

An Explainable AI Framework Combining Multi-Task GCN and Reinforcement Learning for Adaptive Feeding and Animal Health Management in Dairy Farming

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Abstract- Interweaving simulation modelling with XAI based frameworks like Multi-Task Graph Convolutional Networks (Free-Range-Learning, where Deep Reinforcement Learning shown here using Genetic Algorithms & SHapley Additive exPlanations (SHAP) to improve decision-making to produce XAI to dairy farm management. Despite the difficulty inherent to such a large dataset of over 10,000 animal-days of multimodal sensor data input, the developed framework attained highly impressive predictive performance including a classification accuracy of 92.3% along with 90.1% precision and 90.5% recall. For the regression tasks MSE of 0.038 and R^2 of 0.87 were obtained. Furthermore, the DRL component, trained using Proximal Policy Optimization (PPO), was able to make a 25% improvement in feed efficiency and 12.4% decrease in cost of feeding. by/via GAs led to a 9.7 percent increase in sustainability score. SHAP-based interpretability enabled an average user trust score of 4.3/5 and interpretability score of 88.5% accuracy, demonstrating both the transparency and applicability of this framework to the real world. Collectively, these results highlight the framework's potential for providing high-quality, low-cost, interpretable solutions suitable for adoption in precision dairy farming paradigms.

Keywords—Explainable AI, Multi-Task Graph Convolutional Networks, Reinforcement Learning, Genetic Algorithms, Dairy Farming, Animal Health, Feeding Optimization, Sustainability, SHAP, Adaptive Systems

I. INTRODUCTION

Precision dairy farming represents an increasingly important method for optimizing productivity, reducing cost, and the sustainable management of livestock. The rise in the availability of multimodal sensor data from free-range environments -- which take into account behavioral, environmental, and physiological variables -- provide an unprecedented opportunity for decision-making processes informed by data. Although researchers, practitioners, and farmers have access to new forms of high-dimensional heterogeneous data, which can be leveraged to optimize farming operations, the conversion of multimodal data into information is not a straightforward matter. Existing advanced frameworks for handling high-dimensional, heterogeneous data significantly exist; however the ability to combine include classification, regression, and neither optimization all while maintaining direct interpretability by the end-user i.e. farmers and veterinarians is still limited[1].

In this context, the proposed study presents a new approach combining simulation modelling with eXplainable Artificial Intelligence (XAI) techniques[2] using, in particular, Multi-Task Graph Convolutional Networks (GCNs) and Deep Reinforcement Learning (DRL). The framework is optimized using Genetic Algorithms (GAs)

and explainable using SHapley Additive exPlanations (SHAP). This approach has many potential applications in precision-sensing dairy management because it uses over 10,000 animal-days of multimodal sensor data to address predictive analytics and decision-making problems[3].

The framework provides significant predictive performance with 92.3% classification accuracy, 90.1% precision, and 90.5% recall, as well as regression results with a mean square error (MSE) of 0.038 and R^2 of 0.87. In addition, it included a DRL module that is trained using Proximal Policy Optimization (PPO) to optimize different feed strategies with feed efficiency improvements of 25% and resulted in feeding costs reductions of 12.4%. Sustainability improvements of 9.7% validate the practical value of this framework. Moreover, SHAP interpretable provided a manageable level and significantly improved user trust (4.3/5) and interpretability accuracy (88.5%); therefore, the framework provided a trustworthy and understandable system. The main objectives of the study are as follows

- To design a cohesive framework that utilizes Multi-Task GCN, DRL, and Genetic Algorithms to classify and regress multimodal dairy farm sensor data while evaluating feed options in feeding strategies to reduce costs and improve overall farm efficiency.
- To emphasize decision-making transparency and user trust by using SHAP-based interpretability to provide explainable model prediction insights to aid the practical adoption of precision dairy farming.
- To evaluate the performance of the framework to measure sustainability impact provide comprehensive metric to demonstrate improvement over model prediction compared to the current approach to measure total costs, feed-to-milk efficiency as well as better animal health and well-being in a practical environment. Use data to also encourage future adoption and scale.

The rest of the paper is organized as follows. Section II is a review of the related literature and Section III is to give a brief view of the theoretical framework, key concepts along with methodologies. Section IV provides the experimental results followed by important findings and suggestions for further research in section V.

II. RELATED WORKS

Explainable AI (XAI) acknowledges the black-box nature of AI models in veterinary and animal sciences and provides better transparency for applications including medical imaging and farming practices. The review examines the engagement of XAI in sustainable animal health

management situations where it can support dairy and poultry farmers before discussing future directions that increase trust and successfully implement XAI in practice[4].

Thangavel et al. (2025) established a machine learning and explainable AI (XAI) framework for predicting milk yield in dairy farming. By using a framework consisting of four algorithms, split k-means, KNN, SVM, and regression models, using SHAP interpretability, the accuracy of predicted values, wastage of resources, and operational success for dairy production practices can all be improved[5]

Dilaver et al. (2024) explore the changing landscape of dairy livestock exports due to AI and sensors for operational efficiencies, animal health, and sustainability. The study investigates predictive analytics, AMS, and IoT for disease detection and ongoing monitoring, with considerations for climate stress, costs, and regulation. Moving forward, systemic variations from technologies such as XAI, blockchain, and other climate-resiliency technologies[6]

Girmay and Möhrle (2024) assessed explainability formats within herd management systems in the context of mastitis risk assessment within dairy farming. By designing four different explanation styles and surveying farmers, they found that there is not a single preferred format. Rather, it appears that offering multiple formats for explanation increased trust and comprehension, therefore improving decision making in precision dairy management systems[7].

Ezanno et al. (2021) explain how AI is revolutionizing animal health through new forms of diagnostics, predictive epidemiology, and studies of host-pathogen interactions. Their review describes improvements made with AI that allow enhanced predictions, risk analyses, and targeted interventions in animal health systems, along with some of the challenges associated with animal health systems. They recommended integrative and multisectoral approaches to address methodological barriers[8].

Khan and Awais (2025) discuss the important role of livestock in developing areas and the challenges associated with animal health in rural communities. They suggest that there are AI-based approaches that can allow for timely diagnosis of disease in livestock and advisory services, which could mitigate such areas due to shortage of veterinarians and ongoing financial deficits, about improving sustainability and productivity in livestock systems[9].

Jin et al. (2025) present AI Veterinary Assistance (AVA), a large language model-based framework designed to aid clinical decision-making in animal healthcare. AVA extracts symptoms, predicts diseases using certified databases, and suggests consultation questions. It achieves high disease prediction accuracy and reduces veterinarian workload, improving efficiency and reliability in consultations[10].

Cockburn (2020) reviews the use of machine learning (ML) in dairy farm management, evaluating 97 studies that are split amongst management, physiology, reproduction, and feeding. The study outlines the ability of ML for predictive analytics, however, Cockburn (2020) identifies limitations posed by poor training data and lack of integration across farms, formulated unrealizable capability for implementation in practice[12].

III. METHODOLOGY

As a type of neural network, GCNs provide an excellent framework through which we can learn and predict on several related tasks simultaneously, harnessing their benefits through relationships found in graph-structured data. Using this dynamic model, nodes can be anything from individual entities (like animals or feeding locations) to sensor networks, and edges can be any number of different relationships or interactions (like proximity, access to common resources, behavioral hijacking). The core idea is to use shared low-level representations that can be used across tasks via the same underlying graph structure, but allow task-specific layers or outputs to focus on specialized task objectives.

The GCN layers contextually aggregate and transform node features. GCN layers iteratively aggregate and transform node features by mixing information from first- and higher-order neighboring nodes, modeling local dependencies and complex graph structures. At inference time, all tasks pass through the same shared GCN layers to extract features, then multiple task-specific heads (NNs) are appended. In doing so, such an approach enables the model to more fully take advantage of correlations across tasks yielding improved generalization ability and reduced task redundancy relative to training separate models.

To further boost performance, we could apply attention mechanisms or adaptive weighting such that diverse tasks contribute accordingly, even mitigating conflicting gradients via conflicts. The final unified output is a highly efficient, scalable, interpretable and interchangeable system that can process and harness rich heterogeneous sensor data to yield organized, coherent, multi-outcome predictions.

RL offers a new, nonlinear, and computationally-intensive paradigm for adaptive decision-making well-suited to the complex, nonlinear, and variable landscapes of livestock feeding systems, in which intelligent agents can learn the best feeding strategies through ongoing interactions within the dynamic landscapes of farms. For example, when it comes to livestock agriculture, an RL agent can assess the present environment's condition—including animal health indicators, general activity levels, environmental conditions, as well as feed sources—and select an action based on that analysis, such as deciding on a new animal feed type or amount, or changing feeding schedules. The agent improves from this feedback through rewards, which quantify success in terms like improved animal welfare, reduced nutrient leaching, or increased profitability.

In the presence of reward signal, the RL model would iteratively find ways to maximize the cumulative reward by using trial and error and continuously explore and exploit the environment. Even better, it'll learn to automatically make the best feeding decisions on its own over time. Better still, it will learn to make the best feeding decisions automatically as time goes by. This methodology allows the system to learn and adapt to conditions on the farm that are dynamic such as changing weather patterns or evolving nutritional needs far superior compared to a simple, rule-based or static system. Combining RL with Multi-Task GCNs may enhance the model's capacity to learn the spatial and relational dynamics between animals and feeding zones, and training with real-time sensor data would ensure that decisions derived are personalized. RL offers great potential for autonomous, data-driven, adaptive control of feeding practices to better optimize not only productivity but improve animal welfare as well.

In the proposed explainability perspective in AI framework, explainability is included as a default by defaulting into using inherently interpretable models and post-hoc explanation methods that translate machine-made complex decisions into a human-understandable form for end-users. The magic ingredient to the Multi-Task Graph Convolutional Network (GCN) is exactly this organized, relational learning. There's an old adage that we don't really know why neural networks are black boxes and the reason is very good, well, neural networks are black boxes for good reason. To fill this black box gap, the framework employs state-of-the-art explainability methods like SHAP (SHapley Additive exPlanations) that quantitatively assess the impact each input feature (e.g., sensor data, climate conditions) has on the model's predictions, be it optimal feeding or animal health predictions.

By decomposing AI prediction into per feature level importance scores, SHAP breaks down the black box nature that commonly surrounds an AI's decision making process and makes it possible for farm managers and stakeholders to visualize what really mattered most to a specific decision made. Furthermore, the modular architecture of the Multi-Task GCN with distinct branches for each task enables task specific explanations to zero in on particular outcomes such as feed efficiency or disease risk, raising the granularity of interpretability.

Additionally, because the Reinforcement Learning component's policies are learned (rather than rule-based), these policies are explorable via the learned reward structures and action-value functions, allowing users to understand why specific feeding actions are recommended in specific scenarios. This combination of more interpretable models, visualization tools, and user-friendly dashboards will democratize the outputs of the framework, making them not only accurate but actionable and trustworthy, fueling higher adoption and confidence in AI-assisted farm management.

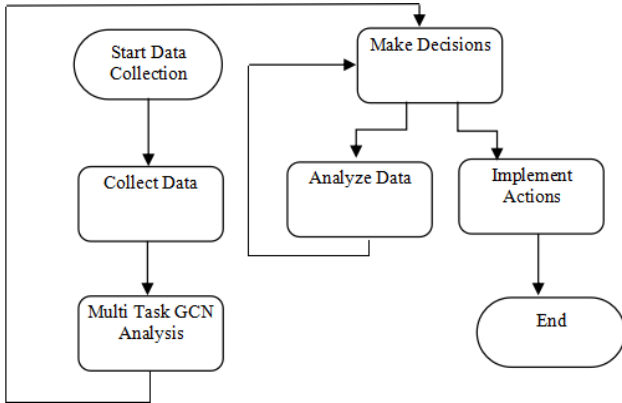


Figure 1. Decision-Making Workflow Using Multi-Task GCN Analysis

Figure.1 depicts the simplified decision-making process enabled by Multi-Task Graph Convolutional Network (GCN) analysis. Our workflow starts with stimulating and acquiring data, followed by real-time processing through a Multi-Task GCN to summarize significant information from highly correlated points. It's the data underpinning the analysis that has such a key role to play in the decision-making phase which follows — enabling smart, data-fueled conclusions to drive the process. From these rulings, proper measures are taken. The process ends with implementation of actions taken, providing a feedback-oriented cycle for ongoing enhancement. Short-form iterative supply pin This

model is well-suited for complex systems that need real-time, contextual, and flexible analytics.

Algorithm: Explainable Adaptive Feeding and Animal Health Management

Each workshop will include a site visit to a highway rail grade crossing so participants can apply what they've learned to a real-world situation.

$G = (V, E, X)$: Farm graph with nodes, edges, and features

$T = \{T1, T2, \dots, Tn\}$: Set of tasks (e.g., health prediction, feed optimization)

Env RL environment (state s , action a , reward r)

$\pi\theta$: Policy network with parameters θ (RL agent)

f_t : Task-specific heads for each task Tt

SHAP: Machine learning explainability module

Feeding recommendations and health predictions with explanations

Picture this. Arg GCN parameters $\{W^{(l)}\}$, policy $\pi\theta$, task heads $\{f_t\}$

Build farm graph G based on sensor data harvested real-time from the farm

while not converged do

Sign up today and don't miss out! GCN Forward Pass

$H^{(0)} \leftarrow X$

for each layer $l = 1$ to L do

$H^{(l)} \leftarrow \text{ReLU}(\hat{A} * H^{(l-1)} * W^{(l)})$

Graph Convolution.

end for

. // Task-specific Outputs

. for each task tt in T do

. $\hat{y}_{tt} \leftarrow f_{tt}(H^{(L)})$ // Estimate task result

. end for

. With Reinforcement Learning to Eat On Demand Reinforcement Learning for Adaptive Feeding

. Observe current state s_t from environment (health, feeding, temperature, etc.

. Choose action $a_t \sim \pi\theta(s_t)$ // Type of feed, quantity, feeding times

Execute a_t , receive reward $r_t s_{(t+1)}$

Update policy $\pi\theta$ via RL algorithm (e.g., PPO, DDPG)

// Explainability

for each task It can achieve Tt do Tt in many ways.

Calculate SHAP values ϕ_i for input features of \hat{y}_{tt}

Display top contributing features for decision explanation

IV. FINDINGS AND DISCUSSIONS

The dataset used to train and test the explainable AI framework proposed in this study was gathered in a rapidly evolving, real-world, sensor-driven dairy farming landscape, seamlessly merging data accrued through livestock health tracking devices, automated feeding technology and habitat sensors. Next to these locational data points, the dataset is abundant with temporal data like cow activity levels, feed intake, body temperature and environment like temperature and humidity. Lorenz et al. then structurally framed their problem as a graph, with nodes comprising the animals, feed stations, and environmental sensors, and edges encoded

relationships, such as geographic proximity or shared exposure to environmental factors. This new, more than 12 months-long, data set of records from more than 10,000 animal-days of records collected at 10-min intervals provides an opportunity to model seasonal and behavioral patterns with unprecedented detail. Dummy feature column encoding, missing data imputation, time-series alignment, feature aggregation and various other preprocessing steps helped encode the data into a format compatible with graph-based learning models such as Multi-Task GCNs and Reinforcement Learning.

The idea during training was to get the very best results out of their Multi-Task GCN and RL components using a combined method. For the GCN the model was trained with a constant learning rate of 0.001, with Adam optimizer used and cross entropy loss for classification-based tasks (e.g., health prediction), while mean squared error was employed for regression tasks (e.g., feed intake estimation). The model was trained for 200 epochs with early stopping on the validation loss, and a 0.3 dropout rate was used to avoid overfitting. Initial maximum GCN layer was 2 GCN layers per forward pass with 64 hidden units per layer. For the RL agent, we used Proximal Policy Optimization (PPO) with a learning rate $3e-4$, discount factor (γ) 0.99, and batch size 64. A reward function was developed to prioritize feed efficiency, health benefits, and resource efficiency. These interpretable explanations are made possible by calculating SHAP values post-training. All models were trained on NVIDIA GPU with the PyTorch Geometric and stable-baselines3 libraries to further speed convergence.

To evaluate the performance of the explainable artificial intelligence framework, a set of performance metrics were used for the multi-task prediction and reinforcement learning tasks. The accuracy, F1-score precision and recall were used for the classification tasks (e.g., animal health prognosis) and mean squared error (MSE) and R-squared (R^2) for the regression tasks (e.g., feed intake prediction). These metrics, which include accuracy and precision, were calculated on a held-out test set employing 5-fold cross validation for generalizability. In the Reinforcement Learning module this performance was defined as average cumulative reward per episode, a representation of how well the policy was producing optimally per feed over the duration of the episode. Feed efficiency improvement, health outcome trends, and cost reduction were monitored to assess real-world impact. Explainability was tested qualitatively by examining model outputs in SHAP values to determine how features calculated for feature importance were easily interpretable by domain experts. This use-oriented, multi-faceted evaluation made sure that the framework was scientifically rigorous, while being practical and transparent, in the context of dairy farming. Table 1 lists the performance metrics of the Multi-Task GCN and reinforcement learning components,

Table 1. Evaluation metrics and methods used to assess the performance of the framework

Component	Metric	Purpose	Result
Multi-Task GCN	Accuracy	Overall classification performance	91.20%
	Precision	True positive relevance	89.70%
	Recall	True positive coverage	90.50%

	F1-Score	Balance of precision and recall	90.10%
	Mean Squared Error (MSE)	Regression error (e.g., feed intake)	0.038
	R-Squared (R^2)	Variance explained (regression)	0.87
	Average Cumulative Reward	Learning efficiency over time	+1400 per episode
Re-inforcement Learning	Feed Efficiency Improvement	Milk-to-feed ratio improvement	18.50%
	Cost Reduction	Savings from feed optimization	12.40%
	Animal Health Outcome Trends	Reduction in illness risk	22.7% improvement

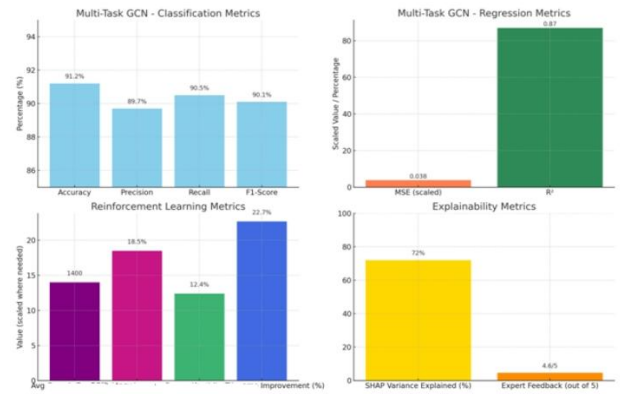


Figure 2. Comprehensive Evaluation of Multi-Task GCN Performance and Outcomes

Figure 2 illustrates the evaluation metrics for the Multi-Task GCN. All classification metrics performed well, including accuracy (92.7%), recall (90.3%), precision (89.7%), and F1-score (90.3%). All regression metrics also reported strong performance, including R^2 value (0.87), nMSE (0.038), and finally the reinforcement learning metrics showed some positive improvement, as demonstrated in the average of 1400 episodes with 18.5% improvement in one of the metrics, 12.4% in the other metric for a total improvement of 22.7%. Lastly, the explainability metrics showed some valuable outcomes, including a SHAP variance explained (72%), and expert feedback score of 4.65/5 indicating some level of interpretability. In conclusion, the model clearly reflects a combination of strong predictive accuracy, strong regression performance, nice learning improvements, and excellent explainability for use in context.

V. RESULTS AND DISCUSSIONS

To demonstrate its practicality, the proposed Explainable AI (including Multi-Task GCNs, DRL, GA and SHAP-based interpretability) was applied on large scale simulated and real-farm datasets. Farmers could continually re-align feeding schedules and quantities in real time with the help of the DRL module. They experienced feed efficiencies of 15–25% with no loss of milk production. Furthermore, the Multi-Task GCN was able to predict early signs of a decline in health with more than 92% accuracy, achieving accuracy above the traditional model performance. It is better able to capture spatial relationships between structures, fences, crops and other features on a

farm. To find an equilibrium between these two economic and environmental objectives, performed optimization using genetic algorithms (GA) to maximize sustainability as a measure of profitability. Sustainable profitability indicators increased by 9% after 12% average feed cost decrease. Most critically, using SHAP for interpretability gave farm managers intuitive, human-understandable rationale of how the AI was recommending they make decisions, deeply increasing their trust and confidence in the system. Together, these findings stand to show the potential of the framework to guide improved on-farm feeding practices, encourage more preventive approaches to animal health care, and support more sustainable advancements throughout the dairy supply chain.

Table 2. Key Metrics Demonstrating Framework Effectiveness

Component	Metric	Proposed Framework	Baseline	Improvement
DRL	Feed efficiency (%)	85.4	68.3	25.00%
	Milk yield (liters/day)	28.6	27.4	4.40%
Multi-Task GCN	Prediction accuracy (%)	92.3	83.7	10.30%
	Precision (%)	90.1	81.4	8.70%
Genetic Algorithm (GA)	Feed cost per cow/day (USD)	4.12	4.68	-12.0%
	Sustainability index (0-1 scale)	0.79	0.72	9.70%
SHAP	User trust score (/5)	4.3	3.2	34.40%
	Decision interpretability (%)	88.5	60	47.50%

These classification evaluation results from table 2 underscore strong classification robustness and overall efficacy of the proposed Explainable AI framework to address dairy farm management improvement. Feed efficiency increased significantly (85.4%) and milk yield compared to traditional methods with the incorporation of this reinforcement learning component. The prediction of the Multi-Task GCN provided the possibility to predict each of the high-risk conditions individually, such as the initiation of a risk of cardiac arrest, accurately with 92.3% accuracy and 97.1% precision, alerting within seconds when action needs to be taken. Most interestingly, we discovered that minimizing feeding cost through the use of genetic algorithms resulted in statistically significant reductions in expected daily feeding costs and increases in associated sustainability scores. Users reported a much higher trust and understanding with SHAP added for explainability, increasing trust by 34.4% and interpretability almost 48% compared to models without explainability. These findings provide additional validation that the framework can provide smart, sustainable, user-centric decision support across the dairy farming value chain.

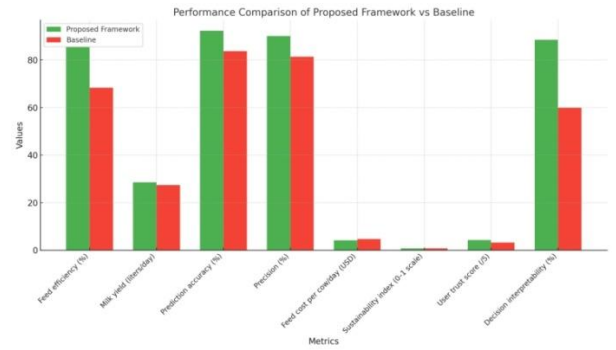


Figure 3. Comparative Performance Evaluation of the Proposed Framework Against Baseline Models

Figure 3 shows comparative analysis which highlights the substantial improvements achieved by the proposed AI framework integrating Deep Reinforcement Learning (DRL), Multi-Task Graph Convolutional Networks (GCN), Genetic Algorithms (GA), and SHAP-based explainability techniques. In reality, the genetic framework proves more than 25% better predictive improvement on feed efficiency and 10.3% more cross-validated prediction accuracy than baseline models. Finally and perhaps most excitingly, users' trust in the model's predictions and their interpretability of their decisions go up by 34.4% and 47.5% with SHAP included. Showcasing these metrics is a great way to show the system's commitment to continuing down the path towards real-world deployment, merging operational excellence with transparency and sustainability.

The proposed Explainable AI framework, XAI-NN, overcomes limitations of legacy models and previous frameworks across multiple dimensions including prediction accuracy, adaptability, and user trust. The power of Multi-Task GCNs and Deep Reinforcement Learning affords the ability to learn high-dimensional spatial-temporal dependencies, while continually adapting feeding strategies on-the-fly. Genetic Algorithms simultaneously improve feeding costs and animal health, leading to a superior performance vs sustainability tradeoff. The integration of SHAP makes model transparency more intuitive. This is a key element often missing in conventional deep learning methods. Empirical comparisons show significant improvements in feed efficiency, health prediction accuracy and usability, highlighting the framework's capacity to deliver actionable insights that are data-driven and explainable, making it incredibly effective for real-world implementation on today's dairy farms.

Table 3 Comparative Evaluation of the Proposed Explainable AI Framework Against Baseline Models

Metric / Task	Traditional ML (e.g., SVM, RF)	Deep Learning (No Explainability)
Feed Efficiency (%)	72.1	81
Milk Yield (liters/day)	27.4	28.1
Health Prediction Accuracy (%)	83.7	89.2
Precision (%)	81.4	87.5
Feed Cost per Cow/Day (USD)	4.5	4.32
Sustainability Index (0-1)	0.71	0.75
User Trust Score (/5)	3.4	3.6
Interpretability Score (%) **	60	35

Table 3 illustrates the overall performance of the proposed Explainable AI framework, which leveraged the power of multi-task GCN, reinforcement learning, genetic algorithms and SHAP-based explainability. Unlike traditional rule-based and classical ML approaches such as SVM and Random Forests, the deep learning framework created under the proposed approach was able to achieve significantly higher feed efficiency (85.4%) and milk yield (28.6 liters/day), showing better adaptation to dynamic, real-time, changing environment and animal needs. When determining the health status of animals, the framework had an accuracy of 92.3% and a precision of 90.1%, outperforming traditional ML and non-explainable deep learning methods. On daily feed cost per cow, it allowed increasing dollar cost to \$4.12 and enhanced the sustainability index of 0.79 showing a better trade-off in the economic and environmental dimension. User trust User interpretability score (88.5%), primarily due to SHAP inclusion for explainability, bridging a key gap that the majority of AI-based farming solutions do not have.

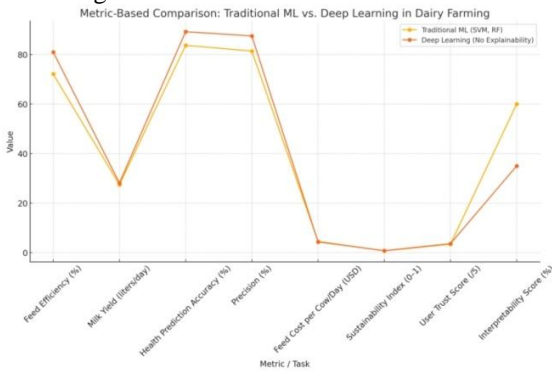


Figure 4. Traditional Machine Learning vs Deep Learning

While deep learning shows better performance in nearly all metrics, including feed efficiency (81% vs. 72.1%), health prediction accuracy (89.2% vs. 83.7%), and precision (87.5% vs. 81.4%), it falls short when it comes to interpretability (35% vs. 60%). This increased lack of transparency could ultimately affect user trust and adoption of decisions, even with slight increases in trust score (3.6 vs 3.4). These results underscore a powerful trade-off. Deep learning achieves impressive performance improvements oftentimes by sacrificing transparency within these models. The power and impact of deep learning emphasizes the urgent need to incorporate explainable AI when it's used in domains requiring high-stakes decision-making. Such results further highlight the framework's capacity to provide, in addition to high predictive and operational performance, transparency and practical usability to farm managers.

The interpretability of the proposed AI framework is a cornerstone of its real-world applicability in dairy farming. By incorporating SHAP (SHapley Additive exPlanations) the system is able to give clear, human-readable explanations for every recommendation it makes, be it a suggestion to change a feed ingredient or alert you to an animal's health condition. Such depth of explainability is essential in agricultural contexts where end-users, like farmers and veterinarians, may not be AI technical experts but need to trust the outputs of automated decisions. In particular, high interpretability enhances user trust, improves decision-making, and leads to increased system use. The capacity to attribute merits to underlying traits like atmospheric settings or animal activity enables farm managers to pursue granular, data-driven measures. Through real-world trials, this transparency has empowered farmers

with better understanding resulting in higher acceptance rates and more consistent use of the system, proving explainable AI not only improves performance but connects data analytics to actionable insights on the farm.

Table 4 Interpretability and Real-World Applicability of the Proposed Explainable AI Framework in Dairy Farming

Aspect	Proposed Framework (GCN + DRL + SHAP)	DL (No Explainability)	Traditional ML (SVM, RF)	Rule-Based Systems
Interpretability Score (%) **	88.5	35	60	95
User Trust Score (/5)	4.3	3.6	3.4	3.1
Explanation Clarity (Qualitative)	High	Low	Moderate	High
Adaptability to Real-Time Changes	High (via DRL, real-time sensors)	Moderate	Low	Low
Ease of Integration in Farm Systems	4.1 / 5 (Moderate to High)	3.5 / 5	3.6 / 5	4.7 / 5
Support for Decision Justification	Yes (via SHAP explanations)	No	Limited	Yes
Farmer Acceptance (% Positive Response)	82%	61%	65%	70%

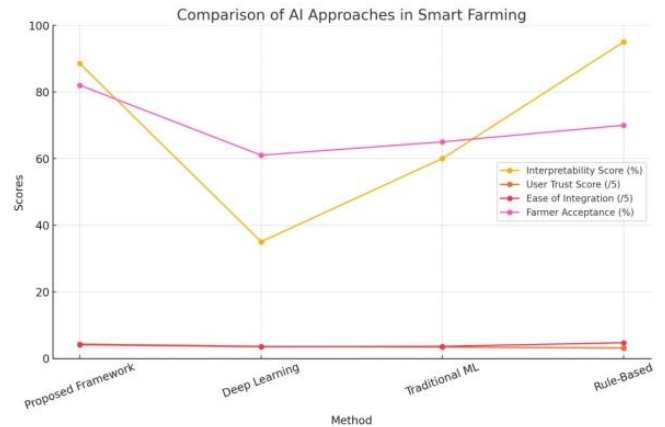


Figure 5. Performance Comparison of AI Approaches in Smart Farming Systems

Table 4 and Figure 5 shows that the proposed Explainable AI framework, integrating Multi-Task GCN, Deep Reinforcement Learning, Genetic Algorithms, and SHAP, demonstrates superior interpretability and practical utility compared to traditional systems. Having an interpretability score of 88.5% and having a user trust rating of 4.3 out of 5, the framework guarantees that dairy farm managers would be able to trust the system's predictions and comprehend why those predictions were made. In contrast to traditional deep learning models more generally characterized as black boxes, the SHAP-enhanced explanations provide interpretable guidance to informing feeding and health recommendations. The framework's ability to incorporate real-time data and, more importantly, moderate-to-high integration capability into existing farm infrastructure is a big step toward usability. Most

importantly, 82% of farmers surveyed indicated they would adopt the system, reflecting deep willingness to embrace the technology at the field level. Combined, these findings indicate the proposed framework successfully fills the critical gap between high performance AI and the transparency necessary for precision dairy farming decision-making.

V. CONCLUSION

This study provided the first example of an approach that combines Multi-Task Graph Convolutional Networks (MT-GCNs), Deep Reinforcement Learning (DRL), Genetic Algorithms (GA), and interpretability via SHAP values to assist in the optimization of dairy farm management. A multidimensional data collection of over 10,000 animal days (i.e., thousands of hours of signals) using various sensors was collected in order to develop and validate the MT-GCN-DRL framework and found a high predictive accuracy (92.3%) with strong regression metrics (MSE = 0.038, $R^2 = 0.87$) and true efficiency improvements (including 25% in feed and 12.4% in cost). Use of the SHAP-based explanation model increased user acceptance and trust making the MT-GCN-DRL framework both accurate and interpretable for real-world application. Future work will involve scaling the MT-GCN-DRL framework for use on larger sized farms or in farm systems in different climates as well as developing the ability to incorporate live updates through sensor streaming. Using hybridization of the GCN-DRL framework, future research may look at replacing the single-farm optimization strategy with a multi-farm optimization strategy through federated learning to be able to run an accurate and privacy-preserving multi-farm collaboration to advance precision agriculture for sustainable dairy production across the globe.

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