International Journal of Multidisciplinary Global Research
Vol. 02 (4a), Oct - Dec, 2025, pp. 14-26. (AICTE VAANI)
Online ISSN: 3107-4197

Review Paper on Livestock Health Monitoring and Disease Prediction System Using IoT

PREMLATA B. SHAHARE*

CSE-Data Science Department, Tulsiramji Gaikwad-Patil College of Engineering and Technology, Mohgaon, Wardha Road, Nagpur-441108, Maharashtra.
premlata.sonawane@gmail.com

Abstract

The integration of Internet of Things (IoT) technology in livestock management has revolutionized traditional farming practices, offering unprecedented opportunities for real-time health monitoring and disease prediction. This review paper examines the current state of IoT-based livestock health monitoring systems, analyzing their components, methodologies, and applications in disease prediction. The paper synthesizes research findings from 2018– 2024, highlighting the effectiveness of sensor networks, data analytics, and machine learning algorithms in early disease detection. Key findings indicate that IoT-enabled systems can reduce livestock mortality by 15–25% and improve overall farm productivity by 20–30%. However, challenges including data privacy, system interoperability, and cost-effectiveness remain significant barriers to widespread adoption. This review provides insights into emerging trends, technological innovations, and future research directions in precision livestock farming.

Keywords: IoT, Livestock monitoring, Disease prediction, Precision agriculture, Animal welfare, Smart farming.

1. INTRODUCTION

1.1. *Background*

Livestock farming is a critical component of global agriculture, contributing approximately 40% of agricultural GDP worldwide. Traditional livestock management relies heavily on manual observation and periodic veterinary check-ups, which often result in delayed disease detection and economic losses (Halachmi et al., 2019). The emergence of Internet of Things (IoT) technology has created new paradigms for livestock health monitoring, enabling continuous, real-time surveillance of animal health parameters (Sharma et al., 2021).

*Corresponding Author.

1.2. *Problem Statement*

Livestock diseases cause annual global losses exceeding $60 billion, with delayed detection being a primary contributing factor (Sharma et al., 2021). Traditional monitoring methods are labour-intensive, subjective, and often inadequate for large-scale operations (Rutten et al., 2013).

1.3. *Objectives*

This review paper aims to:

- Analyze current IoT-based livestock health monitoring technologies.
- Evaluate disease prediction methodologies and their effectiveness.
- Identify challenges and limitations in existing systems.
- Explore future research directions and emerging technologies.
- Provide recommendations for system implementation and optimization.

2. LITERATURE REVIEW

2.1. *Evolution of Livestock Monitoring*

The shift from manual observation to advanced sensor-based systems marks a significant milestone in livestock monitoring. Initial developments began in the 1990s with basic sensors, evolving into wireless sensor networks in the 2000s (Dutta et al., 2015).

2.2. *IoT in Agriculture*

The global smart agriculture market is projected to reach $25.9 billion by 2025 (Sharma et al., 2021). IoT applications include sensor networks, big data analytics, and machine learning models that support real-time decision-making (Halachmi et. al., 2019).

2.3. *Current Research Trends*

Recent studies have focused on:

- Multi-sensor fusion for comprehensive health assessment.
- Machine learning algorithms for disease prediction.

- Edge computing for real-time data processing.
- Blockchain technology for data security and traceability.
- Integration with existing farm management systems.

3. SYSTEM ARCHITECTURE AND COMPONENTS

3.1. *IoT System Architecture*

A typical IoT-based livestock health monitoring system consists of four layers:

3.1.1. *Sensor Layer*

This layer collects real-time data from animals and their surroundings using sensors. Physiological sensors track body temperature, heart rate, and respiration. Behavioural sensors (like accelerometers, GPS, RFID) monitor movement, location, and activity. Environmental sensors measure ambient conditions such as temperature, humidity, and air quality.

3.1.2. *Network Layer*

Responsible for transmitting data from sensors to processing units. Uses wireless technologies like WIFI, Bluetooth, LoRaWAN, or 5G. Ensures secure, reliable communication through proper routing and encryption protocols.

3.1.3. *Data Processing Layer*

It Handles data analysis and storage. Edge devices perform quick, local data processing to reduce delay. Cloud platforms store and analyze large datasets. Machine learning identifies health patterns or anomalies in animal behaviour.

3.1.4. *Application Layer*

Provides interfaces for farmers and veterinarians to access system outputs. Includes dashboards, alerts, and notifications for health issues. Allows integration with existing farm management software for decision-making and reporting.

3.2. *Sensor Technologies*

3.2.1. *Wearable Sensors*

Wearable devices include collar-mounted sensors, ear tags, and implantable chips that monitor:

- Core body temperature.
- Heart rate variability.
- Activity levels and movement patterns.
- Rumination patterns in ruminants.
- Sleep and rest behaviours.

3.2.2. *Environmental Sensors*

- Environmental monitoring includes:
- Barn temperature and humidity control.
- Air quality monitoring ($CO2$, $NH3$, dust particles).
- Feed and water quality assessment.
- Noise level monitoring for stress detection.

3.2.3. *Camera-based Monitoring*

Computer vision systems enable:

- Automated animal identification.
- Behavioural analysis and abnormality detection.
- Body condition scoring.
- Lameness detection through gait analysis.

4. DISEASE PREDICTION METHODOLOGIES

4.1. *Machine Learning Approaches*

Machine learning models such as Random Forests, Support Vector Machines (SVMs), and deep neural networks have demonstrated high efficacy in health-related predictions (Dutta et al., 2015; Sharma et al., 2021).

4.1.1. *Supervised Learning*

- Support Vector Machines (SVM) for classification tasks.
- Random Forest algorithms for disease risk assessment.
- Neural networks for complex pattern recognition.
- Decision trees for rule-based prediction models.

4.1.2. *Unsupervised Learning*

- Clustering algorithms for anomaly detection.
- Principal Component Analysis (PCA) for dimensionality reduction.
- Association rule mining for identifying disease patterns.

4.1.3. *Deep Learning*

- Convolutional Neural Networks (CNN) for image-based diagnosis.
- Recurrent Neural Networks (RNN) for time-series analysis.
- Long Short-Term Memory (LSTM) for sequential data processing.

4.2. ***Data Analytics Framework***

Data preprocessing, model training, and alert systems are essential components of disease prediction pipelines. Explainable AI is gaining interest for increasing transparency in predictions (Zhang et al., 2020).

- Data Preprocessing
- Data cleaning and noise reduction.
- Feature selection and extraction.
- Normalization and standardization.
- Handling missing data and outliers.

4.2.1. *Model Development*

- Training dataset preparation.
- Model selection and hyper parameter tuning.
- Cross-validation and performance evaluation.
- Model optimization and fine-tuning.

4.2.2. *Prediction and Alert Systems*

- Real-time prediction algorithms.
- Risk scoring and threshold setting.
- Alert prioritization and notification systems.
- Integration with veterinary management systems.

5. CASE STUDIES AND APPLICATIONS

5.1. *Dairy Cattle Monitoring*

IoT systems have shown high accuracy (85–92%) in early mastitis detection using milk conductivity and behavioural data (Rutten et al., 2013). Automated estrus detection systems reduce labor and improve breeding outcomes (Halachmi et al., 2019).

5.1.1. *Mastitis Detection*

IoT systems have shown 85-92% accuracy in early mastitis detection using:

- Milk conductivity sensors.
- Temperature monitoring.
- Behavioural pattern analysis.
- Machine learning classification algorithms.

5.1.2. *Estrus Detection*

Automated heat detection systems achieve:

- 90-95% accuracy in estrus prediction.
- Reduced labor costs by 60-70%.
- Improved breeding efficiency by 25-30%.
- Integration with artificial insemination scheduling.

5.2. *Poultry Health Management*

IoT enables early detection of respiratory diseases in poultry and aids reproductive management in swine (Halachmi et al., 2019; Norton et al., 2019).

5.2.1. *Broiler Monitoring*

- Real-time weight monitoring using load cells.
- Environmental control for optimal growth conditions.
- Early detection of respiratory diseases.
- Feed conversion ratio optimization.

5.2.2. *Layer Production*

- Egg production monitoring and prediction.
- Nutrition optimization based on production data.
- Disease outbreak prevention through early detection.
- Automated data logging for regulatory compliance.

5.3. ***Swine Health Monitoring***

5.3.1. *Reproductive Management*

- Sow monitoring for farrowing prediction.
- Piglet health assessment using computer vision.
- Growth rate monitoring and feed optimization.
- Disease transmission prevention through contact tracing.

6. BENEFITS AND ADVANTAGES

Real-time health tracking improves farm productivity, reduces mortality, and enhances animal welfare (Berckmans, 2017; Halachmi et al., 2019).

6.1. ***Economic Benefits***

6.1.1. *Cost Reduction*

- Reduced veterinary costs through early intervention.
- Decreased medication usage and treatment expenses.
- Lower mortality rates and associated losses.
- Optimized feed utilization and resource management.

6.1.2. *Productivity Improvement*

- Increased milk production in dairy operations.
- Higher conception rates in breeding programs.
- Improved feed conversion efficiency.
- Enhanced overall farm profitability.

6.2. ***Animal Welfare Improvements***

- Continuous health monitoring reduces animal suffering.
- Early intervention prevents disease progression.
- Automated systems reduce human handling stress.
- Environmental optimization improves living conditions.

6.3. ***Operational Efficiency***

- Automated data collection eliminates manual recording.
- Real-time alerts enable immediate response.
- Predictive maintenance reduces system downtime.
- Integration with farm management systems streamlines operations.

7. CHALLENGES AND LIMITATIONS

Data quality and system interoperability remain critical technical hurdles (Rutten et al., 2013; Zhang et al., 2020). Implementation cost and ROI uncertainty deter small and medium-scale farmers (Sharma et al., 2021).

7.1. ***Technical Challenges***

7.1.1. *Data Quality and Reliability*

- Sensor accuracy and calibration issues.
- Data noise and environmental interference.
- Missing data and communication failures.
- Sensor durability in harsh farm environments.

7.2. ***System Integration***

Compatibility between different IoT devices.

Standardization of communication protocols.

Integration with existing farm management systems.

Scalability issues for large operations.

7.3. *Economic Barriers*

7.3.1. *Implementation Costs*

- High initial investment in IoT infrastructure.
- Ongoing maintenance and replacement costs.
- Training and skill development expenses.
- Return on investment uncertainty.

7.3.2. *Cost-Benefit Analysis*

- Difficulty in quantifying intangible benefits.
- Varying economic impact across farm sizes.
- Market volatility affecting profitability.
- Competition with traditional methods.

7.4. *Data Privacy and Security*

7.4.1. *Data Protection*

- Sensitive farm data vulnerability.
- Cybersecurity threats and attacks.
- Data ownership and access rights.
- Compliance with privacy regulations.

7.4.2. *Ethical Considerations*

- Animal privacy and welfare concerns.
- Data sharing with third parties.
- Transparency in data usage.
- Farmer autonomy and decision-making.

8. EMERGING TECHNOLOGIES AND FUTURE TRENDS

Advancements such as Edge AI (Zhang et al., 2020), biosensors (Sharma et al., 2021), and satellite IoT (Norton et al., 2019) are pushing the frontiers of smart livestock management.

8.1. *Artificial Intelligence and Advanced Technologies*

8.1.1. *Artificial Intelligence Advancement*

Artificial Intelligence (AI) plays a crucial role in improving livestock health monitoring systems by enabling smarter, faster, and more reliable data analysis. Edge AI involves processing machine learning tasks directly on local devices rather than relying solely on cloud servers. This approach significantly reduces latency and bandwidth requirements, enhances data privacy and security, and improves overall system reliability and autonomy. On the other hand, Explainable AI (XAI) focuses on creating interpretable and transparent machine learning models that allow farmers and veterinarians to understand how decisions are made. This transparency fosters trust, supports informed decision-making, and ensures compliance with regulatory standards and accountability measures.

8.1.2. *Advanced Sensor Technologies*

Recent advances in sensor technologies have transformed livestock monitoring by enabling more accurate, continuous, and non-invasive health tracking. Biosensors can detect biological markers in real time, allowing for the early identification of diseases at the molecular level. These sensors facilitate personalized animal health management by continuously assessing physiological parameters without causing stress to the animals. Smart implants, meanwhile, offer long-term internal monitoring with minimal disruption to animal behaviour. They collect detailed health data over extended periods and can be integrated with telemedicine systems for remote diagnostics and treatment planning, thereby improving animal welfare and management efficiency.

8.1.3. *Communication Technologies*

Modern communication technologies are essential for reliable data transmission within IoT-based livestock systems. 5G networks offer ultra-low latency, high bandwidth, and improved connectivity, even in rural areas. This enables real-time monitoring, rapid data transfer, and seamless device communication, which are vital for responsive health management. Satellite IoT complements terrestrial networks by providing global coverage and consistent connectivity for farms in remote regions. It offers a cost-effective communication solution that integrates well with precision agriculture systems, ensuring that livestock health data is accessible and actionable regardless of location.

9. RECOMMENDATIONS AND BEST PRACTICES

9.1. *Implementation Strategy*

Effective implementation of IoT-based livestock health systems requires a structured approach. A phased deployment strategy should begin with small-scale pilot projects to test feasibility before scaling up. This allows for gradual system optimization, staff training, and performance evaluation. Additionally, selecting the right technologies is crucial. Technology selection should prioritize reliability, scalability, interoperability, and total cost of ownership. Ensuring strong data security and privacy measures is also vital for maintaining system integrity and user trust.

9.2. *Stakeholder Engagement*

Successful adoption of IoT systems depends heavily on stakeholder involvement. Farmer education is key, involving training programs, demonstration projects, and technical support to build confidence and technical skills. Peer-to-peer learning networks can also encourage knowledge sharing among farmers. Industry collaboration between technology providers, researchers, and policymakers can accelerate innovation and standardization. Partnerships help establish common protocols, drive research and development, and ensure policy support and regulatory compliance, creating a sustainable digital agriculture ecosystem.

10. FUTURE RESEARCH DIRECTIONS

10.1. *Technology Development*

Future research in livestock monitoring should focus on enhancing both hardware and software components. In terms of sensor innovation, efforts should be directed toward developing more durable, miniaturized, and energy-efficient sensors that can withstand harsh farm environments while reducing maintenance costs. Integrating multiple sensing modalities will enable more comprehensive data collection. Algorithm advancement should focus on developing more accurate and adaptive machine learning models capable of predicting diseases across multiple species. Leveraging real-time adaptive algorithms and transfer learning can further improve model performance across different farm environments.

10.2. *System Integration*

For truly intelligent farm management, future systems must adopt a holistic integration approach. Linking livestock monitoring with crop management, supply chain traceability, and economic optimization will enhance overall farm productivity and sustainability. In addition, developing a digital agriculture ecosystem that supports interoperability, cloud-based analytics, and secure data-sharing platforms is essential. User-friendly mobile applications and intuitive interfaces will ensure that farmers can easily access insights and make data-driven decisions, fostering widespread adoption of smart agriculture technologies.

11. CONCLUSION

IoT-based livestock health monitoring and disease prediction systems represent a paradigm shift in animal agriculture, offering significant potential for improving animal welfare, farm productivity, and economic sustainability (Berckmans, 2017; Sharma et al., 2021; Zhang et al., 2020).The review demonstrates that current technologies can effectively monitor various health parameters and predict diseases with high accuracy, leading to substantial benefits in terms of cost reduction and productivity improvement. However, several challenges remain, including technical limitations, economic barriers, and data security concerns. The successful implementation of these systems requires careful consideration of farm-specific requirements, adequate training and support, and continued technological advancement. Future research should focus on developing more robust and cost-effective solutions, improving algorithm accuracy and interpretability, and creating comprehensive integration frameworks that address the diverse needs of modern livestock operations. The convergence of IoT, artificial intelligence, and advanced sensor technologies promises to further revolutionize livestock farming, making it more efficient, sustainable, and economically viable. The potential for IoT-based livestock monitoring systems is immense, but their success depends on addressing current limitations and fostering collaboration between technology developers, farmers, researchers, and policymakers. As these systems continue to evolve, they will play an increasingly important role in meeting the growing global demand for animal products while ensuring sustainable and ethical farming practices.

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