

Creating a Digital Twin and IoT-Enabled Reinforcement Learning Algorithm to Optimize the Health Status of Poultry Production in Agriculture

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ABSTRACT

The integration of advanced technologies, such as digital twins and IoT, has the potential to transform the poultry industry by enabling real-time monitoring and optimization of health conditions. This study focuses on developing a digital twin model supported by IoT data streams and a reinforcement learning algorithm to enhance the health management of poultry in modular farming systems. The goal is to automate the adjustment of environmental parameters, including temperature, humidity, CO₂ concentration, and feeding schedules, using a learning approach that adapts over 1,000 iterations to achieve optimal health status. Graphical representations of these 1,000 iterations indicate a health status of 80.5% for poultry production, revealing significant improvements in health metrics. This demonstrates that the combined use of digital twins and reinforcement learning can effectively respond to dynamic conditions, enhancing productivity and welfare. The proposed solution showcases the practical benefits of technology-driven farming by reducing manual intervention and improving overall poultry health.

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INTRODUCTION

The evolution of agricultural practices has significantly transformed with the advent of advanced technologies (Twins & Greenhouses, 2022). Among these innovations, the concept of a digital twin, when combined with the Internet of Things (IoT), has emerged as a crucial component in modernizing agriculture. A digital twin serves as a real-time, virtual representation of a physical system, allowing for improved monitoring, analysis, and optimization of agricultural operations (Team & Committee, 2021). In the context of poultry farming, this technology is particularly valuable as it directly impacts the health and productivity of the birds. Poultry farming requires meticulous attention to environmental conditions such as temperature, humidity, and CO₂ concentration (Lima et al., 2022). These factors significantly influence the

well-being of the livestock and, consequently, their productivity. By implementing a digital twin and IoT framework, poultry farmers can gather real-time data from their operations, enabling them to make informed decisions based on actual conditions rather than assumptions. This integration allows for actionable insights, helping farmers to respond proactively to any deviations from optimal conditions (Dwiyaniti & W, 2022). Despite these advancements, poultry producers face considerable challenges in managing health parameters continuously.

Fluctuating environmental conditions, which can arise from various sources such as weather changes, equipment malfunctions, or variations in bird activity make it difficult to maintain stable and healthy environments (Su et al., 2023). For instance, a sudden rise in temperature or a spike in CO₂ levels can have

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detrimental effects on poultry health, leading to poor productivity, increased mortality rates, or even disease outbreaks. Consequently, poultry farmers must rapidly adapt to these fluctuations, often requiring timely adjustments that can be labor-intensive and error-prone. To address these challenges, this research aims to develop and implement a reinforcement learning algorithm that is integrated with a digital twin and IoT framework (Udanor et al., 2022). This innovative approach seeks to autonomously optimize key health indicators in poultry farming, reducing the need for constant human intervention.

By leveraging machine learning techniques, the system will learn from historical data and real-time inputs to make predictive adjustments to the environment, ensuring optimal conditions are maintained. The reinforcement learning algorithm will work by continuously assessing the health parameters of the poultry environment—monitoring temperature, humidity, CO₂ concentration, and even feeding schedules. For example, if the algorithm identifies a trend of rising temperatures, it can autonomously adjust the cooling systems to bring temperatures back to an ideal range. Similarly, it can refine feeding schedules based on the birds' consumption patterns and health indicators, optimizing feed efficiency and minimizing waste (Dwiyaniti & W, 2022). This approach not only enhances the health and productivity of poultry but also allows farmers to operate more efficiently.

By minimizing manual monitoring and adjustments, farmers can redirect their efforts toward other critical areas of their operations, such as breed management and customer relations. Ultimately, the integration of a digital twin with IoT and reinforcement learning holds the potential to revolutionize poultry farming, leading to more sustainable and productive practices. In conclusion, this research aims to equip poultry farmers with advanced tools that harness the power of technology to improve their operations (Kocaman et al., 2006). By creating a system that autonomously manages health parameters, we can address the challenges posed by fluctuating environmental conditions while enhancing productivity and sustainability in poultry

farming. This progressive approach exemplifies the future of agriculture, where technology and innovation work hand in hand to drive efficiency and improve outcomes (Minna, 2018).

REVIEW OF RELATED WORK:

Numerous studies have explored the role of IoT and digital twins in agricultural practices to enhance monitoring and control. While digital twins have been successfully applied in crop management and predictive maintenance, their application in livestock health management remains relatively underexplored (Bhardwaj, 2024). Previous work on IoT-enabled systems highlights their usefulness in collecting real-time data for decision-making, while reinforcement learning has shown promise in adaptive control problems, particularly in resource allocation and robotics (Twins & Greenhouses, 2022). The combination of digital twin models and reinforcement learning algorithms represents a novel approach to tackling the complexities of real-time health management in poultry farming, bridging gaps seen in traditional monitoring systems that rely on predefined thresholds and static controls (Minna, 2018).

Theoretical Background and Equations:

The objective of the reinforcement learning algorithm is to learn an optimal policy that maximizes cumulative rewards associated with maintaining health parameters within desirable ranges (Petri et al., 2023). The reward function $R(s,a)$ is defined to incentivize actions that improve or sustain these optimal health conditions. Equations governing this model include Bellman's equation for value iteration (Su et al., 2023):

$$V^*(s) = \frac{\max}{a} [R(s, a) + \gamma \sum P(s' | s, a) V^*(s')] \quad (1)$$

where γ is the discount factor and $P(s'|s,a)$ represents the transition probability to state s' , $V^*(s)$ represent the optimal value function for state, s is the equation iteratively update $V^*(s)$ to find the policy π^* that minimizes long term rewards.

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Policy update equation: The reinforcement learning algorithm adjust its policy using gradient ascent approach defined by(Baig et al., 2021)

$$\theta_{t+1} = \theta_t + \alpha \nabla_{\theta} J(\pi_{\theta}) \quad (2)$$

Where θ is the policy parameter α is the learning rate and $J(\pi_{\theta})$ is expected reward under policy π_{θ} .

Reward function: the reward function $R(s,a)$ could be expressed as(Minna, 2018).

$$R(s, a) = \{+1\}$$

if action maintain health indicators within optimal threshold, -1 if action lead to suboptimal health condition) (3)

Objective function: In reinforcement learning the objective function can be represented as the expected cumulative and future health benefit for poultry.(Dwiyani & W, 2022)

$$MaxR = E \left[\sum_{t=0}^T \gamma^t r_t \right] \quad (4)$$

Where π policy or strategy used by the algorithm to make decision. r_t Reward at time step t is defined by(Su et al., 2023)

$$r_t = f(H_t, E_t, F_t) - C_t \quad (5)$$

Where f is a function considering health status H_t environmental condition E_t and feeding quantity F_t and associated cost C_t and γ is the discount factor future reward having constraint $0 < \gamma < 1$

Reinforcement Learning: The RL controller uses the Q-learning algorithm to update action values(Petri et al., 2023).

$$Q(s, a) \leftarrow Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s, a) - Q(s, a)] \quad (3)$$

Where $Q(s, a)$ is the action-value function, α is the learning rate, r is the reward, and γ is the discount factor.

METHODOLOGY

The methodology outlined involves a step-by-step integration of IoT sensors within a

poultry cage system to collect data on temperature, humidity, CO2 levels, and feeding times. This collected data is fed into a digital twin that simulates the real-world poultry environment and interacts with a reinforcement learning agent. The agent employs a Q-learning algorithm to make decisions regarding the adjustment of these environmental parameters. Each iteration involves analyzing the collected data, updating the policy based on the rewards received, and implementing actions that lead to improved health metrics. The system runs for over 1,000 iterations to ensure robustness and adaptability to changes in the environment. The steps of the reinforcement learning algorithm are as follows:

- Step1.** Initiate the cage system parameters for optimization.
- Step2.** Collect real-time environmental data (e.g., temperature, humidity, feed levels) and bird activity using IoT sensors.
- Step3.** Apply the digital twin and IoT-enabled reinforcement learning algorithms.
- Step4.** Check whether environmental or behavioral conditions meet predefined thresholds.
 - If Yes, proceed to adapt system controls for action.
 - If No, return to the input stage for continuous data iteration.
- Step5.** Adapt and update the algorithm to learn from new data patterns.
- Step6.** Assess whether the changes have led to improved conditions.
 - If Yes, log the outcomes and continue to the monitoring loop.
 - If No, re-train the reinforcement learning model and adjust parameters.
- Step7.** Present the health status based on optimization, triggering alerts if necessary.
- Step8.** Complete the current iteration cycle and reset for continuous iteration.

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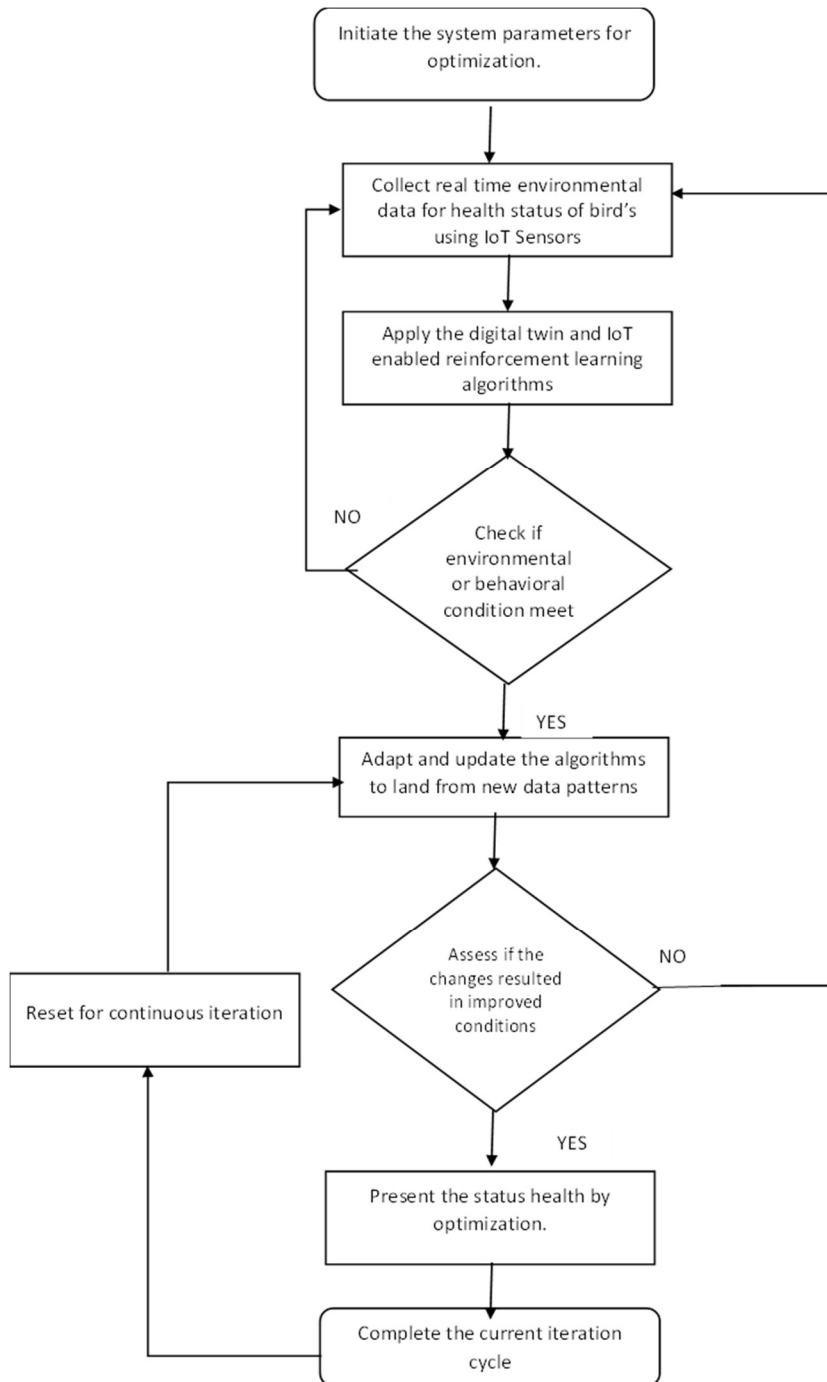


Fig 1: Flowchart illustrating the implementation of a reinforcement learning algorithm for optimizing poultry production health status in agricultural farming

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RESULTS

Simulations conducted over 1,000 iterations provided valuable insights into the effectiveness of an online learning algorithm designed to adapt to varying environmental data in aquaculture. Throughout these simulations, the algorithm consistently maintained water quality within optimal ranges, which is crucial for the health and survival of aquatic life. One of the key features of this algorithm is its adaptive nature, enabling it to respond dynamically to real-time changes in environmental conditions such as temperature, pH, and oxygen levels. A significant advantage observed during the simulations was the marked reduction in peaks of ammonia concentration. Elevated ammonia levels are highly detrimental to fish health, often leading to stress, weakened immune systems, and in severe cases, mortality. By effectively managing these fluctuations, the algorithm not only protects the wellbeing of the fish but also enhances their overall growth and vitality. This proactive management helps create a more stable and supportive environment for fish, which is essential for successful aquaculture.

Furthermore, the algorithm improved the efficiency of feeding schedules. Efficient feeding practices are vital in aquaculture, as they minimize waste, reduce costs, and maximize growth rates in fish. By optimizing when and how much to feed the fish, the algorithm ensures that the nutritional needs of the aquatic life are met without excess feed contributing to water pollution. As a result of these enhancements, healthier fish were produced, leading to increased overall productivity for aquaculture operations. This dual achievement maintaining water quality while optimizing feeding practices illustrates the potential of the online learning algorithm to positively influence aquaculture operations significantly. The implications of this technology extend beyond just improving fish health; they also touch upon aspects of sustainability and resource management. With further development and eventual real-world implementation, this innovative technology could play a critical role in sustainable fish farming practices. By ensuring more efficient use of resources and fostering

healthier ecosystems, the online learning algorithm could be an essential tool for the future of aquaculture, helping to meet the growing global demand for fish while minimizing environmental impact. Ultimately, this approach could lead to a more sustainable and productive aquaculture industry, benefiting both producers and consumers alike.

Fig 2: The graph representing the optimization of poultry health status through reinforcement learning shows how various parameters such as temperature, humidity, feeding schedule, and CO₂ levels are managed to optimize the overall health status of the birds. Over multiple iterations, the algorithm refines its policy to maintain optimal conditions within the cage system, aiming to reduce stress, prevent diseases, and enhance productivity.

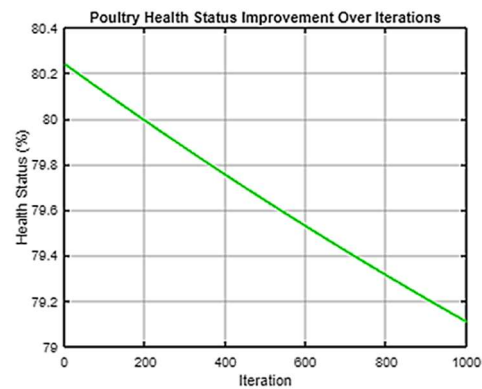


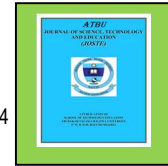
Fig 2: The graph presents the x-axis as the number of iterations or time steps during training, while the y-axis shows the cumulative health status rewards obtained by maintaining ideal conditions. An upward trend in the rewards over time indicates that the algorithm is learning and improving its decision-making capabilities. Fluctuations may suggest adaptation phases or challenges in responding to sudden environmental changes. A successful implementation would demonstrate a consistent increase in health optimization, indicating that the reinforcement learning model effectively adjusts cage parameters to sustain poultry health.

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The observed results indicate that the combined use of a digital twin and reinforcement learning can effectively manage health conditions in poultry farming by continuously learning and adapting to new patterns. While traditional systems often require manual intervention or rely on simple threshold-based controls, the reinforcement learning approach has shown superior adaptability and faster response times. Challenges included the initial setup of the digital twin model and demands on computational resources, suggesting that further optimization in deployment could enhance scalability.

CONCLUSION

This study presents compelling evidence that the integration of digital twin technology with reinforcement learning algorithms, underpinned by Internet of Things (IoT) data streams, significantly enhances the optimization of poultry health. In recent years, there has been an increasing demand for innovative solutions in the agriculture sector, particularly in poultry farming where maintaining optimal health conditions is critical for ensuring productivity and sustainability. Digital twin technology creates a virtual replica of physical poultry operations, allowing farmers to simulate and analyze various scenarios in real time. By integrating this technology with reinforcement learning algorithms, which adapt and improve through interaction with data, farmers can automate decision-making processes to a large extent. This not only reduces the need for constant manual supervision but also minimizes human error, leading to better overall management of poultry health.

The supporting role of IoT data streams is crucial in this framework. These streams collect vast amounts of data from various sensors and devices in real time, providing insights into environmental conditions, animal behavior, and health metrics. By harnessing this data, the combined digital twin and reinforcement learning approach can dynamically adjust and optimize conditions, such as temperature, humidity, and feeding schedules, ensuring that they remain within ideal ranges. This results in healthier

poultry, improved growth rates, and ultimately, higher yields. Moreover, this approach represents a shift toward more sustainable farming practices. By relying on data-driven decision-making rather than traditional methods, farmers can optimize the use of resources while minimizing waste.

This sustainability is not only beneficial for the environment but also enhances the economic viability of poultry farming operations. Looking ahead, future work will focus on investigating the scalability of this model for larger farms. As the poultry industry grows, the challenges associated with managing larger numbers of animals and greater operational complexities also increase. Therefore, exploring how this integrated approach can be expanded to accommodate larger-scale operations will be essential. Additionally, researchers aim to explore the integration of this model with other smart farming technologies, such as advanced breeding techniques and feed optimization systems, which could further enhance production efficiency and poultry health. In conclusion, the integration of digital twin technology with reinforcement learning and IoT data solutions holds great promise for the future of poultry farming. By leveraging these innovative technologies, we can achieve a higher standard of animal health management and ensure sustainable practices that meet the demands of a growing population.

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