A Survey of Automated Livestock Monitoring and Data-Driven Agriculture Technologies

Abstract

Automated livestock monitoring, leveraging advanced technologies such as the Internet of Things (IoT), big data analytics, and precision agriculture, is revolutionizing livestock management by enhancing productivity, sustainability, and animal welfare. This survey provides a comprehensive exploration of these technologies, emphasizing their role in addressing critical agricultural challenges. The integration of IoT devices and sensor technologies facilitates real-time monitoring of animal health and resource optimization, significantly improving operational efficiency and welfare outcomes. The application of blockchain enhances transparency and traceability across supply chains, ensuring compliance with quality standards. However, the adoption of these technologies faces challenges, including technological and infrastructure limitations, data management and privacy concerns, and economic and educational barriers. Future directions focus on emerging technologies and trends, such as the Internet of Robotic Things (IoRT) and federated learning, which promise to enhance connectivity, data processing, and decision-making in agriculture. Emphasizing sustainability and resource optimization, these advancements aim to create more efficient, ethical, and sustainable livestock management practices. The survey underscores the need for continued research and development to overcome existing challenges and fully harness the potential of these technologies in modern agriculture.

1 Introduction

1.1 Overview of Automated Livestock Monitoring

Automated livestock monitoring represents a transformative advancement in modern agriculture, utilizing cutting-edge technologies to improve the efficiency and sustainability of livestock management. This shift is largely propelled by Precision Livestock Farming (PLF) technologies, which facilitate continuous, non-invasive monitoring of animal health and welfare parameters [1]. For instance, radar systems for tracking sheep behavior exemplify innovations that enable real-time data collection without inducing stress in animals [2].

Such technologies are vital for meeting the escalating dietary needs of the global population, particularly in extensive livestock systems where traditional monitoring is often unfeasible [3]. Beyond productivity enhancements, these systems significantly contribute to animal welfare. In Europe, considerable investments have been directed toward developing welfare assessment methods in commercial livestock operations, ensuring compliance with welfare standards [4].

The integration of IoT applications has further transformed smart farming by enabling data-driven, automated processes. These intelligent technologies are crucial in addressing productivity, welfare, and sustainability challenges within the livestock sector [5]. Automated systems also play a key role in early disease detection, equipping farmers with tools to identify conditions such as bovine respiratory disease and neonatal calf diarrhea at earlier stages, thereby preventing widespread outbreaks [6].

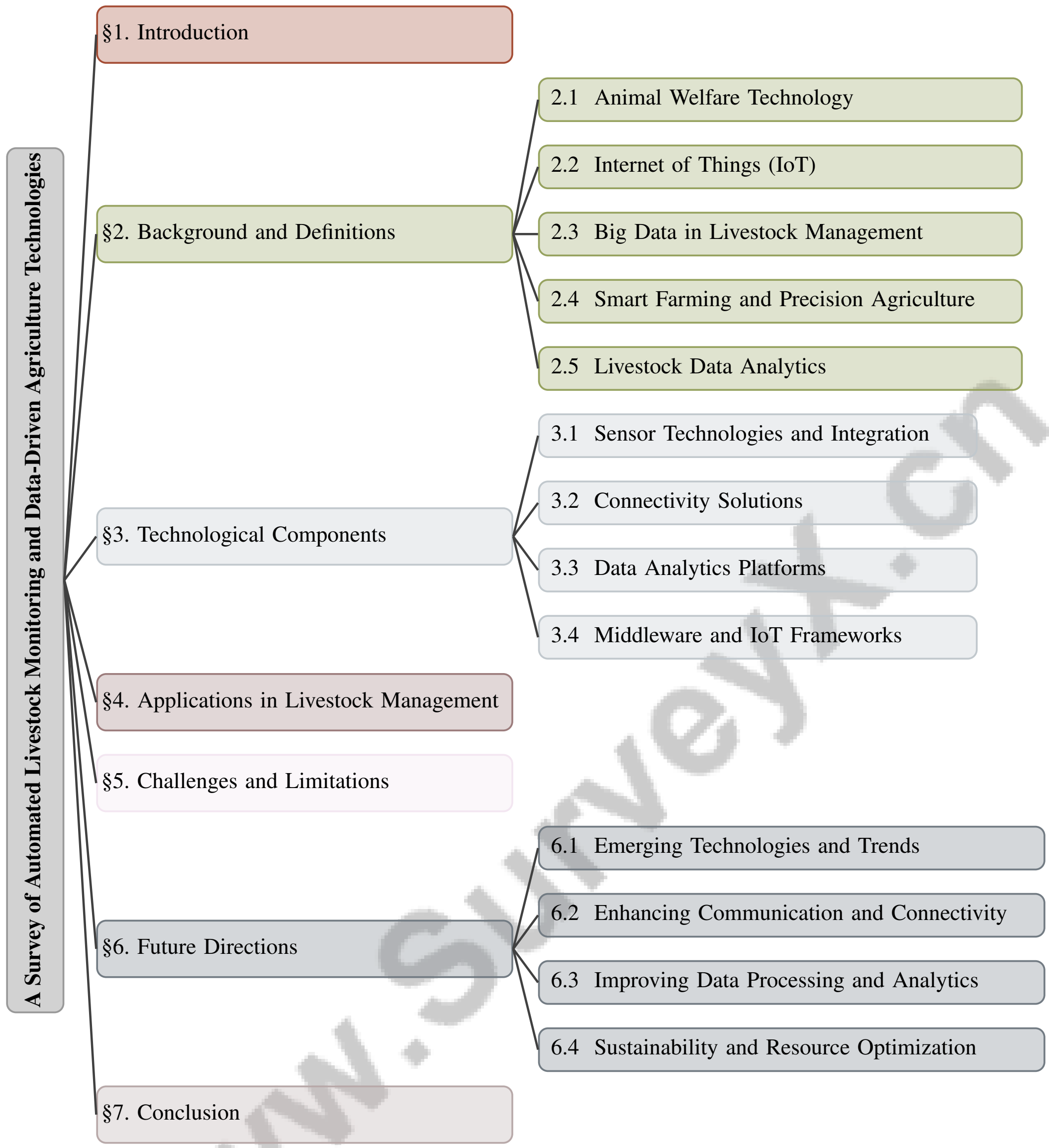


Figure 1: chapter structure

Moreover, biosensors for livestock health monitoring have demonstrated significant potential in enhancing disease detection and overall productivity in agriculture [4]. As the industry evolves, the importance of automated livestock monitoring in mitigating environmental stressors, such as heat stress in cattle, becomes increasingly evident, underscoring its relevance in contemporary agricultural practices [7].

1.2 Significance of Data-Driven Agriculture Technologies

Data-driven agriculture technologies are instrumental in reshaping the agricultural landscape by boosting productivity, fostering sustainability, and enhancing animal welfare. These technologies address pressing challenges such as climate change, resource constraints, and ethical considerations regarding animal treatment [8]. PLF technologies, a subset of data-driven strategies, improve livestock welfare and health while rendering farming operations more economically viable and environmentally sustainable [1]. By employing biometric sensors, big data, and blockchain, these technologies provide comprehensive solutions for enhancing productivity and sustainability in livestock farming [1].

The implementation of IoT in agriculture has been crucial in addressing challenges like adverse weather, water scarcity, and labor shortages [9]. IoT-enabled systems enhance monitoring capabilities, leading to improved farm management efficiency and animal welfare [10]. These systems facilitate precise resource allocation, thereby reducing labor costs and optimizing resource utilization in livestock management [8]. The benefits of IoT technologies, particularly highlighted during the COVID-19 pandemic, underscore their significance in modern agriculture [9].

Furthermore, data-driven technologies are vital in overcoming the limitations of traditional disease detection methods in livestock. Manual health checks frequently fail to identify sick animals promptly, leading to delayed interventions [3]. By utilizing validated PLF tools, farmers can more effectively monitor animal welfare, ensuring timely disease detection and intervention, which directly impacts productivity and sustainability [11]. Establishing benchmarks for these technologies is essential for advancing animal welfare assessments and providing reliable tools for farmers [12].

The livestock sector faces increasing pressure to boost production while addressing ethical concerns regarding animal treatment [13]. Data-driven technologies not only enhance productivity but also address these ethical issues by improving animal welfare. The evolution of genomic breeding programs, complemented by precision technologies in routine management practices, intensifies production systems and enhances genetic progress in productive efficiency traits in livestock [14]. As the industry progresses, adopting these technologies is crucial for mitigating the environmental impact of livestock farming while fulfilling the global demand for animal products [15]. Additionally, effective monitoring and mitigation strategies for heat stress in cattle due to climate change further emphasize the importance of data-driven approaches in enhancing animal welfare and productivity [7].

1.3 Structure of the Survey

This survey is systematically organized to comprehensively explore automated livestock monitoring and data-driven agriculture technologies. The paper begins with an **Introduction**, discussing the significance of integrating advanced technologies into agriculture, emphasizing benefits for efficiency, productivity, and sustainability. This section includes an **Overview of Automated Livestock Monitoring**, highlighting its importance in modern agriculture, and the **Significance of Data-Driven Agriculture Technologies**, addressing their impact on productivity, animal welfare, and sustainability.

Following the introduction, the survey provides an in-depth exploration of the **Background and Definitions**, elucidating essential concepts such as automated livestock monitoring, which leverages real-time data to enhance animal welfare; animal welfare technology focused on improving livestock health; the Internet of Things (IoT) as a framework for connecting devices for better management; big data's role in livestock management for optimizing resources; smart farming techniques integrating advanced technologies for sustainability; precision agriculture methodologies maximizing efficiency; and livestock data analytics utilizing statistical algorithms for informed decision-making [16, 1, 17]. Each term is defined and contextualized within modern agriculture.

The **Technological Components** section discusses various technological elements involved in automated livestock monitoring, including sensors, connectivity solutions, and data analytics platforms. The integration of these components is crucial for effective data collection and analysis in livestock management. Subsections cover **Sensor Technologies and Integration**, **Connectivity Solutions**, **Data Analytics Platforms**, and **Middleware and IoT Frameworks**.

In **Applications in Livestock Management**, the practical applications of these technologies are explored, demonstrating their contributions to monitoring animal health, optimizing resource use, and improving farm operations. This section provides examples of current implementations and their outcomes, with subsections on **Enhancing Animal Health Monitoring**, **Optimizing Resource Use**, **Improving Farm Operations**, and **Current Implementations and Outcomes**.

The survey then addresses the **Challenges and Limitations** associated with adopting automated livestock monitoring and data-driven agriculture technologies. Discussions encompass a wide range of critical issues, including technological and infrastructure challenges in implementing IoT systems, complexities of data management and privacy among diverse stakeholders, economic and educational barriers hindering widespread adoption, operational and maintenance challenges, and regulatory and ethical considerations in the design and deployment of IoT technologies [18, 9, 19, 20, 21].

Finally, the paper concludes with **Future Directions**, discussing potential advancements and emerging trends in the field. This section highlights the prospects for further enhancing the efficiency and

AI-generated, for reference only.

sustainability of livestock management through emerging technologies and trends, improvements in communication and connectivity, advancements in data processing and analytics, and future directions in sustainability and resource optimization.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Animal Welfare Technology

Animal welfare technology represents a crucial advancement in agriculture, focusing on enhancing livestock well-being through advanced monitoring systems and innovative practices. Precision Livestock Farming (PLF) technologies address challenges such as managing large herds, economic constraints, and labor shortages, which impede effective individual animal monitoring and welfare [12]. These technologies utilize sensors, boluses, image and sound-based systems, and RFID to comprehensively track health and behavior [11]. Non-invasive monitoring methods reduce stress and improve welfare by eliminating invasive electronic tags [6]. Wearable sensors and machine learning algorithms enhance predictive capabilities, such as forecasting calving, enabling timely interventions to promote welfare [6]. Real-time monitoring of metabolic energy balance helps assess animal mental states and welfare [11]. The adaptation of veterinary medicine to include telemedicine services enhances accessibility and the timeliness of medical interventions [12].

Validating and benchmarking these technologies are essential for effective welfare assessments. Commercially available PLF technologies are scrutinized for validation status and potential to enhance welfare evaluations [6]. The integration of blockchain and IoT technologies enhances transparency and traceability in supply chain management and healthcare applications [7]. Animal welfare technology is indispensable for sustainable agriculture, providing tools to ensure livestock health while addressing farmers' challenges in large-scale operations [12].

2.2 Internet of Things (IoT)

The Internet of Things (IoT) transforms agriculture by creating interconnected farming ecosystems. IoT enables real-time data collection and analysis through connected devices, enhancing farm management efficiency and sustainability [8]. This continuous monitoring provides farmers with advanced insights and predictive analytics for proactive decision-making. However, device heterogeneity and communication protocols create closed ecosystems, limiting IoT's potential [22]. The rapid sensor data growth and real-time analytics demand robust data management solutions [23]. Security and privacy concerns are critical to maintaining trust in autonomous agricultural systems [24].

Integrating IoT with blockchain technology offers secure sensor data management, addressing decentralization, interoperability, and security vulnerabilities [25]. Blockchain enhances transparency and traceability in supply chains, while smart contracts within IoT frameworks facilitate transactions, boosting operational efficiency [15]. IoT's economic implications are profound, optimizing resource usage and enhancing productivity [26]. Yet, IoT deployment introduces cyberattack vulnerabilities, necessitating threat simulation benchmarks [27]. Edge computing integration with IoT, supported by advancements in mobile communication, distributed computing, and AI, promotes diverse IoT applications [28].

Transitioning to Green IoT is crucial for sustainable agriculture, focusing on reducing carbon footprints and promoting energy efficiency [29]. IoT technologies promise enhanced agricultural sustainability and productivity while addressing practical and ethical considerations. The intersection of pervasive computing and AI, particularly resource-efficient distributed AI techniques, aligns with IoT's agricultural role, offering innovative solutions to existing challenges [30].

2.3 Big Data in Livestock Management

Big data analytics significantly advance livestock management by enhancing decision-making capabilities that improve operational efficiency and animal welfare. IoT devices and sensors deployed across farms enable real-time data collection and analysis, crucial for optimizing livestock operations and productivity outcomes [31]. This data-centric approach facilitates early health issue detection, improving animal welfare and ensuring sustainable farming practices [32]. Integrating heterogeneous data sources and devices poses challenges for implementing Web of Things (WOT) solutions [33].

Machine learning algorithm application faces challenges such as model selection, tuning, updating, and concept drift [27]. Communication overhead from vast IoT-generated data hampers performance and increases energy consumption, necessitating robust data management solutions [28].

A systematic framework converts low-level IoT sensor data into higher-level process events, enhancing big data's utility in process mining [34]. This approach improves data processing efficiency and facilitates better decision-making in livestock management by providing actionable insights. However, integrating diverse IoT devices remains challenging, particularly ensuring interoperability and maintaining data privacy and security [25]. Security and privacy concerns are paramount given the increasing volume of data from IoT devices, especially in small networks where traditional security measures may be inadequate [35]. Ensuring quality of service (QoS) in data trading between IoT users and service providers is essential for maintaining reliability and integrity in livestock management systems [36]. IoT's potential to enhance human resource development (HRD) by providing real-time data for better workforce management highlights big data analytics' broader implications in agriculture [37].

2.4 Smart Farming and Precision Agriculture

Smart farming and precision agriculture are pivotal methodologies in modern agricultural practices, leveraging advanced technologies to enhance efficiency, productivity, and sustainability in livestock management. Smart agriculture, defined as an IoT-based model, aims to improve the quality and quantity of agricultural outputs while optimizing labor and resource use to meet global food production demands [8]. This approach emphasizes integrating IoT devices, big data analytics, and geospatial technologies for precise monitoring and management of farm operations.

Deploying IoT devices in smart farming allows continuous granular data collection, essential for informed decision-making and efficient resource management. However, the proliferation of IoT middleware platforms, each with similar functionalities but different underlying technologies, presents challenges for developers seeking effective system implementation [38]. The lack of standardization and interoperability among these platforms complicates seamless integration of diverse technologies, critical for optimizing agricultural tasks.

Precision agriculture, a subset of smart farming, focuses on fine-tuning agricultural practices to enhance productivity and sustainability. Leveraging geospatial analytics and satellite data, this approach comprehensively monitors environmental conditions, facilitating improved crop and livestock management practices. By integrating advanced technologies such as IoT, precision agriculture enables real-time data collection and analysis, promoting sustainable practices that adapt to climate change and optimize resource utilization for food security [39, 40, 41]. Advanced modeling techniques, such as Digital Twins, provide continuous learning and predictive capabilities that enhance agricultural systems' lifecycle management.

In livestock management, precision agriculture utilizes biometric sensors, machine learning, and IoT for real-time monitoring of animal health and behavior. This integration allows farmers to detect diseases early, optimize resource allocation, and enhance animal welfare while promoting environmental sustainability by minimizing waste and reducing the ecological footprint of livestock farming. By adopting these intelligent systems, the livestock industry can improve productivity and management practices in response to growing global demands for animal products [16, 1, 42]. Big data analytics is crucial, encompassing data storage, cleaning, analysis, and visualization stages, essential for deriving actionable insights from complex datasets.

2.5 Livestock Data Analytics

Livestock data analytics is fundamental in modern agriculture, providing a data-driven framework to enhance decision-making in livestock management. IoT devices in farming generate large data volumes, which, when effectively analyzed, can significantly improve animal health, welfare, and farm productivity. Precision Livestock Farming (PLF) technologies use physiological signals, such as heart rate and movement, to monitor stress levels and detect early disease signs, enhancing welfare outcomes and operational efficiency [12].

Managing and processing extensive data from IoT devices presents challenges, primarily due to these devices' limited resources, complicating the application of traditional networking and security techniques [22]. Advanced frameworks like MULTIIOT enable integration and learning from diverse sensory data for comprehensive livestock monitoring tasks, including gaze estimation and gesture classification [29]. Machine learning (ML) models deployed over cloud-fog networks offer promising solutions to enhance energy efficiency in livestock data analytics. Optimization models like Mixed Integer Linear Programming (MILP) optimize resource allocation and improve diverse data stream analysis, ensuring efficient extraction of meaningful insights [29]. Middleware solutions, such as IoT-MP, facilitate effective IoT device management while ensuring user privacy and secure data handling [22].

Integrating smart contracts within IoT applications addresses challenges in managing heterogeneous information and interactions among multiple stakeholders. This integration ensures security, access control, and interoperability, crucial for effective livestock management systems [29]. However, challenges such as statistical heterogeneity of client data, resource management, and privacy risks remain critical [43].

3 Technological Components

Category	Feature	Method
Sensor Technologies and Integration	Energy Solutions	PMCS[44]
	Continuous Tracking	RCPS[6], FID[33]
Connectivity Solutions	Localized Processing	FEC[45], DPEA[46]
	Resource and Energy Optimization	EEMPL[47]
	Security and Transparency	SC-IoT[19], MLHIS[48]
	Protocol and Connectivity	GIMP[49]
Data Analytics Platforms	Edge Computing	DTDTC[50], GCDS[35], MFCA[51], SEC[52]
Middleware and IoT Frameworks	Data Efficiency	CADDOT[53], PDF[34]
	Integration and Interoperability	IoT-MP[54], ViSIoT[55]

Table 1: This table provides a comprehensive summary of the key technological components and methodologies utilized in the development of automated livestock monitoring systems. It categorizes these components into sensor technologies and integration, connectivity solutions, data analytics platforms, and middleware and IoT frameworks, highlighting specific features and methods relevant to each category. The table serves as a resource for understanding the integration of IoT devices and advanced computational techniques in modern agriculture.

Modern agriculture increasingly relies on technological advancements to improve livestock management efficiency. This section examines the technological components essential for developing automated livestock monitoring systems, focusing on real-time data collection and analysis. As illustrated in **??**, the hierarchical structure of these technological components highlights key sensor technologies, connectivity solutions, data analytics platforms, and middleware frameworks. Each category is further divided into specific technologies and methodologies that enhance monitoring efficiency, data processing, and system interoperability. Table 1 presents an in-depth overview of the technological components essential for automated livestock monitoring systems, detailing the various categories and methodologies that enhance monitoring efficiency, data processing, and system interoperability. Additionally, Table 2 presents a comparative analysis of the technological features essential for automated livestock monitoring systems, focusing on integration capabilities, data processing efficiency, and security features. This depiction underscores the integration of IoT devices and advanced computational techniques in modern agriculture, which is critical for effective monitoring of animal health, behavior, and environmental conditions. The following subsection highlights recent sensor technology advancements and their integration, emphasizing their role in this dynamic landscape.

3.1 Sensor Technologies and Integration

Sensor technologies are central to automated livestock monitoring, providing critical data on animal health, behavior, and environmental conditions. Integrating various sensor types is key for comprehensive monitoring and informed decision-making. Recent advancements enable real-time monitoring of individual cattle, aiding in heat stress mitigation and welfare improvement [7]. A wide array of sensors is used for tracking nutrition, physical environment, health, and behavior [6]. These range from experimental to commercial products, demonstrating sensor technology's evolution. For example, sensors on cattle monitor activity and temperature, showcasing practical applications [6].

Advanced frameworks ensure seamless connectivity and data interoperability. The Gateway Controller with Deep Sensing (GCDS) method autonomously manages IoT gateways, enhancing sensor network connectivity and data exchange [35]. The Smart-Edge-CoCaCo algorithm optimizes computation, caching, and communication in heterogeneous IoT environments, reducing delays and improving data processing efficiency [52]. Power management is crucial, with solutions like solar energy harvesting ensuring continuous operation in remote settings [44]. Standards like OData and SensorML facilitate smooth data flow from sensors to analytics platforms [33].

Radio resource management (RRM) frameworks incorporating data importance metrics optimize sensor network performance, ensuring critical data prioritization and enhancing monitoring system efficiency [56].

3.2 Connectivity Solutions

Connectivity solutions are vital for efficient data transfer in livestock monitoring systems, enabling real-time data analysis. Integrating fog computing with cloud capabilities enhances connectivity by allowing localized data processing, reducing latency and improving system responsiveness [45]. Multi-protocol gateways interconnect IoT nodes via standards like WiFi, Bluetooth, and ZigBee, normalizing data for cloud transmission [49]. This ensures efficient communication among diverse IoT devices. Smart contracts within IoT frameworks enhance security and transparency, managing information exchanges efficiently [19].

As illustrated in Figure 2, the hierarchical structure of connectivity solutions in livestock monitoring systems highlights key areas such as data processing, security models, and energy efficiency. Each category encompasses various technological advancements and methodologies, underscoring their role in enhancing data transfer, security, and energy management within IoT frameworks. Security in data transmission is prioritized with multi-layer hierarchical inter-cloud security models (MLHIS), which inspect session packets at various checkpoints, ensuring secure analytics access [48]. Communication technologies (BLE, LoRaWAN), data reduction strategies (compression, aggregation), and emerging concepts (Edge AI) minimize communication overhead and optimize data transfer [28].

Energy-efficient virtual machine placement across cloud-fog networks is critical for processing machine learning tasks, optimizing resource use, and minimizing energy consumption [47]. Distributed methods employing low-performance ARM-based devices and central nodes with powerful GPUs ensure efficient data processing task allocation [46]. Advanced connectivity solutions, including biometric sensors, big data analytics, and blockchain technology, enable real-time health and behavior monitoring, facilitating robust, secure, and efficient data transfer across agricultural environments. These innovations enhance animal welfare, optimize resource use, and ensure product traceability, addressing challenges like disease outbreak prevention and environmental sustainability [16, 1, 4].

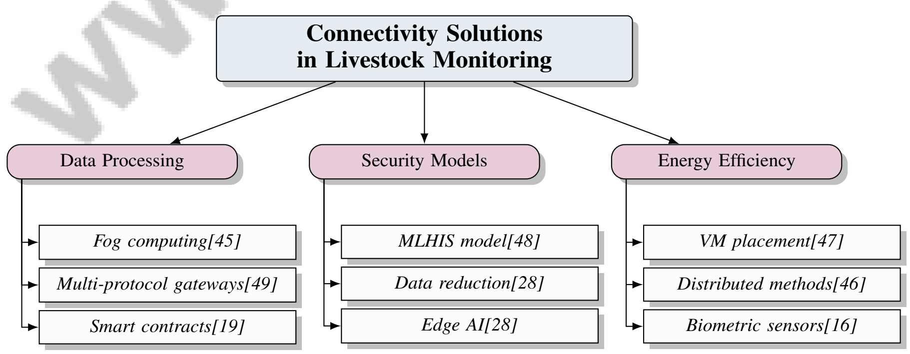


Figure 2: This figure illustrates the hierarchical structure of connectivity solutions in livestock monitoring systems, highlighting key areas such as data processing, security models, and energy efficiency. Each category encompasses various technological advancements and methodologies, underscoring their role in enhancing data transfer, security, and energy management within IoT frameworks.

3.3 Data Analytics Platforms

Data analytics platforms are crucial for managing livestock by processing extensive data from IoT devices. These platforms integrate diverse data sources, employing advanced computational techniques to derive actionable insights, enhancing decision-making and operational efficiency. Machine learning integration with IoT applications is significant, as highlighted in surveys emphasizing data processing frameworks in livestock data analysis [57]. Platforms like the Mist-Fog-Cloud Computing Architecture demonstrate localized data processing's effectiveness, minimizing data transfer and enhancing timely decision-making [51]. The Gateway Controller with Deep Sensing (GCDS) method autonomously collects and processes IoT device data, improving real-time decision-making [35].

Decision-triggered data transmission methods, such as the DTDTC method, integrate compressive sensing and machine learning, facilitating efficient data handling by transmitting only relevant sensor data [50]. Importance-aware radio resource management (RRM) techniques prioritize data based on importance, significantly outperforming traditional methods in learning speed and accuracy [56]. This ensures critical data is processed efficiently, enhancing monitoring system effectiveness.

Edge computing and caching strategies, as seen in the Smart-Edge-CoCaCo algorithm, optimize computation offloading decisions based on real-time user demands, improving data analytics platforms' responsiveness [52]. These advancements are essential for managing livestock data complexities, ensuring prompt and accurate insights.

3.4 Middleware and IoT Frameworks

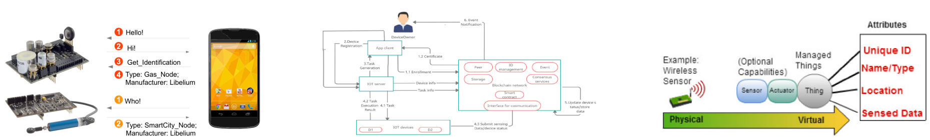
Middleware and IoT frameworks are essential for deploying IoT applications in agriculture, facilitating seamless data integration, processing, and management. These frameworks provide a structured environment for communication between IoT devices and platforms, ensuring efficient data handling across diverse settings [58]. By categorizing research into functional blocks (perception, network, middleware, application, business layers), a multi-layered IoT architecture supports dynamic interactions necessary for effective agricultural applications [58].

Integrating blockchain technology into IoT systems, conceptualized as the Blockchain of Things (BCoT), enhances interoperability and security [25]. This middleware architecture leverages decentralized data storage, crucial for maintaining agricultural data integrity and transparency [59]. The Pareto Data Framework optimizes data collection and processing, ensuring machine learning application sustainability and efficiency within IoT-driven agriculture [34].

Interoperability challenges necessitate flexible architectures for dynamic device interactions [60]. The ViSIoT innovation addresses this by integrating multiple sensor repositories and abstracting IoT environments' complexity, offering a user-friendly sensor deployment interface [55]. This is vital for efficiently managing and utilizing diverse sensor data in agriculture.

A taxonomy for Web of Things (WOT) in agriculture highlights technology interconnections and applications, providing a comprehensive overview of the current landscape and future trends [61]. This aids in understanding middleware's role in facilitating these interconnections, ensuring effective IoT application integration into agricultural operations.

Privacy-preserving data aggregation is critical in resource-constrained environments. By categorizing research based on performance parameters (computational complexity, communication overhead, privacy level), frameworks ensure sensitive agricultural data protection while maintaining efficient system performance [62].



(a) Smart City Node Identification and Identification of Smart City Node[53]

(b) IoT System Architecture[63]

(c) Managed Things and Attributes in IoT[54]

Figure 3: Examples of Middleware and IoT Frameworks

As shown in Figure 3, understanding the technological components and frameworks underpinning the Internet of Things (IoT) ecosystem is crucial. The examples illustrate middleware and IoT frameworks' intricacies, showcasing elements that facilitate connectivity and interaction within smart systems. "Smart City Node Identification" emphasizes initial device-user communication and device type identification. "IoT System Architecture" presents IoT system structure, highlighting user interface, server, and device interaction through a blockchain network for secure, efficient operations. "Managed Things and Attributes in IoT" delves into IoT entity management, illustrating physical sensor integration with attributes like unique IDs and location for precise control and monitoring. These examples underscore IoT frameworks' complexity and sophistication, essential for developing smart cities and advanced technological solutions [53, 63, 54].

Feature	Sensor Technologies and Integration	Connectivity Solutions	Data Analytics Platforms
Integration Capability	Wide Sensor Range	Multi-protocol Gateways	Diverse Data Sources
Data Processing Efficiency	Real-time Monitoring	Localized Processing	Actionable Insights
Security Features	Not Specified	Smart Contracts	Not Specified

Table 2: This table provides a comparative analysis of key technological features relevant to automated livestock monitoring systems. It highlights the integration capabilities, data processing efficiency, and security features across various sensor technologies, connectivity solutions, and data analytics platforms. This comparison underscores the importance of diverse technological components in enhancing system interoperability and monitoring efficiency.

4 Applications in Livestock Management

4.1 Enhancing Animal Health Monitoring

Advanced technologies have revolutionized animal health monitoring by providing comprehensive insights and enabling timely interventions. The use of combined GPS and accelerometer systems surpasses single-sensor systems in detecting abnormal behaviors, which are critical health indicators [17]. Non-invasive radar systems, exemplifying these advancements, track sheep behavior accurately without causing stress [2]. Real-time monitoring systems facilitate early detection of welfare issues by providing immediate feedback on animals' mental states, maintaining health in commercial settings [64]. Platforms like ViSIoT offer user-friendly interfaces for sensor deployment, accessible to both technical and non-technical users [55].

Figure 4 illustrates the categorization of advanced technologies in animal health monitoring, highlighting sensor systems, IoT frameworks, and data processing techniques as key components. This visual representation underscores the interconnectedness of these technologies, emphasizing their collective role in enhancing monitoring capabilities. Satellite IoT technologies ensure consistent monitoring in extensive farming operations, enhancing coverage and reliability [65]. IoT frameworks adapt to diverse agricultural scenarios, facilitating flexible data transmission and integration of advanced algorithms for health monitoring [33]. These systems detect deviations in behaviors, activity levels, and body temperature before clinical symptoms appear, particularly in calves, enabling timely veterinary interventions [66].

AutoML techniques enhance decision-making and operational efficiency in anomaly detection within IoT frameworks [67]. Blockchain technology ensures data security and privacy, maintaining trust in automated health monitoring systems [15].

4.2 Optimizing Resource Use

Resource optimization is crucial for sustainable livestock farming, driven by technologies that enhance efficiency and minimize environmental impact. The DE-LIoT approach improves energy efficiency and data communication reliability, reducing dependence on conventional power sources [68]. IoT devices enable precise monitoring of resources like feed, water, and energy, allowing informed decisions on resource allocation. Smart feeding systems optimize feed distribution according to individual needs, reducing waste and enhancing efficiency, thus contributing to environmental sustainability [16, 1, 8, 41]. Automated watering systems conserve water resources by monitoring consumption and detecting leaks.

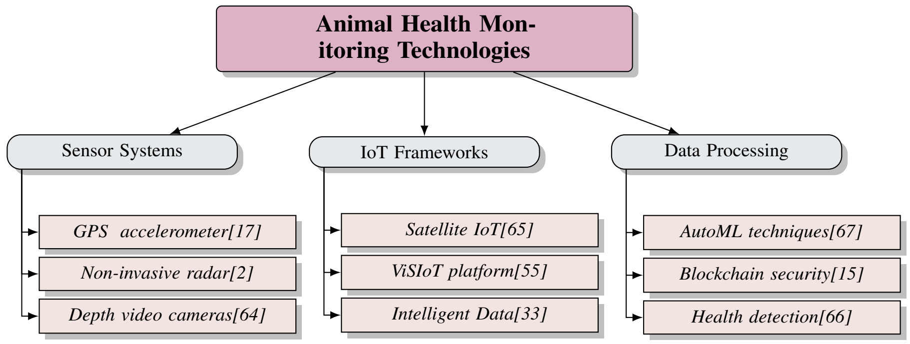


Figure 4: This figure illustrates the categorization of advanced technologies in animal health monitoring, highlighting sensor systems, IoT frameworks, and data processing techniques as key components.

Geospatial technologies and satellite data in precision agriculture provide insights into soil health, weather patterns, and vegetation indices, empowering farmers to implement targeted interventions that improve productivity and sustainability [8, 16, 1, 61, 41]. Renewable energy sources like solar and wind power further enhance resource optimization, reducing greenhouse gas emissions and ecological footprints [16, 69, 41].

4.3 Improving Farm Operations

The integration of advanced technologies has significantly enhanced farm operations, improving efficiency, productivity, and sustainability. AI techniques optimize network throughput, energy efficiency, and security, addressing modern farming challenges [70]. IoT devices revolutionize farm operations through real-time data collection, enabling informed decisions on crop and livestock management. The Web of Things (WOT) facilitates interoperability among diverse devices, addressing challenges in IoT applications within agriculture. Precision Livestock Farming (PLF) technologies, including biometric sensors and big data analytics, continuously monitor animal health and behavior, providing actionable insights that enhance operational efficiency and transparency [1, 61]. IoT-enabled systems automate irrigation and feeding schedules, optimizing resource allocation and reducing waste.

Machine learning algorithms enhance predictive capabilities in farm management by utilizing historical and real-time data to forecast weather patterns, pest outbreaks, and crop yields, enabling proactive strategies that enhance operational efficiency and support sustainable practices [71, 41]. Geospatial technologies and satellite imagery support precision agriculture by providing insights into soil health, crop growth, and land use.

Blockchain technology enhances transparency and traceability across supply chains, ensuring compliance with quality and safety standards. Smart contracts within blockchain frameworks improve transaction processes, providing a secure, decentralized platform that boosts operational efficiency through real-time data analytics from IoT devices, reducing administrative overhead and facilitating better decision-making [25, 15, 59, 19, 1].

4.4 Current Implementations and Outcomes

The integration of advanced technologies in livestock management has led to significant improvements in productivity, animal welfare, and resource optimization. IoT devices and sensor technologies enable real-time monitoring of livestock health and behavior, facilitating timely interventions [8]. Wearable sensors continuously track physiological parameters such as heart rate and body temperature, critical for health assessments [12]. These sensors, combined with machine learning algorithms, enhance health assessments and enable early disease detection, reducing mortality rates and improving herd health [6].

IoT-enabled systems optimize resource use, with smart feeding systems tailoring feed distribution to individual needs, resulting in efficient utilization and reduced waste [8]. Automated watering systems ensure optimal water consumption and leak detection, conserving resources and lowering costs.

Benchmark	Size	Domain	Task Format	Metric
SFLG[72]	26,490	Health	Speech Command Recognition	Accuracy, Training Time
TBP[73]	150,000	Iot Messaging	Data Throughput Measurement	Messages per Second, Throughput
MULTIIOT[74]	1,150,000	Human Activity Recognition	Gesture Classification	F1-score, Mean Absolute Error
PLF-WA[75]	83	Animal Welfare	Validation Assessment	Accuracy, Sensitivity
TSDB-Benchmark[76]	4,000,000	Finance	Time Series Analysis	Throughput, Query Latency
IoT-DCM[77]	10,000	Control Systems	Motor Control	PWM Control Efficiency, Motor Speed Stability
IoT-Benchmark[78]	21	Internet OF Things	Platform Comparison	Stability, Scalability
IoT-ML-Benchmark[79]	1,000,000	Human Activity Recognition	Classification	Accuracy, F1-score

Table 3: Table summarizing various benchmarks utilized in evaluating IoT and machine learning applications across multiple domains. Each benchmark is characterized by its size, domain of application, task format, and the metrics used for performance evaluation. This comprehensive overview highlights the diversity and specificity of benchmarks in facilitating advancements in technology-driven solutions.

Precision agriculture technologies, including geospatial analytics and satellite data, enhance livestock management by providing insights into environmental conditions and land use, supporting sustainable practices [8]. Blockchain technology enhances transparency and traceability across supply chains, ensuring data integrity and compliance with quality standards, thereby increasing consumer trust and market access [15].

Table 3 provides a detailed overview of representative benchmarks utilized in the evaluation of IoT and machine learning applications, underscoring their relevance in advancing technology integration in livestock management and other domains. The integration of real-time monitoring, machine learning, and IoT into livestock management has led to substantial improvements in productivity, operational efficiency, and animal welfare. These innovations facilitate early disease detection and continuous health monitoring while minimizing waste and lowering the ecological footprint of livestock farming, promoting a more efficient, humane, and sustainable industry [16, 69]. By leveraging data-driven insights and innovative solutions, the agricultural sector continues to progress towards more efficient and ethical farming practices.

5 Challenges and Limitations

The integration of automated livestock monitoring and data-driven agricultural technologies faces multifaceted challenges and limitations, predominantly stemming from technological and infrastructural barriers. Interoperability issues within IoT applications, exacerbated by existing infrastructure constraints, hinder the efficiency and scalability of these innovations. This includes integrating diverse networking solutions, ensuring security, and managing data effectively [60, 22, 19, 80]. Addressing these challenges is essential to enhance IoT systems' functionality in agriculture, necessitating an exploration of specific technological and infrastructural hurdles to facilitate successful deployment.

5.1 Technological and Infrastructure Challenges

Significant technological and infrastructure challenges impede the adoption of automated livestock monitoring and data-driven agriculture technologies. Interoperability among diverse IoT applications necessitates low-cost, energy-efficient, and reliable communication solutions, as traditional single-cloud access models often prove inadequate, requiring alternatives that function under limited bandwidth and intermittent connectivity [22]. Resource constraints, such as limited processing power and memory in IoT devices, exacerbate these issues, especially in managing large datasets and ensuring data security [43]. The computational demands of processes like Singular Value Decomposition highlight the need for innovative data management approaches. Algorithmic challenges also arise in developing reliable livestock monitoring systems, requiring sophisticated algorithms to accurately interpret dynamic environments. The integration of biometric sensors, big data analytics, and blockchain technology is crucial for enhancing animal welfare and optimizing resource use, yet complicated by data privacy, security, and real-time processing requirements [16, 1, 17]. The lack of integrated IoT systems and comprehensive comparisons of IoT middleware platforms further hinders smart agriculture practices [22]. Additionally, manufacturers face challenges in integrating IoT technologies into existing practices, particularly regarding communication overhead, privacy, and latency management [43]. The variability in animal responses complicates the application of Precision Livestock Farming technologies, necessitating adaptations in management practices to meet unique welfare needs [69, 16, 17, 14, 1]. These challenges underscore the need for ongoing research and development to overcome technological and infrastructure barriers.

5.2 Data Management and Privacy Concerns

Data management and privacy concerns are critical in deploying IoT-driven livestock monitoring systems, which generate vast amounts of sensitive information. Interoperability challenges among diverse IoT devices, compounded by limitations in wearable devices like battery life and data processing capabilities, complicate these issues [22]. The incorporation of AI in resource-constrained environments further complicates data management and privacy, requiring tailored solutions for effective operation [30]. Blockchain technology introduces regulatory challenges concerning data immutability and privacy, where the transparency of smart contracts can inadvertently expose sensitive data, necessitating robust privacy-preserving mechanisms [19]. Cybersecurity vulnerabilities are a significant concern, especially in industrial control systems where IoT integration can expose systems to various attacks, highlighting the need for advanced security measures [48]. In cold supply chains, data security concerns are critical barriers to IoT adoption [81]. Federated Learning in IoT networks presents unique challenges regarding privacy and efficient data processing [24]. Traditional centralized AI algorithms raise significant data privacy issues, necessitating decentralized approaches [23]. Future research should focus on developing robust solutions to mitigate privacy and security challenges, including standardizing communication protocols and creating lightweight security mechanisms tailored to IoT devices' unique constraints [82, 83, 18, 21]. Addressing data management and privacy concerns requires a comprehensive approach incorporating standardized frameworks, robust security measures, and ethical considerations.

5.3 Economic and Educational Barriers

Economic and educational barriers significantly impede the adoption of IoT and data-driven technologies in agriculture. High initial implementation costs, encompassing sensor and connectivity solutions, maintenance, and system upgrades, deter farmers, especially those operating on smaller scales, from adopting innovations that enhance sustainability and efficiency [84, 1, 41]. The complexity of IoT systems and the need for specialized knowledge present educational barriers. The manual selection of keywords in surveys may introduce bias, underscoring the need for comprehensive educational programs to inform farmers about new technologies' benefits and challenges [32]. The inability to balance trade-offs between computation, communication, and model precision represents a core obstacle in optimizing IoT systems, necessitating advanced training for effective technology leverage [23]. Without adequate educational support, the full potential of IoT and data-driven agriculture technologies remains unrealized.

5.4 Operational and Maintenance Issues

Operational and maintenance challenges impede the effective implementation of IoT and data-driven technologies in agriculture. High computational resource requirements for real-time context analysis and model reconfiguration present barriers, especially in resource-constrained settings [85]. The transition to new business models necessitated by IoT integration poses operational challenges, requiring significant changes in traditional farming practices [26]. The complexity and unpredictability of Non-Linear Dynamic Systems in agricultural environments affect state estimate accuracy, necessitating refined sensor reporting and scheduling methods [86]. These challenges underscore the need for robust and adaptable systems to accommodate the dynamic nature of agricultural environments.

5.5 Regulatory and Ethical Considerations

The deployment of automated livestock monitoring and data-driven agriculture technologies necessitates a comprehensive examination of regulatory and ethical considerations to ensure responsible innovation. Rapid technological advancements introduce complex security vulnerabilities central to regulatory and ethical discussions, highlighting the need for comprehensive frameworks addressing IoT and robotics integration challenges, particularly concerning ethical considerations, data management issues, and alignment with Sustainable Development Goals [87, 8]. Implementing IoT technologies requires an interdisciplinary approach integrating insights from technology, philosophy, law, and specific agricultural applications. Ethical considerations must address the challenges of ensuring responsible design, safeguarding user autonomy, and achieving sustainable goals. Regulatory compliance is critical, particularly in sectors like cold supply chains, where adherence to standards drives implementation [81]. Existing frameworks often lack comprehensive measures to address non-functional requirements such as security and quality of service, emphasizing the need for regulatory frameworks that address diverse privacy needs. Promoting sustainable practices through Green IoT initiatives relies on supportive governmental policies addressing IoT technologies' environmental impact [88]. As technologies evolve, benchmarks in Digital Twins must adapt to represent all potential use cases, especially in rapidly changing domains [89].

6 Future Directions

6.1 Emerging Technologies and Trends

Emerging technologies and trends in automated livestock monitoring are poised to transform agricultural practices by enhancing connectivity, data management, and decision-making. The integration of the Internet of Robotic Things (IoRT) is a key trend, promising increased operational efficiency in precision agriculture [87]. Research should focus on developing robust Precision Livestock Farming (PLF) technologies that address privacy concerns and ensure equitable access globally [1]. Establishing standardized frameworks for Web of Things (WOT) applications is also crucial for facilitating technology integration and addressing existing gaps [61].

Advancements in IoT integration with other technologies are vital, especially for enhancing security frameworks and exploring applications in healthcare and industrial settings [10]. This includes developing context-aware middleware solutions and investigating the Internet of Nano-Things for improved IoT interoperability [90]. Automating the reconfiguration of IoT agents based on environmental changes represents an emerging trend [85].

In data processing, emerging technologies will enhance filtering capabilities through techniques like header compression, crucial for low-latency industrial applications [91]. Addressing challenges such as optimizing sensing strategies, enhancing context discovery, and ensuring robust security in sensor configurations will be critical [92]. Developing scalable Intrusion Detection Systems (IDS) that operate efficiently in resource-constrained IoT environments is essential, emphasizing improved detection accuracy through advanced machine learning techniques [93].

Future work could enhance UDP communication robustness and explore additional applications of distributed sensor systems like BeeTS in various IoT scenarios [94]. Integrating AI in processing healthcare data for improved decision-making is an emerging trend applicable to livestock monitoring, enhancing health assessments and interventions [37]. Novel frameworks combining contract theory with market principles represent promising developments in automated livestock monitoring and data-driven agriculture [95].

By focusing on these areas, researchers and practitioners can create more efficient, secure, and scalable solutions that address the agricultural sector's evolving needs, driving innovation and sustainability in automated livestock monitoring. Future research could extend benchmarks to include additional datasets and algorithms while exploring federated learning approaches for resource-constrained IoT devices [79]. Enhancing the security and scalability of IoT systems is crucial for advancing automated livestock monitoring technologies [57].

6.2 Enhancing Communication and Connectivity

Improvements in communication and connectivity for livestock monitoring are crucial for advancing agricultural efficiency and sustainability. Integrating Green IoT technologies is essential, focusing on developing energy-efficient communication networks and protocols that minimize the carbon footprint of IoT applications [88]. These technologies are vital for enhancing the sustainability of livestock monitoring systems by reducing energy consumption and promoting environmentally friendly practices.

Implementing advanced communication frameworks that incorporate Green ICT principles is expected to significantly enhance data transmission efficiency in livestock monitoring systems. This improvement is critical for supporting real-time monitoring capabilities essential for Precision Livestock Farming (PLF), which utilizes biometric sensors and big data analytics to optimize animal health, welfare, and productivity. Enhanced data transmission facilitates timely decision-making and comprehensive analyses of animal behavior and health, ultimately contributing to more sustainable and humane livestock management practices [16, 1, 17]. By leveraging energy-efficient protocols, these frameworks enable seamless communication between IoT devices, supporting real-time data collection and analysis without compromising environmental sustainability.

Moreover, integrating next-generation wireless networking technologies, such as 5G and beyond, is anticipated to significantly improve connectivity in livestock monitoring applications. The amalgamation of advanced technologies like IoT, machine learning, and real-time monitoring in modern agricultural systems enhances operational efficiency by delivering increased bandwidth, reduced latency, and improved reliability. These advancements are essential for meeting the high data demands required for sustainable farming practices, enabling farmers to optimize resource use, monitor livestock health, and adapt to climate change effectively [16, 71, 1, 61, 41]. Adopting such advanced communication technologies will enable more robust and scalable livestock monitoring solutions capable of managing the complexities of large-scale agricultural operations.

6.3 Improving Data Processing and Analytics

Advancements in data processing and analytics are vital for optimizing livestock management and enabling precise decision-making. Developing complex numerical models and semantic representations of large-scale time series data is expected to significantly enhance data processing methodologies [96]. Optimizing existing algorithms, such as the TWLGA, across various sensor networks and data processing scenarios remains a critical focus area, promising improvements in adaptability and efficiency of data analytics frameworks [97].

Incorporating diverse datasets and exploring novel query types will further enhance the robustness and comprehensiveness of data analytics platforms [76]. Developing robust data management systems for the Internet of Things (IoT) is essential, addressing issues related to data quality, security, and the integration of semantic technologies to enhance event processing capabilities [82]. Enhancements in compression algorithms are anticipated to improve adaptability across diverse IoT applications, facilitating efficient data handling and processing [98].

In livestock management, refining data collection methods and integrating welfare traits into breeding programs are crucial for advancing animal welfare and productivity [14]. The integration of the Pareto Data Framework with edge computing is expected to support real-time applications, optimizing data processing for immediate decision-making [34]. Furthermore, adopting distributed privacy-preserving approaches in IoT networks is emphasized, enhancing model performance and scalability through distributed learning [24].

Identifying dominant Big Data technologies within specific domains can significantly improve data processing and analytics, offering tailored solutions for better livestock management [32]. Additionally, optimizing Singular Value Decomposition (SVD) implementations and exploring the statistical properties of anomaly detection methods are promising areas for future research that could advance data processing techniques [99]. The proposed Efficient Adaptive Federated Optimization (EAFO) algorithm, which minimizes learning error by jointly considering local updates and parameter compression, exemplifies the potential for adaptive data processing in federated learning environments [23]. Collectively, these advancements will contribute to more effective and sustainable livestock management practices, leveraging data-driven insights for enhanced operational efficiency and animal welfare.

6.4 Sustainability and Resource Optimization

Future directions in sustainability and resource optimization in agriculture are set to leverage advanced technologies to enhance environmental and economic outcomes. Developing standardized protocols for device interoperability is crucial for seamless integration of diverse IoT systems to optimize resource use and reduce waste [37]. This standardization ensures effective utilization of data collected from various sources to enhance decision-making processes in agricultural operations.

Enhancing user interfaces is crucial for improving the accessibility and usability of IoT systems in agriculture. Simplifying interactions with complex data analytics platforms allows farmers to implement sustainable practices that enhance productivity and reduce environmental impact. Additionally, exploring the ethical implications of data privacy in Wearable Internet of Things (WIoT) applications is vital to ensure that sustainability efforts do not compromise individual privacy rights [37].

Integrating sustainable practices that enhance animal welfare while considering economic viability is another important research area. Developing practices that align welfare and economic goals allows the agricultural sector to achieve a balance between productivity and sustainability [12]. This approach supports livestock well-being while ensuring that farming operations remain economically feasible.

In data processing, future research could explore further improvements in adaptive mechanisms within federated learning scenarios. The Efficient Adaptive Federated Optimization (EAFO) algorithm, for instance, holds promise for optimizing communication and computation costs in pervasive AI systems, directly related to sustainability and resource optimization in agriculture. By reducing learning errors and improving data processing efficiency, advancements in digital technologies and intelligent systemization can play a crucial role in fostering sustainable agricultural practices. These innovations enhance livestock productivity and welfare while contributing to climate-smart agriculture, optimizing resource use, and minimizing greenhouse gas emissions, thereby promoting a more sustainable and resilient food system [16, 41].

The future of sustainability and resource optimization in agriculture is poised to benefit significantly from the ongoing Digital Agricultural Revolution, emphasizing the integration of advanced technologies such as IoT, Artificial Intelligence (AI), and real-time monitoring systems. These technologies enhance traditional farming practices and facilitate climate-smart agriculture by reducing greenhouse gas emissions and promoting sustainable intensification for food security. As agricultural stakeholders increasingly adopt intelligent systems that optimize resource use and improve productivity, the successful implementation of these innovations will hinge on balancing environmental sustainability with economic viability, ultimately contributing to achieving the United Nations' Sustainable Development Goals [16, 71, 8, 41]. Through implementing standardized protocols, user-friendly interfaces, and adaptive data processing mechanisms, the agricultural sector can achieve more sustainable and efficient resource management.

7 Conclusion

The integration of advanced technologies in agriculture, particularly through IoT and data-driven methodologies, holds transformative potential for livestock management by enhancing productivity, sustainability, and animal welfare. This survey highlights a notable inclination among farmers towards adopting smart farming practices, with a significant portion already implementing IoT solutions. This trend underscores the pivotal role these technologies play in addressing pressing agricultural challenges.

The deployment of power management control systems (PMCS) in ecosystem monitoring exemplifies their adaptability and cost-effectiveness, which are crucial for sustainable farming practices. Additionally, the critical need for real-time monitoring systems to manage heat stress effectively accentuates the significance of these technologies in bolstering cattle welfare and productivity.

Furthermore, the survey identifies the importance of developing adaptable UAV systems, which paves the way for future exploration in multi-task learning and decentralized implementations. The potential of veterinary telemedicine to enhance veterinary care and animal welfare also emerges as a key area for further regulatory support and research to maximize its benefits.

Privacy concerns remain a critical consideration, with a call for the development of lightweight and efficient privacy-preserving data aggregation (PPDA) techniques that balance privacy protection with the operational constraints of IoT sensor nodes. Continued research and innovation in these domains are essential to overcoming existing challenges and fully realizing the potential of advanced agricultural technologies, ultimately leading to more efficient, sustainable, and ethical livestock management practices.

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