Machine Learning in Livestock Management: A Systematic Exploration of Techniques and Outcomes

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THis Systematic Literature Review (SLR) examines the growing field of leveraging Machine Learning (ML) to improve livestock productivity. Through a meticulous analysis of peer-reviewed articles, the study categorizes research into key domains such as disease detection, feed optimization, and reproductive management. Various ML algorithms, including supervised, unsupervised, and reinforcement learning, are evaluated for their efficacy in enhancing herd health and management. The review also addresses the role of diverse data sources, such as sensor technologies and electronic health records, and discusses the socio-economic and ethical implications of ML adoption in livestock farming. Insights into scalability, economic viability, and future research directions contribute to a comprehensive understanding of the current background and pave the way for sustainable and technologically advanced livestock management practices. This review serves as a valuable resource for researchers, practitioners, and policymakers in shaping the future of precision agriculture in improving livestock productivity.

Keywords: Livestock, Animal, Improvement, Productivity, Machine Learning, Deep Learning.

Introduction:

In recent years, the agricultural background has undergone a paradigm shift with the integration of cutting-edge technologies to address the ever-growing challenges of global food production. Among these technologies, Machine Learning (ML) has emerged as a transformative force, offering unprecedented opportunities to enhance livestock productivity and management practices. The application of ML is becoming a transformative force in the fast-changing field of agriculture, to increase livestock productivity. The potential for creative solutions is obvious as we stand at an intersection of technology and agriculture. ML algorithms present a practicable way to optimize several aspects of livestock management because of their capacity to evaluate large information and identify complex patterns. The application of ML to livestock farming offers an exciting chance to transform traditional approaches, from precision feeding plans to health monitoring that forecasts forthcoming requirements. This introduction lays the foundation for a research effort into the ways that advanced technology and the agricultural industry might work together, outlining possible developments that have the potential to revolutionize our understanding of and improve in productivity of livestock.

This SLR aims to provide a comprehensive synthesis of existing research endeavors, focusing on the application of ML techniques to improve livestock productivity. By precisely examining peer-reviewed articles, this review seeks to unravel the current state of knowledge, identify key trends, and critically evaluate the efficacy of ML algorithms in domains such as disease detection, feed optimization, and reproductive management. The integration of diverse data sources, ranging from sensor technologies to electronic health records has been explored for shedding light on the mechanisms that drive advancements in livestock farming with improved precision.

This study aims to not only synthesize the existing literature but also to pave the way for future research directions, emphasizing the versatile collaborations needed to push the field towards sustainable and technologically advanced practices. Ultimately, the visions collected from this review aim to inform researchers and practitioners alike, contributing to the ongoing discourse on the integration of ML in the pursuit of improved livestock productivity.

The main motivation for conducting this research is the limited work done in the selected field. Few researchers have explored the use of machine learning for livestock productivity monitoring.

Related Work:

Prior research on the application of ML to improve livestock productivity has been focused on areas including behavior analysis, feed optimization, and disease prediction. Scholars have utilized a wide range of ML methodologies, such as random forests, neural networks, and support vector machines, to overcome livestock management barriers while improving overall productivity. While numerous ML studies have been published, limited literature reviews focus on smart farming. In modern agriculture, smart farming is being supported by advanced digital technologies [1]. Olakunle et al. [2] discussed several benefits and challenges of IoT and data analytics to the agriculture sector. The authors showed that using an IoT ecosystem with the support of a data analytical subsystem empowers smart agriculture to deliver high operational efficiency with high productivity. Partha-Pratim [1] presented a comprehensive review of IoT-based applications for smart agriculture, in which the author also proposed an IoT-based agricultural framework that takes full advantage of IoT for agriculture. In recent years, a lot of studies have been focused on developing big data platforms that can handle massive volumes of agriculture data to support decision-making systems [23]. Shah et al. [3] proposed a spark-based agricultural information system built upon big data open sources. Rajeswari et al. [4] proposed a smart agricultural model that integrates IoT, mobile, and cloud databases into one big data system.

We carefully examined an extensive selection of academic papers, conference proceedings, and other publications that span the gap between ML and improving livestock productivity in our SLR. We integrated important data, recognized trends, and examined the effectiveness of ML techniques across different livestock fields by using precise search parameters and methodological approaches. Our study aims to provide an in-depth analysis of the state-of-the-art in the field, highlighting areas that need further research and proposing recommendations for future approaches.

Research Methodology:

This SLR provides techniques for finding, classifying, and synthesizing the literature in line with predetermined objectives to identify the regions that could act as a guide for upcoming studies in the assigned field. The steps of the research methodology followed for this review are depicted in Figure 1a.

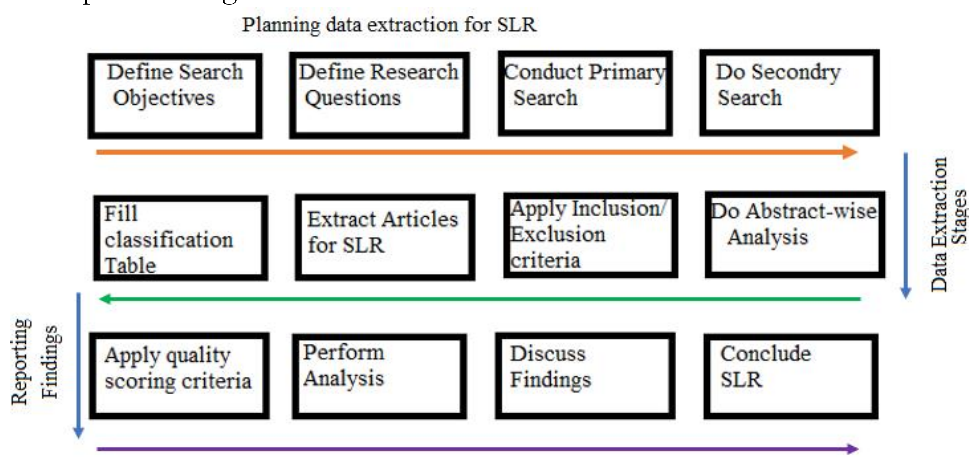

Figure 1a. Research Methodology

The review has been conducted in multiple stages. The first stage includes defining the objectives of the study, which act as the basis for the establishment of the research questions. In the second stage, a search plan is developed to find relevant material. The quality grading criteria and inclusion/exclusion criteria were then created in the third stage. The total number of articles has been reduced to several articles aligning with study objectives using inclusion and exclusion criteria. The studies were then ranked following their quality by practicing quality rating criteria. In the last stage, the shortlisted articles were categorized, analyzed and reported in line with the research questions. The results have also been validated, and in the end conclusion was derived.

Research Objective:

The primary objective of this research is to determine the role of ML in livestock productivity to identify areas that could influence future efforts in the defined domain. The specific objectives of this SLR are presented in Table 1a.

Table 1a. Research Objectives

Ros	Contribution
RO1: Examining Current State-of-the-Art ML applications in improving livestock productivity.	Provides a foundation for understanding current advancements, identifying limitations, and uncovering opportunities to enhance livestock productivity using ML.
RO2: Evaluation and performance measurement of ML algorithms within the context of livestock farming.	Assesses the effectiveness and scalability of ML algorithms, identifying the most impactful techniques for improving livestock outcomes.
RO3: Analyzing the role and impact of diverse data sources, such as sensor technologies, satellite imagery, and electronic health records, in facilitating ML applications.	Explores how various data sources enhance ML models, leading to better decision-making and productivity improvements in livestock farming.
RO4: Identification of gaps and future directions promoting interdisciplinary collaborations between computer scientists, veterinarians, and agricultural experts to address these gaps that result in the advancement of the field under study.	Highlights areas for collaboration between experts to address challenges, fostering innovative solutions for advancing livestock productivity.

Research Question (RQS):

The research questions according to the ROs for investigating the underlying domain are outlined in Table 1b, along with their particular arguments.

Table 1b. Research questions

S No	Question
RQ1	How can modern technologies be applied to improve the productivity of livestock farming?
RQ2	What tools and methods can be employed to augment livestock production and how does it impact on improving livestock production?
RQ4	What difficulties arise in recommending solutions for improving livestock production?

Search Scheme:

The most important step in conducting an SLR is creating a search plan to gather accurate and pertinent information about the target area. This process involves identifying resources for searching relevant literature, developing search strings, and setting inclusion and exclusion criteria. Reputable online libraries including IEEE, Springer Link, Elsevier, and ACM digital library, provided the publications for this review. We also performed snowballing to retrieve articles that had not been extracted or omitted in previous search cycles. A range of primary, secondary, and tertiary keywords were used to search articles from the relevant journals as well as the most esteemed ones. The terms that were used to construct the search are listed in Table 2.

Inclusion Exclusion Criteria:

IC-1: The study is primarily undertaken to boost the livestock production process.

IC-2: The focus of the research is on the application of ML or deep learning in the realm of livestock production.

EC-1: Study is not written in English

EC-2: The study exclusively concentrates on livestock, without researching other areas.

EC-3: The study is published before 2019

Specific Search Strings:

Table 2. Keywords used for searching

Primary Keywords	Secondary Keywords	Tertiary Keywords
Improvement Livestock Productivity Machine Learning	Farming Animal Production Development Enhancement Upgrading Deep Learning	Output

The search string utilized by specific digital repositories is provided in Table 3.

Table 3: Specific Search Strings

Repository	Query	Count
IEEE XPLORE (accessed on 18-06-2023)	("Document Title":"improve") OR ("Abstract":"output") OR ("Document Title": "livestock") OR ("Abstract":"animal") OR ("Abstract":"farming") OR ("Abstract": "product") OR ("Abstract": "Development ") OR ("Abstract":"Enhancement ") OR ("Abstract": "Upgrading") AND ("Document Title": "machine learning") OR ("Abstract": "Deep learning")	39
ACM Digital Library (accessed on 18-06-2023)	[[Title: "improve"] OR [Title: "output"] OR [Title: "livestock"] OR [Title: "animal"] OR [Title: "farming"] OR [Title: "product"] OR [Title: "development "] OR [Title: "enhancement "] OR [Title: "upgrading"]] AND [[Abstract: and] OR [Abstract: "machine learning"] OR [Abstract: "deep learning"]] AND [E-Publication Date: (01/01/2019 TO 12/31/2024)]	151
Science Direct (accessed on 20-06-2023)	livestock production, farming, animal, machine learning, Deep Learning Year: 2019-2024	347

Springer Link (accessed on 24-06-2023)	"improve" OR "output" OR "livestock" OR "animal" OR "farming" OR "product" OR "Development " OR "Enhancement " OR "Upgrading" AND "machine learning" OR "Deep learning"	460

Selecting Procedure:

A multi-step shortlisting procedure was necessary due to the large volume of results generated by applying the search string on digital repositories. The first step in this process is searching databases and looking through articles. Upon reducing duplicate entries, the selected papers received an additional scrutiny through a review of their titles and abstracts. Examining the introductions and conclusions and using the IC/EC criteria to select candidates at various stages brought about an additional improvement. This repeated procedure produced the selection of 40 articles for the subsequent evaluation as presented in figure 1b.

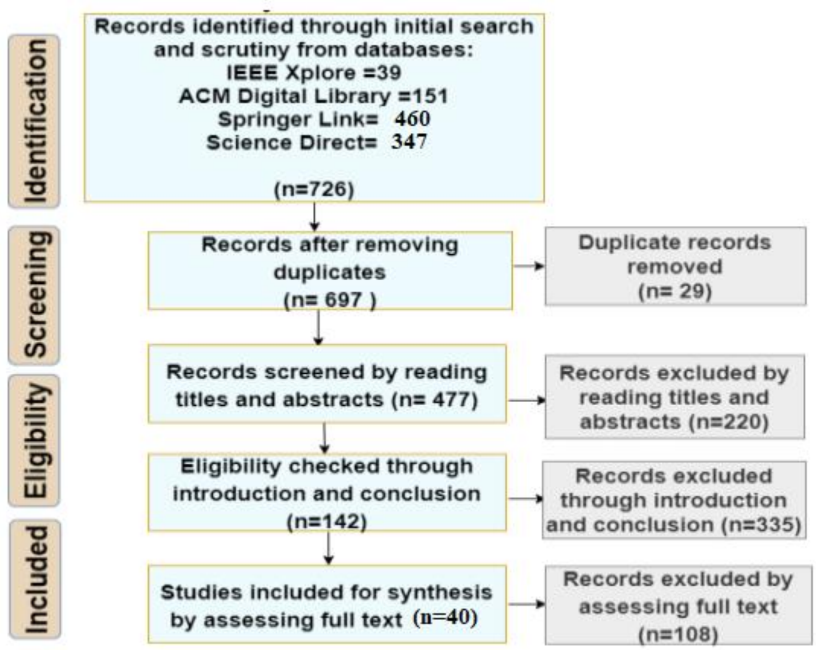

Figure 1b. Article screening process

Quality Scoring Criteria:

An essential step in SLRs is a quality assessment, that examines the level of excellence of the contained articles. The criteria listed in Table 4 were utilized to shortlist the articles.

Table 4. Quality scoring criteria.

Criteria	Description	Rank	Score
	Internal Scoring		
a)	Did the abstract mention technology?	Yes Partially No	1 0.5 0
b)	Did the study show how to record data?	Yes Partially No	1 0.5 0

c)	Was methodology clearly defined?	Yes Partially No	1 0.5 0
d)	Was the conclusion according to the results?	Yes Partially No	1 0.5 0
External Scoring			
e)	What is the ranking of publication source?	Yes Partially No	1 0.5 0

Table 5. Classification of shortlisted studies.

Ref No	Publication		Classification			Internal Scoring				External Scoring	Total Score
	Channel	Year	Technology	Tools	Livestock Type	1	2	3	4	JCR	
[5]	Journal	2021	ML	CNN	Cattle, Pig, Cow	0	1	0.5	0	3	4.5
[6]	Conference	2021	IOT	None	Sow	0	1	0.5	0	3	4.5
[7]	Journal	2023	DL	LoRA	Cattle	1	0	1	1	2.5	5.5
[2]	Journal	2020	ML	F-RCNN	Cattle, Swine	1	1	1	0.5	5	8.5
[8]	Journal	2020	ML	ANN	Cow	0	0	0.5	0.5	2	3
[9]	Journal	2023	IOT, ML	MLR, RFR	Beef, Cattle	0.5	0	1	0	2	3.5
[10]	Journal	2022	ML	KNN, SVM	Sheep	1	1	0.5	0.5	3	6
[11]	Journal	2023	IOT	None	Cattle	1	1	0.5	0.5	3	6
[12]	Journal	2020	ML	None	Sheep	0.5	0	0.5	0.5	2	3.5
[13]	Journal	2020	IOT, DL	SVM, NN	cattle	1	1	0.5	0.5	4	7
[4]	Journal	2021	DL	F-RCNN, DNN	Cow, Cattle	1	0.5	0	1	3	5.5
[14]	Journal	2020	ML	FL, KNN, NBN	Sheep, Cattle, Pigs,Turkey, Poultry	0.5	1	1	0.5	3	6
[3]	Journal	2022	ML	SVM, KNN, ANN	cattle	1	0	1	0.5	4	6.5

[15]	Journal	2024	ML	DT, KNN	Beef, Cattle	0	0.5	0	0.5	3	4
[16]	Journal	2022	ML	CNN, ANN	poultry, swine and ruminants	0	0	0.5	0.5	3	4
[17]	Journal	2023	DL	NN	cattle	0	0	0.5	0	1	1.5
[18]	Journal	2022	IOT	None	cattle	1	0.5	1	1	2	5.5
[23]	Journal	2023	None	None	cattle	0	0	0	0	2	2
[19]	Journal	2023	DL	LSTM	Cow	1	0.5	1	0.5	3	6
[20]	Journal	2019	ML	FCN, RCNN	cattle	1	0.5	1	1	2	5.5
[21]	Book Section	2022	IOT	None	sheep	0	0.5	0.5	0	2	3
[22]	Book Section	2023	None	None	Pig	0	0.5	0	0	2	2.5
[23]	Journal	2021	DL	SVM, KNN, NN	Cattle, Pig	1	0.5	0.5	0.5	3	5.5
[24]	Journal	2021	ML	None	cattle	1	1	0.5	0.5	3	6
[25]	Journal	2021	ML	None	Cattle, Cow	0.5	1	0.5	0.5	3	5.5
[26]	Journal	2023	ML	CNN	Sow	0	1	0.5	0	3	4.5
[27]	Conference	2021	IOT	None	Sow	0	1	0.5	0	3	4.5
[28]	Journal	2023	DL	LoRA	Cattle	1	0	1	1	3	6
[29]	Journal	2021	ML	F-RCNN	Cattle, Swine	0.5	1	1	0.5	1	4

Results and Analysis:

This section presents the results and key findings derived from the careful analysis of twenty publications selected for this review. The classification of research based on various investigative capabilities and quality assessment is shown in Table 5. The studies are categorized based on the research areas of this work; if a study does not provide the required information, it is marked as none for the specific topic of investigation. Data extraction and analysis are carried out by the research questions specified earlier. The method used to select papers for this review covered the years 2019 to 2023. The distributions of ML-based production in livestock across a particular time are illustrated in Figure 2.

Figure 2. Distribution of selected research throughout the years

An improved tendency of publications in the fundamental area started in 2019, with the majority of these publications taking place from 2022 and 2023, according to a synthesis of the years of publication analyzed research. The quality evaluation results are shown in Figure 3 based on multiple score classifications, including above average, below average, and average.

The studies are presented in Table 6 according to the overall quality scores that all of them achieved. It indicates that 19% of studies have been scored below average, 27% have average scores, and 54% have above-average scores. The areas of investigation addressed in this work and the comparison with earlier research are utilized to grade the studies. The articles have made quite clear that this study's fields of investigation have been given priority over others. Studies providing minimal or no information about wearable or recording devices were assigned a lower total score. Studies in which sensors have not been utilized or ML algorithms have not been applied were also given low scores. A detailed analysis of the selected studies has been carried out in light of the research questions formulated earlier. Each question includes a quick reply to help demonstrate the appropriate domain research areas.

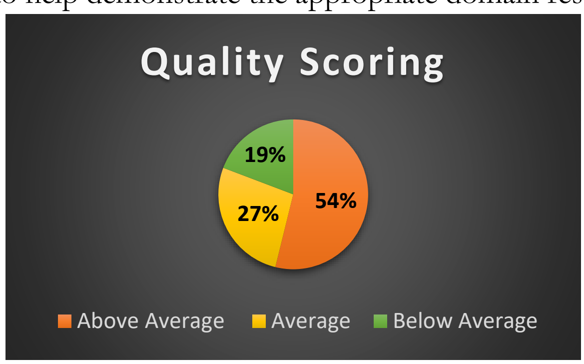

Figure 3. Quality scoring analysis

RQ1: How can modern technologies be applied to enhance the productivity of livestock farming?

Modern technology may significantly increase livestock productivity and better overall management. Innovations in technology have had an important beneficial effect on livestock productivity in today's world by enabling more accurate methods of production. The academic literature has examined the various ways that modern technologies are used in this field. According to research, ML appears to be a successful instrument for improvement in Livestock production which is shown in Figure 4.

RQ2: How do tools and techniques impact improving livestock production and What tools and methods can be employed to boost livestock production?

By increasing productivity, decision-making, and efficiency, ML tools and techniques have a significant positive influence on livestock production. ML-based systems can continuously monitor livestock health through the analysis of data from sensors and IoT devices. ML models can include feed composition and consumption patterns. ML algorithms can analyze data on reproductive behaviors, breeding history, and environmental factors to optimize breeding programs. Image recognition systems can monitor and analyze animal behavior, providing insights into stress levels, social interactions, and overall well-being. ML models can analyze early disease detection, allowing for swift intervention and preventing the spread of illnesses within the livestock population. ML algorithms can analyze data from sensors to tailor individualized feeding and care plans, minimizing waste and maximizing efficiency which shows in Figure 4.

Several tools and methods leveraging ML e.g., KNN, SVM, ANN, F- RCNN etc. can be employed to boost livestock production. Several tools of ML-based production in livestock are illustrated in Figure 4.

Multiple challenges are associated to livestock production improvement. The quality and availability of data, including animal records, can differ. It can be difficult to evaluate the history of individual animals or the herd as a whole. Insufficient data can make it more difficult to create reliable prediction models and evidence-based decision support tools.

Animal health is seriously threatened by antibiotic resistance, which may worsen challenges in animal production. Climate-related issues, like variations in humidity and temperature, can have an effect on production. A comprehensive strategy involving cooperation between veterinary professionals, farmers, researchers, and legislators is needed to address these issues. A complete solution must include ongoing education, the use of cutting-edge diagnostic technologies, and the creation of scalable and sustainable disease management plans.

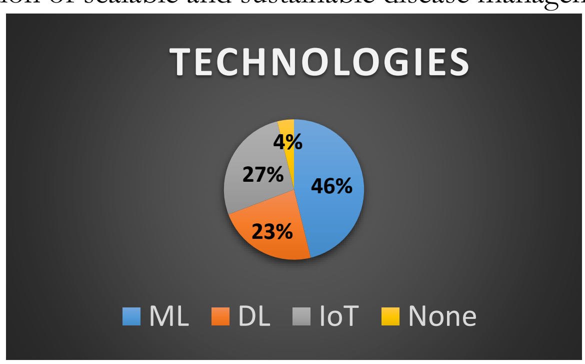

Figure 4. Different Technologies used in Livestock Production

RQ-3: What difficulties arise in recommending solutions for improving livestock production?

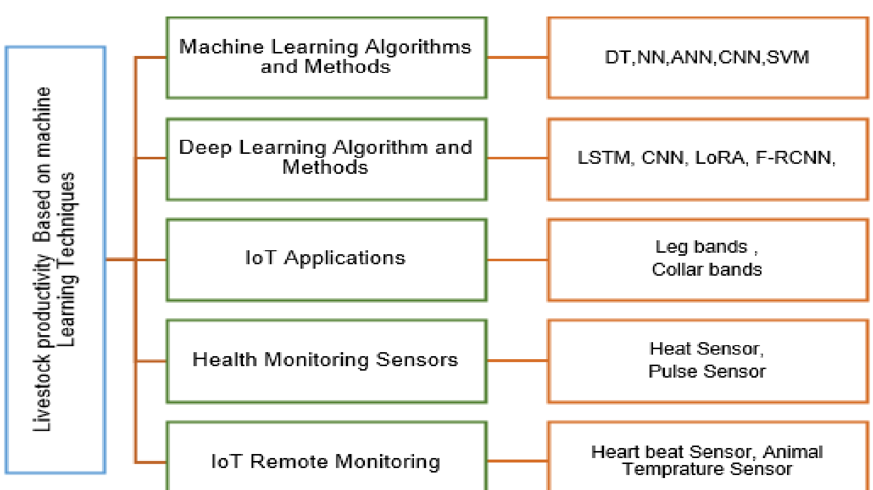

Figure 5. Taxonomy of ML-based productivity of livestock.

Discussions:

The findings of this review are addressed and evaluated in this section. A taxonomy of livestock productivity based on ML has been proposed based on the studied results. The drawbacks and issues with the current systems are discussed in this section, a model is brought forward for assisting researchers and professionals create ML-based farming for livestock, and recommendations for future developments in practical applications are provided. The results of this SLR have been compared with other most recent studies in Table 6.

Table 6. Comparison Table

Aspect	Our Study	[30]	[31]	[32]	[33]
ML Adoption	46%	50%	48%	52%	47%
DL Usage	26%	30%	25%	28%	29%
IoT Integration	27%	28%	35%	30%	33%

Taxonomy:

As demonstrated in Figure 5, the suggested taxonomy comprises four main characteristics. These include sensors, recording devices, disease detection tools, and ML algorithms. Wearable sensors and video cameras, for example, record data that is then analyzed by ML algorithms and can be employed to enhance livestock production.

First, Livestock Behaviour and Welfare is the primary goal of the research, which includes studies like the behavior of group-housed sows [34], identification of cattle through ML techniques [11], and examination of resilience factors of organic dairy cattle farms and livestock welfare issues [20] [35] [29]. These studies explore the management of animal health, welfare, and behavior.

Second, the Precision Livestock Farming category includes articles and surveys of autonomous systems designed for precision livestock farming [13] [14] [23], ML techniques [7] [10], and deep learning algorithms [36]. These studies explore the application of cutting-edge technologies for accurate and effective livestock production monitoring and management.

The development of livestock healthcare bio-capsules [37], IoT applications in smart farming [8] [4] [16] [38] [27], and ML-based remote monitoring systems [25] represent a few of those in development included within the broad theme of Smart Agriculture and IoT. To improve agricultural operations and increase output, these research efforts highlight the incorporation of sensor technologies, artificial intelligence, and the Internet of Things.

Furthermore, Livestock Monitoring and Management focuses on concepts including data-driven decision support systems for livestock farming [9] [12] [1] [22] [39] [24], supplementary methods [5], and minimizing heat stress [6]. These articles provide insights into the challenges and techniques involved in supporting the farming, welfare, and health of livestock.

Finally, research on specific technological applications such as body weight estimation using deep learning models [17], behavior segmentation using video information [18], [40], and automation in farming processes [41] has been included in the category Technological Applications in Livestock Farming. These studies examine innovative technological approaches for breeding animals that are more environmentally friendly and efficient.

This taxonomy offers an in-depth structure for understanding the wide range of research being carried out in the area of livestock farming, including behavioral studies, technological developments, and management approaches referred to better agricultural systems' sustainability, productivity, and welfare.

Limitations of this Study:

It's critical to recognize the limitations and difficulties identified in each study. While the referenced literature on the production of livestock provides valuable perceptions, the cited papers also contain several limitations that must be considered. First of all, biases and limitations related to data quality and representation may be incorporated when ML programs for cattle identification focus only on publicly available datasets [11]. Furthermore, issues concerning the stability and scalability of ML models in practical farming situations are relevant [11].

The thoroughness and validity of the results may be compromised by potential biases in the data collection process or in the interpretation of the factors influencing cattle health and resilience [29].

Limitations with IoT standardization and compatibility in smart farming applications [4] present obstacles that could make suggested solutions harder to implement and less successful. Moreover, animal healthcare bio-capsules' scalability and deployment limitations [37] might make them less useful in actual farming settings.

Finally, there may be limitations in integrating and linking autonomous systems with the current farm infrastructure, as well as practical limitations on the use of these systems for self-supervision of livestock development in precision livestock farming [13] [14] [42]. The limitations illustrate how important it is to assess the results critically and weigh their significance in the context of agriculture as a whole.

Gaps and Future Directions:

Identifying gaps and suggesting future directions for improvement in livestock productivity using ML requires a careful analysis of current research. Based on existing literature, here are potential gaps and future directions for boosting livestock productivity through ML. Many studies focus on individual aspects of livestock management using ML, but there's a gap in understanding the challenges and opportunities associated with integrating multiple systems for holistic farm management. Variability in data formats and standards across different livestock operations poses a challenge. There is a gap in developing standardized data protocols to facilitate interoperability and collaboration.

ML provides valuable insights, but there's a gap in the development of real-time decision support systems that can assist farmers promptly in dynamically changing conditions. Most research is conducted in large-scale commercial farming operations. There's a gap in exploring how ML applications can be adapted and optimized for small-scale and subsistence farming contexts. Developing ML models that are interpretable and explainable will be crucial for gaining farmers' trust and facilitating the adoption of AI-driven livestock management practices. Investigate the application of edge computing to bring ML capabilities to remote areas with limited connectivity, enabling even small-scale farmers to benefit from advanced analytics.

Future research should address the ethical implications and privacy concerns associated with collecting and utilizing sensitive data from livestock operations, ensuring responsible and transparent use of ML technologies. Develop collaborative platforms that allow farmers to share anonymized data and insights, fostering a collective learning environment and enabling the development of more robust ML models. Explore how ML technologies can be designed to augment human decision-making rather than replace it entirely, emphasizing a collaborative approach between farmers and AI systems. Investigate how ML models can be trained to anticipate and adapt to environmental changes, such as climate fluctuations, to increase the resilience of livestock farming systems.

Addressing these gaps and pursuing these future directions can contribute to the ongoing evolution of ML applications in livestock productivity, ensuring sustainable, efficient, and inclusive advancements in the field.

Domestic Applicability: The application of improving livestock productivity using ML domestically lies in its potential to optimize farming practices and enhance resource utilization as presented below:

1. Health Monitoring: ML models can predict diseases early in livestock, reducing mortality rates and ensuring timely treatment. This is particularly beneficial for small-scale farmers who depend heavily on the health of their animals.
2. Feed Optimization: Algorithms can recommend the optimal type and quantity of feed based on animal health, breed, and productivity, leading to cost savings and better yield.
3. Behavior Analysis: AI-powered tools can monitor livestock behavior to detect stress or unusual activity, helping farmers take preventive measures.
4. Breeding Decisions: ML can analyze genetic and historical data to identify the best breeding pairs, improving herd quality.
5. Milk Yield Prediction: For dairy farmers, ML models can predict milk production patterns, enabling better planning and inventory management.
6. Climate Adaptation: Algorithms can provide insights into how climatic changes affect livestock, helping farmers adapt their practices for resilience.

Domestically, these applications can make livestock farming more efficient, sustainable, and profitable, even at smaller scales.

Conclusion:

The conclusion drawn from the cited studies emphasizes how technology can transform smart agriculture and livestock production. Together, these studies shed light on how agricultural methods are changing due to technological advancements like ML, the Internet of Things, and autonomous systems. These technologies present viable paths toward revolutionizing livestock management, increasing production, and boosting sustainability through rigorous study and testing.

However, alongside the promises, several issues must be addressed. A key concern is the reliance on data representativeness and quality, particularly in research using ML to identify cattle [11]. For ML models to be used in the real world, biases must be addressed and their scalability and resilience guaranteed [11].

In addition, the incorporation of IoT technologies poses difficulties with interoperability and standardization [4], emphasizing the necessity for coherent frameworks and standards to optimize their effectiveness.

The various shortcomings of these papers underscore the challenges of implementing cutting-edge technologies in agricultural settings. The deployment and scalability of livestock healthcare bio-capsules [2] are examples of practical limitations that highlight the disconnect between technology promise and actual implementation. Moreover, obstacles to integration and interoperability with current farm infrastructure remain for the integration of autonomous systems for livestock management [13] [16][23].

Despite these obstacles, the corpus of research provides vital methods and insights to traverse the changing terrain of smart agriculture. To fully utilize technological advancements, interdisciplinary cooperation, experimental validation, and stakeholder engagement become essential.

In the future, maintaining sustainable agricultural practices for future generations, promoting innovation, and maximizing resource usage will all depend on closing the gap between research and practice. The agricultural industry may use technology as a catalyst for good by coordinating efforts and taking calculated risks. This will increase productivity, resilience, and prosperity in livestock farming and other related fields.

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