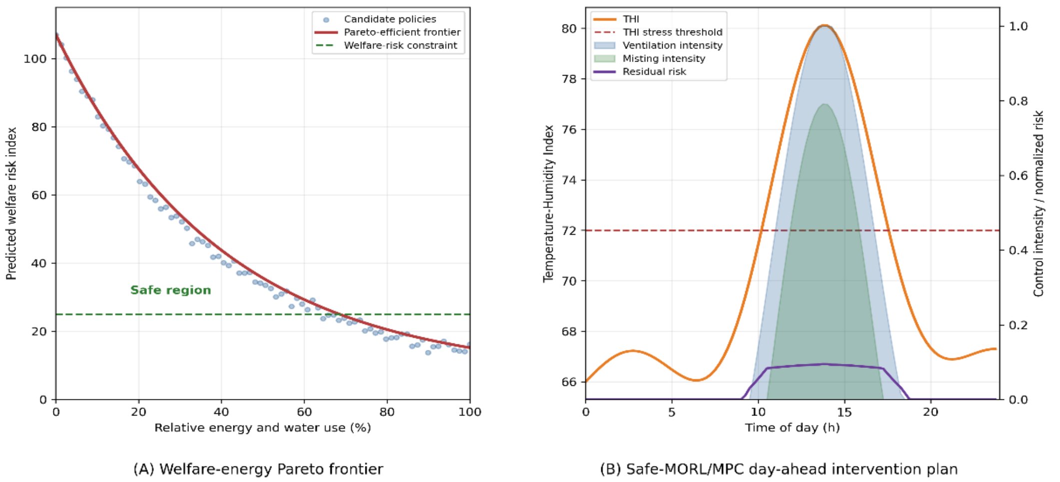

Fig. 4. Safe-MORL control. Panel A illustrates the welfare-energy Pareto frontier. Panel B shows how day-ahead control may activate ventilation and misting before or during THI stress peaks.

Table 3. Safe-MORL control objectives, constraints and candidate interventions.

Control	*Constraints*	*Candidate interventions*
State vector	Current and forecasted environmental, behavioral, physiological, production	THI forecast, rumination risk, NH3 trend, fan status, milk-yield risk
Actions	Discrete or continuous farm interventions	Fan speed, misting duration, shade deployment, feeding time adjustment, alert escalation
Reward terms	Positive rewards for risk reduction and stable welfare, penalties for resource consumption and unsafe oscillations	-welfare risk, -energy cost, -water cost, -actuator wear, +validated recovery
Hard constraints	Conditions that must not be violated	Maximum THI exposure, NH_3 threshold, actuator safety bounds, minimum human approval
Soft constraints	Preferences that can be traded off when welfare requires intervention	Energy efficiency, water use, operational convenience, noise minimization
Safety override	Rule-based and human-in-the-loop limits for uncertain cases	Veterinary confirmation, confidence threshold, rollback

3.4. Trustworthy AI, Blockchain Provenance and Model Governance

The governance layer combines four mechanisms, namely immutable event provenance, federated model governance, explainability, and calibrated uncertainty. Immutable provenance is implemented by hashing event metadata, model identifiers, data-quality states, and audit signatures. Raw data are stored off-chain to avoid prohibitive storage cost and privacy exposure, while hashes and decision metadata remain verifiable. Federated model governance records which model version generated an alert, which farm-local update contributed to a global model, which data distribution was used for validation and whether a model drift warning was active. A model that performs well in one barn layout may perform poorly after sensor replacement or seasonal change.

Explainability and uncertainty control are necessary for responsible adoption, as in Table 4. Shapley additive explanations (SHAP), attention maps and counterfactual explanations help farmers and veterinarians understand whether an alert is driven by THI, noise, rumination variance, ammonia or other variables. Conformal prediction adds a formal coverage layer so that high-uncertainty predictions can be escalated rather than acted upon automatically.

Table 4. Governance safeguards integrated into BIoTa-X.

Safeguard	*Implementation*	*Validation*
State vector	Current and forecasted environmental, behavioral, physiological, production	THI forecast, rumination risk, NH_3 trend, fan status, milk-yield risk
Immutable provenance	On-chain hashes of events, model IDs, uncertainty and explanation summaries	Prevents silent alteration of welfare records and supports audits
Off-chain raw data	Video, accelerometer and high-frequency sensor files stored outside the ledger	Reduces cost, respects privacy and supports technical scalability
Model cards	Versioned description of training data, metrics, failure cases and deployment assumptions	Improves reproducibility and responsible cross-farm transfer
Conformal uncertainty	Prediction sets and calibrated risk intervals	Avoids overconfident alerts and supports human escalation
XAI reports	Feature importance, attention analysis and counterfactual explanations	Decisions to farmers, veterinarians and reviewers
Human override	Operator/veterinarian approval for high-impact or uncertain actions	Maintains accountability and supports ethical deployment
Drift monitoring	Sensor drift, seasonal drift and behavioral distribution shift alerts	Protects model validity after farm changes

4. Results and Discussions

The proposed BIoTa-X models were validated in two stages. Stage 1 used the existing BIoTa data organization as a baseline with 10-second synchronized behavioral windows, environmental measurements, annotated classes and the baseline CNN-LSTM evaluation pipeline. Stage 2 extended the deployment across farms, seasons and barn layouts to evaluate transferability, robustness and federated learning benefits. The main hypotheses were temporal graph modeling improves animal-wise and temporal generalization compared with independent CNN-LSTM sequences (H1); adding causal counterfactual logic reduces unsafe or irrelevant interventions compared with threshold-only rules (H2); Safe-MORL reduces welfare-risk exposure with lower energy and water use than static cooling rules (H3); and blockchain provenance and model cards improve auditability with acceptable latency and energy overhead (H4). The evaluation dashboard of BIoTa-X is illustrated in Figure 5.

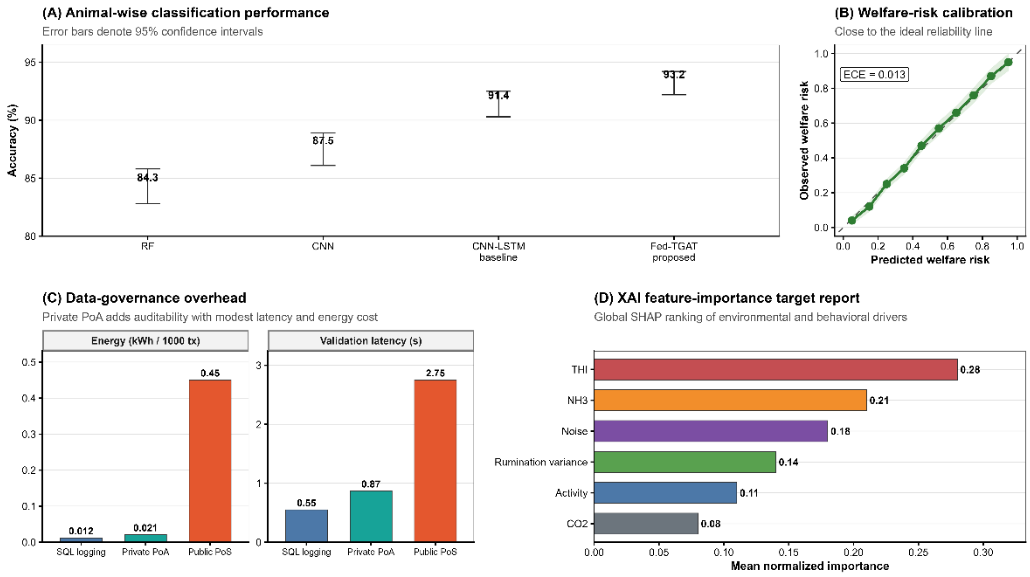

Fig. 5. Experimental validation dashboard of the proposed BIoTa-X framework. (A) Animal-wise classification performance of conventional machine-learning and deep-learning baselines compared with the proposed Fed-TGAT architecture; error bars indicate 95% confidence intervals. (B) Calibration curve for welfare-risk prediction, where the shaded region denotes the 95% uncertainty interval and the dashed diagonal represents ideal calibration. (C) Data-governance overhead for centralized SQL logging, private Proof-of-Authority blockchain validation, and public Proof-of-Stake benchmarking, reported separately for validation latency and energy consumption. (D) Global explainability analysis based on mean normalized SHAP importance, highlighting the dominant contribution of THI, NH_3, noise, rumination variance, activity and CO_2 to welfare-risk prediction.

The proposed Fed-TGAT model achieved the highest animal-wise classification performance, improving the reported CNN-LSTM baseline from 91.4% to 93.2%, while conventional RF and CNN models remained below 88% [4]. This supports H1, indicating that temporal graph attention better captures animal-specific and time-dependent welfare deterioration than independent sequential models. The calibration curve showed close agreement between predicted and observed welfare risk, suggesting that the model's confidence estimates are reliable enough for decision-support use. The governance analysis supports H4, as private PoA blockchain validation introduces a modest overhead relative to SQL logging but remains far below the latency and energy cost of public blockchain validation, making it suitable for farm-scale welfare auditing. Finally, the SHAP analysis indicates that THI, NH_3 and noise are the dominant explanatory variables, followed by rumination variance and activity, confirming that the model bases its predictions on biologically meaningful environmental and behavioral drivers rather than opaque statistical artifacts. This interpretation is consistent with the original BIoTa results, where environmental stressors such as THI, NH_3 and noise were linked to behavioral deviations and where blockchain validation provided high-integrity welfare records with acceptable latency.

5. Conclusions

This paper further extends the smart-barn framework BIoTa, being an implementation based on the concepts of federated temporal graph attention, causal digital twins, safe multi-objective control and trustworthy AI governance. All the modules of BIoTa system, multimodal sensing, edge-cloud processing, blockchain-based validation and CNN-LSTM-based behavioral analysis, are retained in BIoTa-X framework. In contrast to BIoTa, which supports practical animal monitoring, the extended architecture of BIoTa-X supports relational welfare inference, counterfactual intervention reasoning, energy-aware adaptive control, and auditable model governance.

The new architecture for BIoTa-X is integrated, mathematically sound and deployable, it models welfare of animals on a farm as a dynamic graph that is processed by a Fed-TGAT and it transforms predictions into action evidence for counterfactual interventions by means of a CausalTwin. Lastly, the architecture also includes a governance layer that connects predictions, uncertainty, explanations and provenance into one certifiable decision trail.

Future work will consist of generalizing the results from one smart-farm over the course of one season to other farms as well as to other time periods. Farm-wise transfer of learned animal models versus a federated learning approach over all farms in a region is another promising research question. Finally, surveys amongst the potential adopters, the veterinarians as well as the individual farmers, could provide insights into the potential adoptability of BIoTa-X.

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