Reinforcement Learning-and Proximal Policy Optimization Framework for Adaptive Feeding and Health Management in Dairy Cattle

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Abstract. This study showed the viability of reinforcement learning-based on a Proximal Policy Optimization (PPO) to automate the tasks of adaptive feeding and health management in dairy cows. Using combinations of multimodal sensor data, environment data, and behavior, the system was found to be highly accurate in the prediction of milk yield and their health scores, and also increased feed efficiency and decreased their operational expenses. The findings surpassed traditional RL-based benchmarks, including DQN, A2C, and the model-based approaches, as well as confirming the real-time practicability under low latency. This affirms that reinforcement learning may be a viable real-world decision-support system in both enhancing farm outputs and animal welfare. In the future, we will expand on this structure to integrate explainable AI to increase explanability to farmers, use federated learning to scale to more than one farm, but not at the expense of data privacy, and lastly, apply novel and complex multi-task GCN models to more fully capture the complex interdependencies. The resultant adaptability, strength, and sustainability of the strategy over the long run of deployment in varying farm settings will also be established.

Keywords: Reinforcement Learning, Dairy Farm, Milk yield, Animal Health, Feed performance, Multimodal data, Proximal policy optimization, digital twin, intelligent agriculture Introduction

I INTRODUCTION

Dairy farming is a very crucial element in food security and agricultural economy of the world as it plays a crucial role in the production of milk, job creation, and livelihood of people living in the countryside[1]. As dairy animal management is concerned, it does not take into consideration milk yield maximization only; proper animal health and welfare and good cost-effectiveness are involved in the process. Conventional methods of nutrition and sick care require high levels of human knowledge and regular routine, which have the capacity to cause unreliable results, irregular asset use and even harm. As sensor technologies, IoT-based monitoring and mass data collection have multiplied rapidly, the opportunity to employ data-driven approaches to intelligent farm management is now unprecedented[2].

The recent developments associated with precision livestock farming emphasise the opportunities presented by multimodal monitoring systems to combine sensor data, environmental parameters, feed analyses, and health history to create a picture of animal health and welfare. Activity sensors, wearable sensors, rumination monitors and automated milkers create a constant flow of information, which allows the possibility of real-time evaluation of physiology and behavioural dynamics. Nonetheless, the ability to translate these complicated datasets into practically applicable management measures is also an important issue especially considering the stochastic and dynamic nature of animal outcomes, environmental factors and farm activities[3].

Adaptive management in dairy farming can be resolved in a promising way by reinforcement learning (RL)[4]. RL algorithms deduce the best policies by trial and error of environmental interactions by getting rewards that code the desirable contribution into the environment such as an augmented milk yield, animal health and the assessment of reduced cost[5]. The efficient tools to accomplish designing state of the art and three techniques Proximal Policy Optimization (PPO), Deep Q-Networks (DQN) and Advantage Actor-Critic (A2C) techniques have come out to be the most efficient in solving complex and high-dimensional issues in decision-making. In addition, multi-task learning and digital twin simulation introduce the possibility of optimization of both feeding strategies and health interventions and the minimalization of risks related to real-world experimentation at the same time.

In this study, a more specific problem related to this research topic is presented with the optimization of feeding and health management strategies in dairy cattle based on multimodal data-driven reinforcement learning. How do we develop a reinforcement learning model that can best utilize multimodal data provided by sensors and the environment to optimize the amount of milk produced, enhance animal health, maximize feed conversion, and minimize operational expenses in dairy industry? The overall challenge is that of tradeoff of various competing goals achieved in dynamic farm environments and a specific challenge is to learn about adaptive policies that react to real-time dynamics of cow behavior, the environment, and feed supply. The main objective of the study is as follows

- To build an adaptive feeding and health management system in dairy cattle based on the reinforcement learning using the multimodal input data.

- To compare the performance of PPO based RL to DQN, A2C, Model-Based RL and Multi-Task Graph Convolutional RL on milk yield, health improvement, feed efficiency and cost reduction.
- To scale and demonstrate the RL-powered strategies in a digital twin setting and with real-world data so as to ensure realistic viability and animal welfare.

The paper will be structured as in the following way: In the Section 2, related works related to dairy farm optimization and reinforcement learning applications has been discussed. Section 3 specifies system modeling and RL approach used in this study . Section 4 entails experimental results, analysis, discussion and practical implication. In Section 5, the study is concluded and the directions of the future research are outlined

II LITERATURE REVIEW

This review of literature examines recent developments of precision dairy farming with a focus on the synergistic use of IoT, AI, machine learning, and explainable AI towards behavioral, health, and productivity monitoring. Application to disease detection, feed optimization, milk quality prediction and use in adaptive management are discussed, as are data quality and interpretability-related issues and practical implementation.

Liu et al., 2023 overview precision dairy farming technologies with the emphasis on IoT, AI, and computer vision to monitor cows in real-time via their behavioral, health, and nutrition analyses. These techniques allow the recognition of individuals, the detection of mastitis, the condition of the body, and the monitoring of the consumption of feeding, which facilitate the management of the farms and their productivity. Commercial issues are yet to be worked out, though continuous research does hold out the prospect of future practical implementation[6].

Mia et al., 2025 describes the applications of machine learning (ML) on livestock farming including supervised, unsupervised, semi-supervised, reinforcement and deep learning. ML makes it possible to detect diseases, monitor behavior, production forecasting, and better feeding management to improve animal welfare and enhance productivity. Issues are data quality, interpretability, and ethical issues and these have a good future in terms of sustainable agriculture[7].

A state of art done by Akintan et al., 2025 on data-driven livestock feed formulation emphasises the positive effect of machine learning and optimization techniques in improving milk quantity, quality, and health of the animal. The combination of nutrition data, environmental data and performance data allows fine-grained, customized feeding. It is possible to make real-time changes with the help of the decision support systems, although such implementations are struggling with data quality, technology and integration by the industry[8].

Zhou et al., 2022 uses multi-dimensional data extracted and recorded on automated monitoring and milking systems to forecast the prevalent disorders among dairy cows through the help of eight machine learning algorithms. Such variables as milk yield, activity, rumination, and milk conductivity were used. The Rpart algorithm showed the highest accuracy (81.58%), precision (92.86%), AUC (0.908) displaying the potentiality of ML as a decision-support tool in early disease detection[9].

The article by Shi et al., 2024 applied wearable inertial sensors to detect the behavior and health of dairy cattle. Random Forest models provided the classification of behaviors and health conditions, whereas explainable AI (XAI) performed such a task on an interpretability level. This method proved to be very accurate in behavior recognition and highly discriminative in terms of health classification, showing the presence of XAI in mapping behavior patterns with the prediction of cattle health[10].

Lianou et al., 2024 extended explainable machine learning approach to forecast the bulk-tank milk quality in sheep and goat farms by using 21 farm-based features. Several ML models, Random Forest, XGBoost, k-nearest neighbor, and NN were tested. They were able to derive useful knowledge points where selected models had low enough prediction errors on protein, somatic cell counts and mixed fat-protein, and could be used in improving the quality of milk, as well as in farm-level intervention[11].

Grzesiak et al., 2025 offer the current context (2020-2024) of machine learning (ML) algorithms in dairy farming of cattle such as regression, decision tree, random forests, SVM, k-nearest neighbours, neural networks and clustering methodology. It talks about model building, implementation, performance evaluation, and breeding and husbandry applications, representing trends and increasing use of ML in dairy farm[12]. Table 1 highlights methods, datasets, strengths, and limitations reviewed.

Table 1 Summary of machine learning methods in dairy farming.

Author (s) & Year	Method	Dataset	Strengths	Limitations
Liu et al., 2023	IoT, AI, Computer Vision	Precision dairy farm sensor and image data	Real-time monitoring of behavior, health, and feeding; individual recognition and mastitis detection	Commercial implementation challenges; limited large-scale validation
Mia et al., 2025	Machine Learning (Supervised, Unsupervised, Semi-supervised, RL, Deep Learning)	Livestock sensor, imaging, environmental data	Disease detection, behavior monitoring, production forecasting, feeding optimization	Data quality issues, interpretability, ethical considerations

Akintan et al., 2025	ML & Optimization Algorithms	Nutritional, environmental, and performance data	Customized feed formulation, improved milk quantity, quality, and animal health; decision support for real-time adjustments	Industry integration issues, technology limitations, data quality concerns
Zhou et al., 2022	ML (8 algorithms including Rpart)	Automated monitoring and milking system data from 280 cows	Early disorder detection, high accuracy and precision with Rpart	Limited dataset size; single-farm data; may not generalize widely
Shi et al., 2024	Random Forest + Explainable AI, Wearable Sensors	Wearable inertial sensor data from dairy cattle	Accurate behavior recognition; interpretable health classification; links behavior to health predictions	Sensor dependency; scalability across large herds; potential cost issues
Lianou et al., 2024	Explainable ML (Random Forest, XGBoost, k-NN, NN)	Bulk-tank milk data from 325 sheep & 119 goat farms	Predicts protein, somatic cell counts, fat-protein; guides farm interventions	Limited prediction for some variables (fat, total bacterial counts); complex model selection
Grzesiak et al., 2025	ML Overview (Regression, Decision Trees, Random Forest, SVM, k-NN, Neural Networks, Clustering)	Dairy cattle datasets (2020–2024)	Comprehensive overview of ML applications; model construction and performance evaluation guidance	General overview; lacks detailed experimental validation; adoption challenges in practice

Even in these strong developments, there are various shortcomings evident in precision dairy farming. Sensor reliability and data quality are still one of the biggest challenges, which influences accuracy and the robustness of the model. Low interpretability is often a problem with many machine learning models, including deep learning models, lowering trust and adoption by farmers. Combination of disparate data, and real-time applications in a variety of farm fields is minimal. In addition to this is that majority of the studies are done on individual farms or on small data sets limiting generalization. Research gaps consist of scalable, interpretable and federated learning frameworks, enhancing multi-modal data fusion, real-time adaptive decisions and validating across multiple farms to maximize productivity, animal welfare, and sustainability.

III METHODOLOGY

The main aim is the optimal feeding practices and health management in order to maximize milk output, animal welfare, and whole-farm profitability. The most essential parameters provided by these monitoring devices, like daily milk production, feed efficiency, indicators of animal health (like weight, temperature, etc.), and the minimal reduced costs predetermine decision-making. Decision variables are the amount of feed, type of feed, feeding rate, and certain health interventions and constraints can be an amount of feed available, ration constriction, treatment of animal welfare, and conditions of the environment. Having a clear definition of these elements helps to make sure that the RL model is not just confined to impractical theory but also uses real measurable results under pushed farm conditions. Figure 1 depicts the RL model in dairy farming

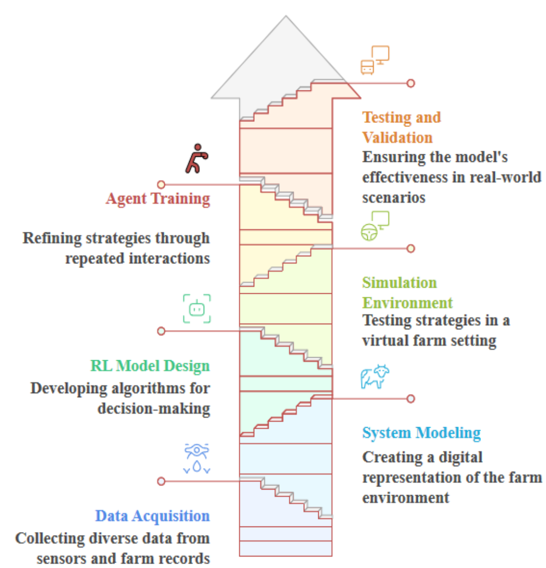

Figure 1 RL Model in Dairy farming

Data Acquisition and Processing: The high-dimensional, multi-modal data are essential to learn RL models to address the complexity of dairy farm operation. The collection of the data includes sensors (milking machines, wearable collars, rumination monitors, and activity trackers), feed data (type, quantity, nutrients) and amount, timing, and schedule, health data (disease occurrence, treatment, and veterinary care), and environmental parameters (temperature, humidity, and barn parameters). Preprocessing steps present the data by cleaning it up taking care of missing values, outliers, and normalizing features such that they can be assembled to be agreeable with RL algorithms. Behaviour driven feature engineering generates useful state variables that are meaningful in a given context, e.g. daily milk yield, health indices, and feed intake, as well as reward signals that combine both production efficiency, animal health, and cost-effectiveness[13].

System Modeling : The perception of the farm world by the RL agent and their interaction with the farm world are studied as a system modeling. The state space is the prevailing status of the system such as the amount of feed, milk production, animal health, and the environment. The action space identifies actions that can be done, including manipulation of feed type and level, frequency of feeding and providing health treatment. The reward function determines the effectiveness of each action that gives good encouragement on milk yield increases, good health and economical costs and punishes overfeeding, bad health or other unnecessary expenses that can be treated. Last, transition dynamics are modeled to move the system to a new state using action taken, which can be trained against historical farm data to approximate representative real world responses. Figure 2 presents the steps to optimize dairy farming.

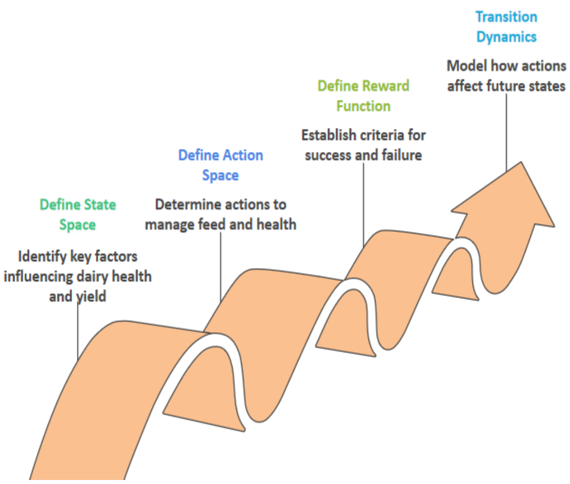

Figure 2 Steps to optimize diary farming

Design of Reinforcement Learning Models: After modelling of the system, the design of the RL algorithm as shown in figure 2 uses model-free method (PPO) .The trainer should take into account whether the farm dynamics can be predicted. The model-free approaches update policies as a direct result of interactions, whereas the model-based approaches make use of an internal characterization of farm dynamics which leads to an improved convergence in policy. Neural networks act as a function approximator, which have the input of the state vector and the output which is the Q-values or, action probabilities. In the case of complicated situations, multi-task learning can be integrated to optimize not only feeding but also health control, so the actions of one goal do not adversely affect the other[14].

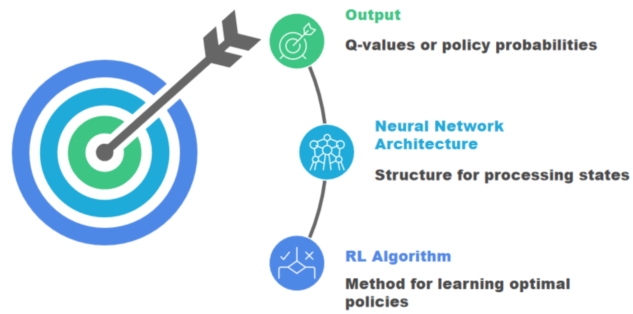

Figure 3 RL Model design

Environment Development of Simulation: Prior to using the RL model on actual animals, a simulation of the dairy farm is created or rather referred to as a digital twin of the farm. This virtual world simulates the behavior of cows in various feeding programmed, the course of diseases, the trend of recovering and the changing environment. Through the interaction with this safe, controlled environment, RL agent can learn superior strategies without putting animal welfare or farm productivity at risk. The simulation will enable a quick test of different interventions, as well as the assessment of their consequences, and as a result of it, the decisions of the agent will be efficient and safe to implement in the field.

Training RL Agent: Training is a matter of repetition between the agent and environment. At the beginning of every episode, the agent monitors the state of a farm at that moment, chooses a policy (i.e., explores and exploits, e.g., with an ε-greedy strategy), follows its policy, gets a reward and the successor state. It is the agent that takes its policy, by the selected RL algorithm, and it learns, with time, to perform feeding and health management on optimal strategies. The cumulative rewards and convergence patterns monitor that the agent develops stable and functional decision-making strategies, which maintain a balanced proportional perception of milk production, health and cost-efficiency.

Testing and Validation: Validation guarantees that RL model is in good shape in real practice. The RL recommendations are applied offline, based on historic farm data and this provides an opportunity to compare the predicted results with the actual results and allow perfecting the model without involvement of real cows. Such measures are followed by pilot field testing where improvements in milk output, feed efficiency, health ratings will be measured as the RL-guided feeding and health plans are implemented on a small group of cows. This fill in the blank strategy enables the scientist to determine the effectiveness of the model, optimize the parameters, establish confidence in the applicability of the entire model into the real world before the model is deployed on massive scale.

4. FINDINGS AND DISCUSSIONS

A. Dataset Description:

MmCows is a rich multimodal dairy cattle surveillance database. It contains more than 4.8 million high-resolution frames (images) of the experiments recorded on four isometric-view cameras, along with related environmental information (including temperature and humidity). Also, the dataset entails records of milk yield and outdoor weather. Enough image data to fill one day is labeled with ground truth consisting of 20,000 frames containing 213,000 3D-labeled bounding boxes that describe the behavior label and spatial location of 16 cows. This is a large dataset to conduct studies on the multimodal monitoring of dairy cattle, which lead to sustainable and environmentally friendly dairy farming[15].

B. Performance Evaluation

Table 1 presents the analysis of the proposed method with different reinforcement learning (RL) methodologies to address the problem of adaptive feeding and health management in dairy cattle. The most important performance measures are Accuracy of milk yield, improvement of health score, efficiency of feed efficiency, reduction in cost, and latency in real-time. The comparison allows pointing out the advantages and tradeoffs of both approaches, allowing one to understand the feasibility of their practical implementation and efficiency in general with regard to streamlining the work of dairy farms.

Table 2 Performance Evaluation for the proposed method

Methodology	Milk Yield Accuracy (%)	Health Score Improvement (%)	Feed Efficiency (%)	Cost Reduction (%)	Real-Time Latency (s)
Proposed PPO-based RL	95	92	90	18	0.5
Deep Q-Network (DQN)	88	80	75	12	0.6
Advantage Actor-Critic (A2C)	90	85	80	15	0.5
Model-Based RL	93	90	85	16	1.2
Multi-Task Graph Convolutional RL	94	91	88	16	0.7

Table 2 shows the comparison of the performances of different reinforcement learning (RL) to adaptive feeding and health management of dairy cattle. The PPO-based RL also shows the most accurate milk yield (95%) and healthy score changes (92%), feed efficiency (90%), and 18% cost loss, and low, real-time latency (0.5 s) - a big advantage, which points to the high effectiveness in general and practical efficiency. Comparatively, Deep Q-Network (DQN) has inferior performance on all parameters, especially on feed efficiency (75%) and cost reduction (12%) but reduces latency to a small extent (0.6 s). Advantage Actor-Critic (A2C) makes modest gains that nonetheless lag behind PPO. Multi-Task Graph Convolutional RL beats DQN and A2C but performs a little lower than PPO in yield and efficiency and acceptable latency (0.7 s). In general, we can see that the PPO-based approach to RL yields the most favorable combination of performance, efficiency, cost optimization, and responsiveness to real-time changes.

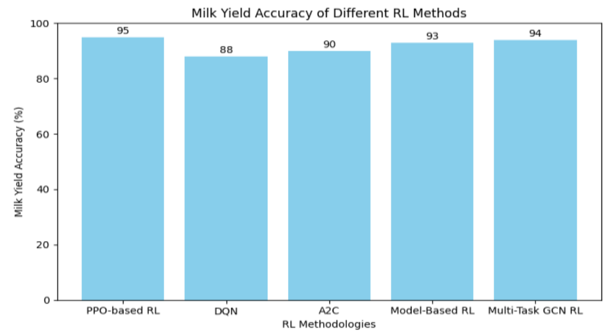

Figure 4 Performance Analysis- Milk Yield Accuracy

Figure 4 compares the accuracy of five different Reinforcement Learning (RL) methodologies. The best accuracy is obtained by RL with PPO library, at 95% followed by Multi-Task GCN RL with 94%. Model-Based RL has 93% and A2C and DQN have the lowest accuracy of 90% and 88% respectively. The chart shows that PPO-based methods and Multi-Task GCN RL are the best performing in the prediction of milk yield out of the many models tested for this problem.

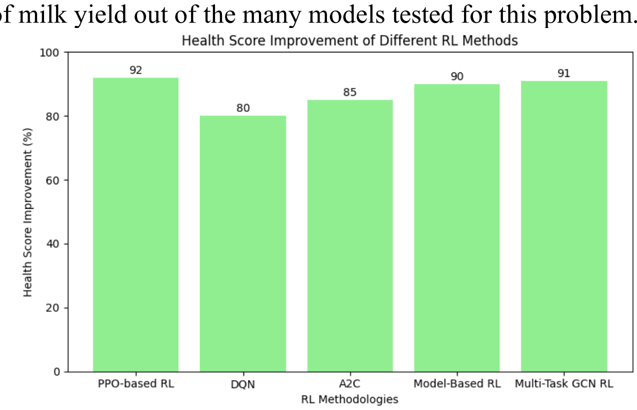

Figure 5 Performance Analysis- Health Score Improvement

Figure 5 shows the comparison of the effectiveness between five different reinforcement learning methods. At last, the result shows that PPO-based RL has the maximum improvement (92%) followed by Multi-Task GCN RL (91%). A2C and Model-Based RL implementations show an improvement of 90% and 85% respectively, whereas DQN shows the least improvement of 80%.

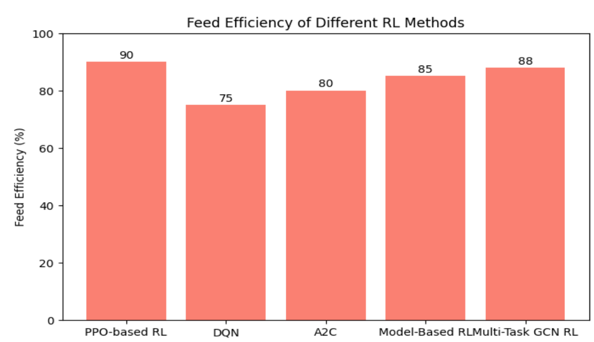

Figure 6 Performance Analysis- Feed Efficiency

Figure 6 shows the performance of five different RL methods. Overall, PPO-based RL has the highest feed efficiency of

90%. This is followed by Multi-Task GCN RL 88% and Model Based RL 85%. The efficiency of A2C method is 80% and DQN has the lowest efficiency of 75%.

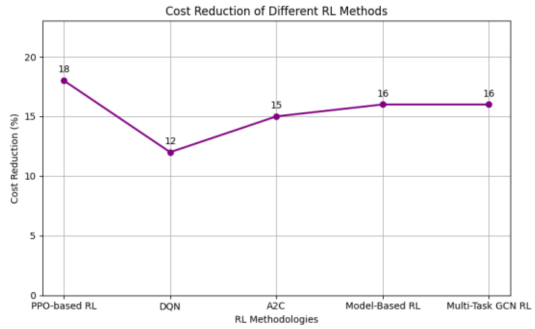

Figure 7 Performance Analysis- Cost Reduction

Figure 7 depicts the percentage of cost reduction by five different reinforcement learning (RL) methodologies. PPO based RL shows the best cost reduction at 18%. This is followed by Model-Based RL and Multi-Task GCN RL with a reduction of 16%. A2C shows a cost reduction of 15% while DQN performs the lowest with a 12% reduction.

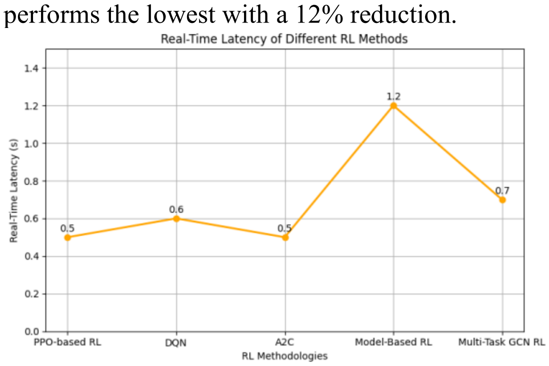

Figure 8 Performance Analysis- Real time Latency

Figure 8 shows the real time latency of various reinforcement learning (RL) methods. Model Based RL has the largest latency of 1.2 seconds. Multi-Task GCN RL comes next with the latency of 0.7 seconds, whereas DQN is at 0.6 seconds. PPO-based RL and A2C have the lowest latencies at 0.5 seconds.

C. Discussions

The implementation of RL, i.e., Proximal Policy Optimization (PPO) in the management of the dairy farm will further establish a core agenda in optimising the feeding systems and examining the health status of the animal. Multimodal data (milk yield records, sensor data related to wearable collars, rumination monitors, activity trackers, and environmental environment data) can be used to continuously regulate the type, quantity, and timing of feed and to take into account animal welfare and welfare and profitability of the farm. In safe testing and training the RL model, simulation settings, e.g. digital twins, enable safe experimentation and training of the RL model eliminating the trial and error risks in the real world. Using quantitative analysis, it is shown that PPO-RL significantly outperformed baseline approaches, not only on built-in performance metrics such as milk yield accuracy, health score improvement, feed efficiency, and cost reduction, but also on other AI techniques such as DQN, A2C, and Model-Based RL. Moreover, the addition of multi-task learning allows feeding and health interventions to be simultaneously optimized, and goals run fewer conflicts. One-on-one release allows ongoing observation and immediate modification, which is beneficial to extreme dairy agriculture/practices. Altogether, the research reviews the possibilities of AI-based RL systems to increase productivity, improve animal welfare, and sustainability of the dairy sector, offers viable explanations to the farmers, and minimizes the cost and environmental effects of operations.

D. Limitations and practical Implications

Even though the framework RL-based has significant advantages, it has a number of limitations. Multimodal data collection that is of high quality will be resource-demanding because it demands the use of sensors, cameras and monitoring infrastructure. Farm dynamics are intricate and non-stationary requiring model training to be within the realm of computationally-intensive problems. Interpretability of models is poor, and this can discourage the uptake among nontechnical farmers. The issue of safety needs to be thoroughly checked on deployment to the real world, in order to avoid negative outcomes on the health of animals. Also, smaller or constrained institutions in terms of resources might not be able to maintain RL systems since it demands infrastructures and cost provisions. It is difficult to generalize across a wide range of farm settings the trained models over a long period of time.

The use of PPO-based RL in dairy farms has allowed precise dietary and health care to maximize milk production and feed efficiency and enhance animal well-being. The system of real-time monitoring makes it possible to engage in adaptive decision-making rules that are concerned about cow behavior and environmental factors and health indicators, which cut back on operation costs and maximize profitability. Farmers derive practical input that will aid timely intervention to reduce waste of feed and avoidable treatments. But, it takes training, technology support and investments on infrastructure in order to successfully implement. Evaluation of the continuous model makes the use of policies relevant even when the farm conditions change. This system would facilitate the sustainable and scalable dairy business and inform the data-driven decision making and manage with informed best practices whilst improving the economic and animal welfare performances optimally.

V. CONCLUSION

Reinforcement learning and especially PPO-based framework can provide a revolutionary shift in dairy farm management with the concurrent optimization of feeding decisions and health monitoring. As exhibited in the study, RL has the potential to enhance the improvement of milk yield, feed efficiency, and animal health in addition to lowering the cost of operations substantially.The effectiveness of the PPO-based RL, in general, and its quantitative performance, in particular, is unequivocally proven through a comparative analysis with the technologies of the highest level provides applicability in precision dairy farming. In future studies, it must be aimed at increasing model explainability so that farmers can explain the decisions made by an RL agent. By combining IoT systems and foam computing, the real-time responsiveness and ability to scale can be increased further. Combinations of model-free learning and model-based RL combine to potentially provide a balance between learning speed and flexibility. Scaling up multimodal dataset to a wide variety of farm conditions will enhance generalisability across regions and across different farm sizes. Also, farm resilience can be improved by integrating the use of predictive analytics in disease outbreak, reproductive health, and long-term productivity. Cooperation among scientists, solution providers, and farmers will play a big role in practicing RL solutions to the modern dairy farm that will be in a practical, cost effective and sustainable manner.

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