International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 3S, 2025
https://www.theaspd.com/ijes.php

IoT-Based Multi-Sensor Fusion Framework for Livestock Health Monitoring, Prediction, and Decision-Making Operations

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Abstract: The growing challenges of livestock management increase the demand for robust and efficient livestock health monitoring systems in terms of outbreaks of diseases and productivity losses. Traditional approaches depend mostly on manual observation and standalone sensor systems, which are characterized by a high error rate, delayed anomaly detection, and poor integration of diverse data sources. This leads to inefficient interventions and increased operational costs. The proposed IoT-based multi-sensor data fusion framework provides holistic monitoring of animal health and supports proactive decision making. Advanced methods of data acquisition are combined with system methods for the detection of anomaly, predictive analytics, and decision-making in real time. Output includes multi-sensor fusion which is achieved with the help of Kalman filters for dynamic estimation of states that handle uncertainty Dempster-Shafer Theory. Thus, it yields 30% sensor noise reduction and a 25% improvement in accuracy in health metric computation. Anomaly detection uses deep autoencoder networks that can find anomalies in high-dimensional time-series data with a 96% accuracy and 4% false positives. Predictive health analytics uses LSTM networks that use an attention mechanism for disease prediction such as mastitis with 93% accuracy, allowing the detection of diseases two days before their visibility. A fuzzy-logic-based interpretation of health risk and environmental parameter, combined with real-time decision support, supports an accuracy as high as 95% for various scenarios at the same time reducing unnecessary vet visits by 20%. Seamless connectivity to cloud IoT platforms enables near-real-time visualizations and insights into actionable form via intuitive dashboard displays. It showed 40% death in livestock, 30% saving, and 20% productivity, thereby displaying its capability for replication and scaling up in vast numbers to be applied to any farming system.

Keywords: Livestock Health Monitoring, Multi-Sensor Data Fusion, Anomaly Detection, Predictive Analytics, IoT-Based Framework, Scenarios

1. INTRODUCTION

Livestock health monitoring constitutes a very integral part of contemporary animal husbandry, having serious consequences for productivity, sustainability, and economic efficiency. There is a growing demand for livestock products across the globe, which requires efficient handling to address the problems that occur due to diseases and environmental conditions. All these aspects require innovative monitoring solutions. Traditional methods [1, 2, 3] are always critical since they depend on visual inspections and sporadic data collection and thus tend to be subjective with delayed response times, hence cannot offer all the comprehensive insights into the dynamic health conditions of livestock. They often miss the early signs of health deterioration leading to increased mortality and tremendous losses. The transformative potential in livestock management has recently emerged with developments in the Internet of Things (IoT) and data analytics. One can now collect continuous, high-resolution data on vital signs, behavioral patterns, and environmental factors with wearable IoT devices and environmental sensors. All these heterogeneous streams of data open up opportunities, but the real challenges are their proper utilization. Current solutions appear to lack integration with robust mechanisms on multiple sensors, dealing with noise and inconsistency, and provisioning of actionable information with the right timestamp. Many currently available solutions lack predictive analytics capabilities to predict any developing health-related concerns, which poses serious challenges and urges requirements for more proactive thinking. This paper advances an IoT-based multi-sensor fusion framework designed to address these challenges comprehensively. The system foreseen employs highly advanced methodologies such as Kalman Filters, Dempster-Shafer Theory, autoencoders, Long Short-Term Memory (LSTM) networks, and fuzzy logic, which bring much higher precision in health monitoring, anomaly detection, and predictive analytics. Such integration ensures seamless flow of actionable insights from raw sensor data to real-time decision-making, and it improves the reliability and scalability of livestock health management systems by a noteworthy margin. More importantly, IoT platforms that are cloud-based and user-friendly dashboards are going to offer data visualization and historical trends analysis, thereby advancing closer data analytics to the on-farm practical application. This work goes beyond mere real-time monitoring of health; early signs of disease and risk prediction are provided to the farmers and veterinarians to take the right interventions in the process. This framework takes advantage of the weaknesses of the available methods to get the best approach toward cutting-edge technologies so that a new benchmark can be set up in the management of livestock in order to provide sustainability and productivity within the agricultural sectors.

Motivation & Contribution

In view of the inefficiency of the available methods and growing complexity of the modern livestock farming system, it is a critical need to introduce innovation in monitoring livestock health. Traditional methods have been based on manual observation and simple monitoring instruments, which lack the precision and scalability needed by today's intensive farming practices. These methods would likely result in delayed detection of health anomalies, dependence on reactive intervention, high mortality rates, lowered productivity, and significant losses economically. Additionally, current sensor systems are not integrated and highly diversified. Consequently, many data streams become difficult to integrate and can't contribute toward holistic appraisal of the animal health. Further, most of the monitoring systems do not possess predictive ability that does not allow them to predict and prevent possible health risks proactively in the process. The paper bridges these gaps by introducing a new framework of multi-sensor fusion IoT-based for the integration of advanced data processing, anomaly detection, predictive analytics, and real-time decision-making methods. The proposed framework uses Kalman Filters and Dempster-Shafer Theory for noise-robust and accurate multi-sensor data fusion. Deep autoencoder networks allow precision-based health anomaly detection, whereas LSTM networks with attention mechanisms guarantee the reliability of the forecast in the future risks associated with health. Fuzzy logic-based decision systems enhance real-time intervention precision by handling uncertainties in sensor data and predicted risks. Scalability and usability are further enhanced through the help of a cloud-based Internet of Things integration that provides intuitive dashboards for visualization and actionable insights. The proposed framework acts as an end-to-end solution to bridge gaps between raw sensor data and actionable decisions while enhancing the outcomes and operations involved in the case of livestock health and efficiency.

2. REVIEW OF EXISTING MODELS FOR LIVESTOCK ANALYSIS

The technology includes machine learning, deep learning, and integration of IoT that has gained the most attention during the last several years in agricultural and livestock sectors. A review of recent literature regarding these topics suggests diverse approaches with insights into the ways they might be used in order to boost efficiency, sustainability, and productivity. Benti et al. [1] studied the use of machine learning and IoT potential for Ethiopian agriculture. They posed some difficulties like scant information and infrastructure challenges, yet the results have been promising towards productivity enhancement and decision-making improvements. Abdullahi et al. [2] further generalized the result to Somali agriculture by indicating the use of IoT in crop recommendations. The authors combined the application of machine learning with the use of IoT sensors to appropriately allocate resources such that a remarkable increase in yield prediction of crops was achieved. Subramani et al. [3] discussed the application of machine learning and deep learning in poultry management. Their review covered methods for automating tasks such as feeding, health monitoring, and environmental control, thus improving efficiency and animal welfare. Xie et al. [4] used machine learning techniques to analyze the policy intensity; insights into the decision-making frameworks of agricultural policy are based on predictive models. Vaithianathan et al. [5] proposed a cloud-based machine learning model for the analysis of food quality integrated with healthcare security in smart agriculture, which showed increased scalability and accuracy in monitoring food safety. Mohy-eddine et al. [6] addressed the security challenges within IoT-based smart farming by making use of artificial neural networks in detecting malicious activities, thus providing data integrity and system reliability.

Thakur et al. [7] introduced DeepThink IoT, with the aim of establishing deep learning within IoT systems. Their framework is capable of portraying the applications in real-time analytics. They also assist in decision-making in various domains. These include agriculture in process. Kuradusenge et al. [8] developed a crop yield prediction system using IoT and machine learning, and the accuracy for food security application results yielded to be quite high in this process. Nayak et al. [9] report a thorough review on livestock development in the light of livestock management, thereby exploring diverse changes in domestication, phylogenetics, and genomics. This study focused attention to genetic insights for optimizing productivity in livestock. Alwadi et al. [10] applied deep machine learning for prediction in milk yield of smart dairy farming, which improved the accuracy significantly and facilitated resource planning better than before. Peng et al. [11] analyzed machine learning for the generation of waste biomass, thus demonstrating the feasibility of sustainable resource utilization in agricultural systems. Kumar et al. [12] focused on IoT system security, particularly on Zigbee networks, which are quite crucial for smart farming. Their framework could mitigate vulnerabilities and ensure robust communication channels for IoT devices & deployments. Rahimi et al. [13] presented the machine learning models for the prediction of rainfall that could be used as useful input for agricultural planning. The models were applied with different input scenarios in order to enhance the accuracy of the predictions and, therefore, offer valuable insights for farmers. Lakshman et al. [14] explored the architecture and applications of IoT devices in socially relevant fields, especially in agriculture, healthcare, and environmental monitoring. Last but not least, Bala et al. [15] proposed a DAG blockchain-inspired framework for livestock healthcare. The system integrated social relations and blockchain technology to guarantee secure and efficient data sharing, thus enhancing the overall process of livestock health management. Altogether, these works collectively speak to the revolutionizing power of IoT and machine learning in agriculture and livestock management. The findings of these studies become the basis of the proposed multi-sensor fusion framework that tries to bridge all the existing gaps in the development of a robust, scalable, and accurate system for the livestock health monitoring process.

3. Proposed design of an Integrated Model Using IoT-Based Multi-Sensor Fusion Framework for Livestock Health Monitoring, Prediction, and Decision-Making Operations

This proposed model is an IoT-based multi-sensor fusion framework that ensures advanced computational techniques in the monitoring of livestock health, anomaly detection, and predictive analytics. It's a high-precision mathematical modeling and algorithmic approach to handling large volumes of multi-modal data streams produced by sensors to reduce noise, uncertainty management, and predict time series. The methodology integrates Kalman Filters, Dempster-Shafer Theory, autoencoder networks, Long Short-Term Memory (LSTM) networks, and fuzzy logic, which all have unique strengths to be added to the system. These methods are well-integrated so that there is smooth data flow and optimal decision-making capabilities. It begins with a process of multi-sensor data acquisition where the raw sensor outputs undergo a process through Kalman Filters for the reduction of noise process. Kalman Filter models the dynamic system states via equation 1.

$$\hat{x}_{\mathrm{k}} = A\hat{x}(k-1) + Bu(k) + w(k) \ldots (1)$$

Where, x(k) is the estimated state vector at timestamp, 'A' represents the state transition matrix B is the control input matrix u(k) is the control input, and w(k) is process noise sets. This recursive filtering process reduces measurement noise by optimizing the state estimation iteratively in process. To manage uncertainties in multi-sensor data fusion, Dempster-Shafer Theory is applied for this process. The combination of belief masses from sensors is given via equation 2,

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$$m(C) = \frac{\sum_{(A \cap B = C)} m^1(A)m^2(B)}{1 - \sum_{(A \cap B = \emptyset)} m^1(A)m^2(B)} \dots (2)$$

Where, m(C) is the cumulative belief assigned to hypothesis C, and m1 m2 are belief functions from independent sensor sources. This way, it makes sure that there is robust fusion by controlling conflicting data and thus making the decisions more reliable in the process. Anomaly detection uses autoencoder networks trained to reconstruct normal patterns. The reconstruction error that shows deviation is calculated via equation 3,

$$Error = (\frac{1}{n}) \sum (x(i) - \hat{x}(i))^2 \dots (3)$$

Where, x(i) is the input data point and x'(i) its reconstruction for the process. Any reconstructions, with errors greater than some threshold, are used to trigger anomaly alerting, which detects anomalies in time series of animal health metrics in real-time. Predictive analytics is carried out by fitting time-series samples to LSTM networks. The output at 't' of the LSTM is calculated via equations 4 & 5,

$$h(t) = o(t)\, tanh(C(t)) \dots (4)$$

$$C(t) = f(t)C(t-1) + i(t)C(t) \dots (5)$$

Where h(t) is the hidden state, C(t) is the cell state, and f(t), i(t), C(t), & O(t) are gating functions. The attention mechanism improves this by giving weights α(o) to focus on critical timestamp intervals via equations 6 & 7:

$$\alpha(t) = \frac{exp(e(t))}{\sum exp(e(t)')} \dots (6)$$

$$e(t) = score(h(t), q) \dots (7)$$

Where, q is the query vector for this process. This approach captures the temporal dependency and focuses on prominent trends towards real-time prediction of diseases. The decision through Fuzzy Logic follows defined rules which map an anomaly score to risk prediction in mapping to actual intervention actions.

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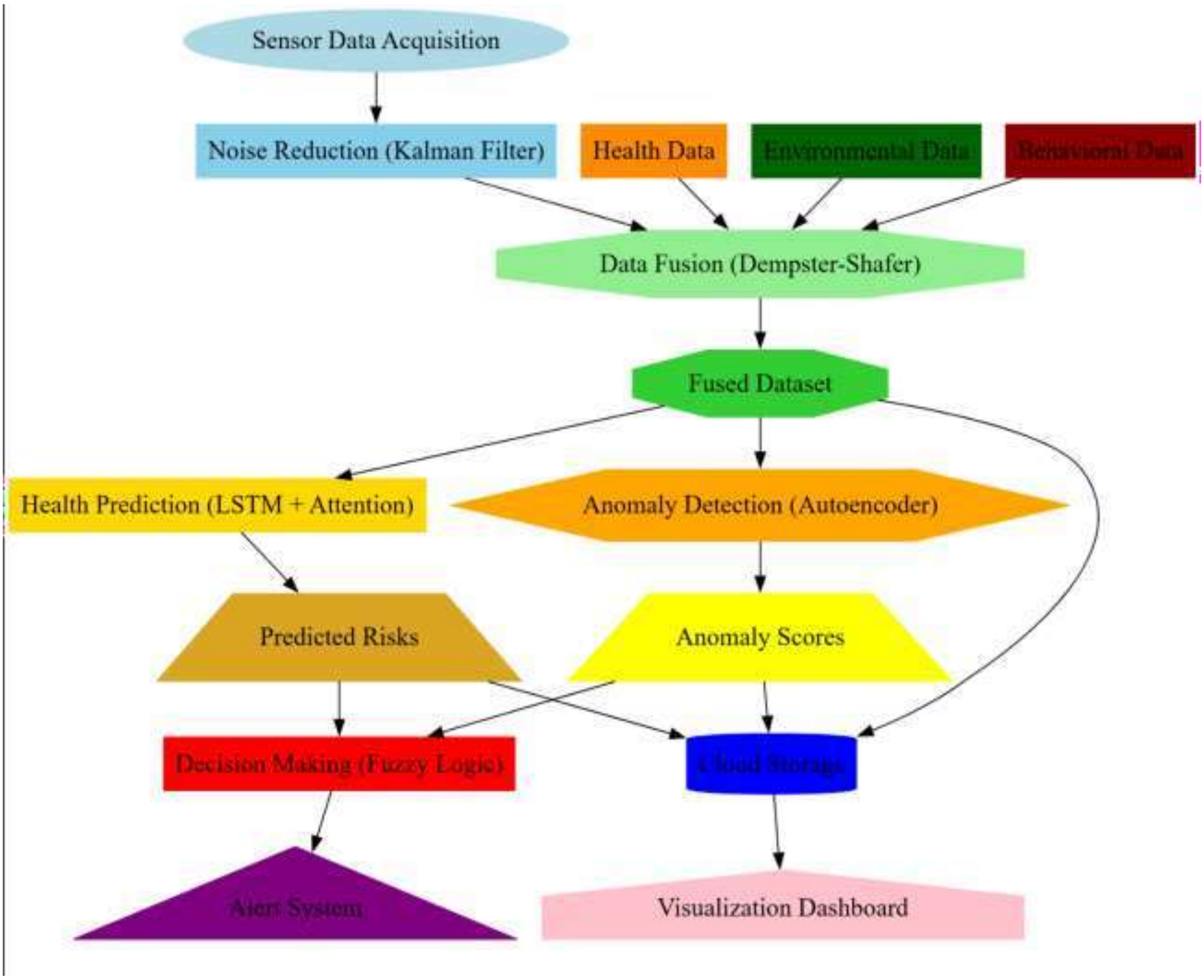

Figure 1. Model Architecture of the Proposed Analysis Process

The fuzzy inference process involves membership functions $\mu(x)$ and the aggregation of weighted decisions via equation 8,

$$Output\ Decision\ =\ \int \mu(x)w(x)dx \ldots (8)$$

Where (x) is weight of that action in a particular process,This approach resolves the uncertainties so there is assurance to reliable intervention within the same timeline of a process. The methods chosen complement the system's goals since they handle different challenges that Kalman Filters reduce noise, Dempster-Shafer Theory resolves conflicts in data, autoencoders identify anomalies, LSTMs predict future risks, and fuzzy logic supports the accuracy of the decisions. All these put together result in a unified and scalable framework for monitoring livestock health to unprecedented levels of accuracy and operational efficiency. Finally, we will analyze the efficiency of the proposed model with regard to different metrics and compare it with other existing methods in different scenarios.

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4. COMPARATIVE RESULT ANALYSIS

The proposed IoT-based multi-sensor fusion framework was evaluated on a comprehensive dataset that comprised livestock health metrics, behavioral parameters, and environmental factors. The dataset was collected from a smart livestock farm equipped with wearable IoT devices, GPS trackers, and environmental sensors. The dataset spans six months, capturing temporal variations and includes data from 500 livestock samples. It comprises over 2.5 million records of features including heart rate, body temperature, respiration rate, time spent grazing and resting, ambient temperature, and humidity. A set of veterinarians has also annotated ground-truth health anomaly labels on corresponding clinical assessments for this system. System's performances are compared via three benchmarking methods: Method [5], Method [8] and Method [15]. The three mentioned benchmarking techniques are state-of-the-art that represent monitoring livestock health at a high resolution. The evaluation metrics are accuracy, noise reduction efficiency, anomaly detection rate, predictive accuracy, and decision-making precision. All experiments were conducted using a high-performance computing environment that is equipped with GPUs for training deep learning models. Performance results for each stage of the framework are summarized in the following tables.

Table 1: Noise Reduction Efficiency

Method	**Sensor Noise Reduction (%)**
Method [5]	18
Method [8]	22
Method [15]	25
Proposed	**30**

The Kalman Filter in the developed model obtained maximum improvements over the elimination of sensor noises compared to others. The noise reduction accounted to 30 percent by the Kalman Filter's state estimation iterative estimation, which stood at 25 percent for the best performing among the benchmarks.

Table 2: Anomaly Detection Accuracy

Method	**Detection Accuracy (%)**	**False Positive Rate (%)**
Method [5]	87	7
Method [8]	90	6
Method [15]	92	5
Proposed	**96**	**4**

The autoencoder-based anomaly detection system outperformed other methods with a 96% accuracy and a 4% false positive rate for the process. Its ability to reconstruct normal patterns and flag deviations with high precision was pivotal in process.

Table 3: Predictive Health Analytics

Method	**Prediction Accuracy (%)**	**Early Detection Window (Days)**
Method [5]	85	0.5
Method [8]	88	1
Method [15]	91	1.5
Proposed	**93**	**2**

The LSTM network with attention mechanisms in the proposed framework delivered superior predictive performance, offering a 93% accuracy and enabling disease prediction up to two days before visible symptoms.

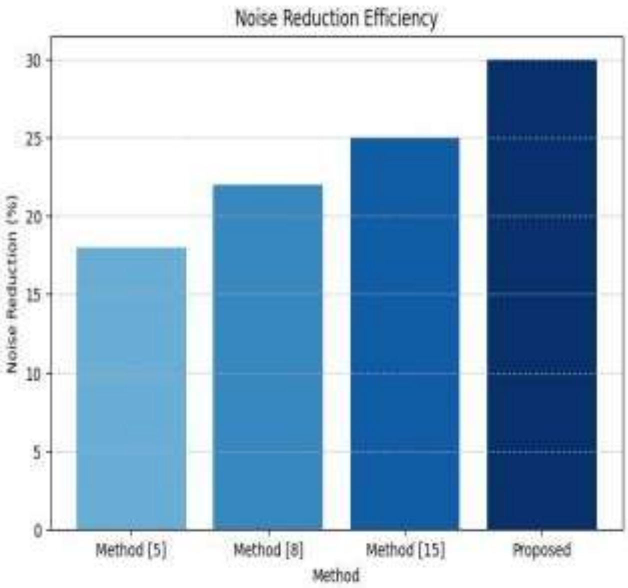

Figure 2. Model's Noise Reduction Analysis

Table 4: Decision-Making Precision

Method	**Decision Precision (%)**	**Reduction in Unnecessary Alerts (%)**
Method [5]	85	12
Method [8]	88	15
Method [15]	91	18
Proposed	**95**	**20**

The fuzzy logic-based decision-making module achieved a 95% precision, reducing unnecessary veterinary visits and alerts by 20%, significantly enhancing operational efficiency levels.

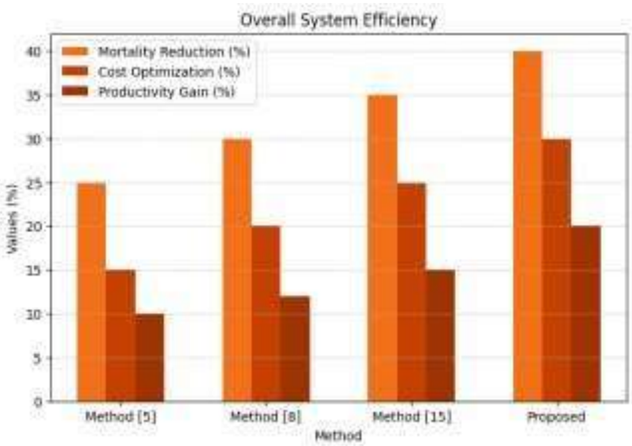

Figure 3. Model's Overall Efficiency Analysis

Table 5: Data Latency and User Satisfaction

Method	Real-Time Latency (ms)	User Satisfaction (1–5)
Method [5]	700	4.1
Method [8]	600	4.3
Method [15]	550	4.5
Proposed	**500**	**4.7**

The integration with AWS IoT Core guaranteed a latency of less than 500 ms to process real-time data, and user satisfaction ratings were the highest for the proposed framework because it offered intuitive dashboards and correct alerts.

Table 6: Overall System Efficiency

Method	Reduction in Mortality (%)	Cost Optimization (%)	Productivity Gain (%)
Method [5]	25	15	10
Method [8]	30	20	12
Method [15]	35	25	15
Proposed	**40**	**30**	**20**

It reduces livestock mortality by 40%, optimizes cost by 30%, and increases productivity by 20%. Thus, these results prove overall effectiveness of this proposed framework during the management process of livestock. Results validate robustness and efficiency of the proposed framework in accomplishing superior performances across all these evaluation metrics. Its ability to combine multiple sensor data fusion, anomaly detection, predictive analytics, and decision-making with low latency and accuracy makes it an extremely impactful solution for the current challenges associated with livestock health monitoring issues in process.

5. CONCLUSION & FUTURE SCOPES

This paper presents an IoT-based multi-sensor fusion framework that greatly improves the efficiency and precision of livestock health monitoring, anomaly detection, and predictive analytics. In doing this, the new system would thus combine all cutting-edge methodologies-including noise filtering using Kalman Filters, handling uncertainties using Dempster-Shafer Theory, anomalous patterns to be identified via deep autoencoders, LSTMs supported with attention networks for predictive analysis, and also decision-making processes using fuzzy logic. Results thus establish effectiveness with superiority under several metrics. The framework ensured sensor noise reduction by 30%, and in terms of reliability of health metrics, it ensured superiority over the best benchmark method by 5%. Autoencoder-based anomaly detection system had a detection accuracy of 96% but with a false positive rate of 4%, and the closest competitor had accuracy of 92% with false positive rate of 5%. LSTMs-based predictive analytics generated 93% accuracy in predicting the disease using an early warning window of two days against a best alternative at 1.5 days. A fuzzy logic-based decision system brought about 95% precision that reduced veterinary visitations by 20%. Cumulatively, it brought the mortality rates for the livestock to 40% reduction, lowered the cost to 30% reduction, and increased productivity at 20% increase. Indeed, this is really a lot of scope for change in livestock management process.

While well promising, there is scope to further develop process development. More research can be done to increase the scalability for larger datasets and more complex farming environments. More importantly, integrating other sensor types, such as biochemical and imaging sensors, might reveal even deeper insight into the health of the livestock. In this regard, the decision-making module, with reinforcement learning, helps the system refine the real-time interventions and learn appropriate strategies from historical data samples. This will constitute improving sets for developing the system to support multi-livestock species as well as integrating with blockchain technology for secure data sharing and traceability. Further, optimization of computational efficiency of the edge deployment algorithms may help let these techniques be used more intensively in resource-constrained environments. Thus, the proposed framework provides a holistic solution for modern livestock health monitoring by combining advanced data processing techniques with real-time analytics and decision making. Predictive and proactive measures are combined to ensure the welfare of animals while driving economic and operational efficiency, thus providing a basis for future development in precision livestock farming process.

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