OPEN ACCESS
International Journal of Innovations in Science & Technology

Role of Machine Learning in Livestock Health Monitoring System: A Systematic Literature Review

Muhammad Mohsin Raza[1], Rabia Tehseen[1,2], Uzma Omer[3,2], Muhammad Qasim[1], Usman Aamer[1], Ramsha Saeed[1], Muhammad Farrukh Khan[4]

[1] Department of Computer Science, University of Central Punjab, Lahore, Pakistan

[2]Department of Computer Science, University of Management & Technology, Lahore, Pakistan

[3]Department of Computer Science, University of Education, Lahore, Pakistan

[4] Department of Computing, NASTP Institute of Information Technology, Lahore, Pakistan

*Correspondence: rabia.tehseen@ucp.edu.pk

Citation | Raza. M. M, Tehseen. R, Omer. U, Qasim. M, Aamer. U, Saeed. R, Khan. M. F, "Role of Machine Learning in Livestock Health Monitoring System: A Systematic Literature Review", IJIST, Vol. 07 Issue. 02 pp 986-1005, May 2025

Received | May 03, 2025 **Revised |** May 26, 2025 **Accepted |** May 27, 2025 **Published |** May 28, 2025.

Machine Learning (ML) can significantly enhance livestock management in various ways by providing real-time insights into animal health, behavior, and well-being. Livestock production, monitoring, and management can be revolutionized by using ML techniques. This study presents a comprehensive review of the literature regarding IoT devices used for monitoring cattle health, key characteristics of these devices, wearable technology used, sensors, and ML algorithms. In order to complete the review, a thorough examination and synthesis of the research articles published in reputable research venues between 2018 and 2023 are conducted. The findings revealed that pressure and pulse-rate sensors are the most often utilized types for recording the health status of animals experiencing health issues.

Keywords: Machine Learning, IoT, Livestock Health System, Precision Livestock, Livestock Monitoring, Animal Welfare, Precision Farming, Livestock diseases

Introduction:

Machine learning is a technique of Artificial Intelligence (AI) that involves training algorithms on huge datasets so that outcomes may be predicted or actions may be taken actions without being explicitly programmed. In healthcare, ML has the potential to revolutionize how we diagnose, treat, and prevent diseases [1]. While ML holds immense potential in healthcare, there are several challenges and considerations that need to be addressed for its effective and responsible application data quality, data availability, city, ethical, and bias considerations. Livestock plays a crucial role in global agriculture, providing a significant source of protein and other essential nutrients for human consumption. They support the economy by producing a range of goods and creating jobs in the agriculture industry. Notwithstanding, the livestock sector encounters obstacles concerning sustainability, animal welfare, and ecological consequences, prompting continuous deliberations and endeavors to enhance methodologies inside the sector [2]. Only about 11% of the world's land area is suitable for the production of foods that can be directly consumed by humans. About 75% of energy intake is consumed by ruminants and 30% from non-ruminants is from waste materials that cannot be consumed directly by the human population. With world food production already inadequately able to provide balanced diets for people of the world, it is important that we continue to utilize livestock [2]. Taking care of the health of livestock is essential for both the animals' well-being and the livestock industry's production, as they may encounter a variety of health issues. Mastitis, foot and mouth disease (FMD), reproductive problems, bovine, lameness, and avian are considered the top dairy cattle diseases [3].

Addressing these health constraints requires a combination of preventative measures, veterinary care, and good management practices to ensure the overall well-being of livestock. Regular monitoring, early detection of health issues, and prompt intervention are essential components of effective livestock health management [4]. The Internet of Things (IoT) can play a significant role in the early detection of livestock diseases by providing real-time monitoring and data analytics. Over the last 20 years ML algorithms and associated methodologies have provided the necessary prediction accuracy to power these technologies through the ability to self-learn and improve over time when new data become available. Thus, there has also been an increased prevalence of ML algorithms employed throughout the dairy literature [4]. The use of ML can revolutionize how livestock is managed and monitored. This will improve livestock production and management. By integrating IoT technologies into livestock management practices, farmers can enhance their ability to monitor the health of individual animals and detect potential diseases at an early stage. Early detection is crucial for implementing timely interventions, reducing the spread of diseases, and improving overall herd health [4].

The main objective of this study is to conduct a state-of-the-art literature review on smart technology aimed to benefit dairy animal health. This review provides a categorization of ML algorithms implemented or discussed in research communities in recent times. The goal of this literature review is to discuss various measures used to improve animal welfare. The scope of this review does not include details on ethics, animal rights, or legislation. While such policy issues are beyond the scope of this survey, relevant stakeholders may find it valuable in initiating ethical, economic, or legal debates on the subject.

This paper has been organized in the following sections: In section II, related work has been discussed. In section III research methodology covering research questions (RQs), research objectives (ROs), search scheme shortlisting criteria, and procedure have been thoroughly listed. Results have been analyzed in section IV. Moreover, findings have been presented. It also provides a taxonomy of approaches and recommendations for practitioners. It is followed by a conclusion and future directions.

Related work:

ML-based disease detection for dairy livestock is a very under-studied field and few studies have been conducted till now. This systematic literature review (SLR) reveals a significant body of research focused on leveraging advanced technologies, particularly artificial intelligence (AI) and the Internet of Things (IoT), to enhance livestock monitoring and disease detection in the agricultural sector. The research investigated a broad spectrum of applications, from lameness detection in dairy cattle [5] to early detection of avian diseases using thermography and AI [6].

The author in [5] Proposed an automatic lameness detection system based on leg swing analysis using image processing techniques. This approach showcases the potential of computer vision in identifying health issues in dairy cattle. Similarly, [6] explored the use of thermography and AI for early detection of avian diseases, highlighting the diverse modalities employed for disease surveillance in different livestock species.

The integration of IoT in smart farming systems is a recurring theme in the literature. A study [7], designed an IoT-based smart farming system, while [8] focused on using IoT for foot-and-mouth disease (FMD) and mastitis detection in cows. [9] Extended this concept by combining IoT and ML for comprehensive livestock monitoring.

Several studies address the application of ML in disease detection. [10] Classified the health status of cows using ML and AWS Cloud, demonstrating the versatility of cloud-based platforms. Another study [11], utilized ML to estimate and predict the risk of bovine respiratory disease, emphasizing the predictive capabilities of these models.

Additionally, the literature covers innovative approaches such as fog computing [12], wearable sensors [13], and tri-axial accelerometer data [14] for detecting lameness and uncovering behavioral patterns in dairy cattle. [12] Presented a fog computing-assisted data-driven approach for early lameness detection, highlighting the role of edge computing in real-time monitoring.

While the majority of the studies focus on disease detection, others, [15] proposed comprehensive on-farm welfare monitoring systems for goats, presenting the broader applications of IoT and ML in livestock management.
This SLR highlights the use of AI, ML, and IoT in precision livestock farming for disease detection, health monitoring, and general livestock management is becoming increasingly common. Together, the studies add to a more complex knowledge of this field's changing landscape and offer insightful information to policymakers, practitioners, and scholars alike.

Research methodology:

This research offers structured methods for searching, categorizing, and synthesizing the literature following pre-established objectives. This highlights the areas that may serve as a roadmap for future research directions in the designated domain. Figure 1 shows the three steps of the research technique used for this review.

The review has been conducted in multiple steps. Initially, the Research Objectives (ROs) were defined; in the second step, ROs were used to develop the Research Questions (RQs). In the third step, the search strategy for locating relevant material was devised. Following that, in the fourth step, the inclusion/exclusion and quality assessment criteria were applied, which led to the next step in which articles were shortlisted. Shortlisted articles were ranked based on the quality rating criteria. The shortlisted papers were classified and synthesized in accordance with the research areas. Finally, the results were discussed and analyzed as per the research questions. This research is a novel contribution to the body of knowledge in the livestock healthcare domain.

Research Objective (RO):

The primary goal of this research is to find the role of ML in the livestock health care system in order to identify areas that might lead to guiding future efforts in this domain. The main objectives of this SLR are listed below:

RO1. To explore the latest technologies to be used for the healthcare of livestock.
RO2. To evaluate the real-time monitoring systems for early detection of health issues in livestock.

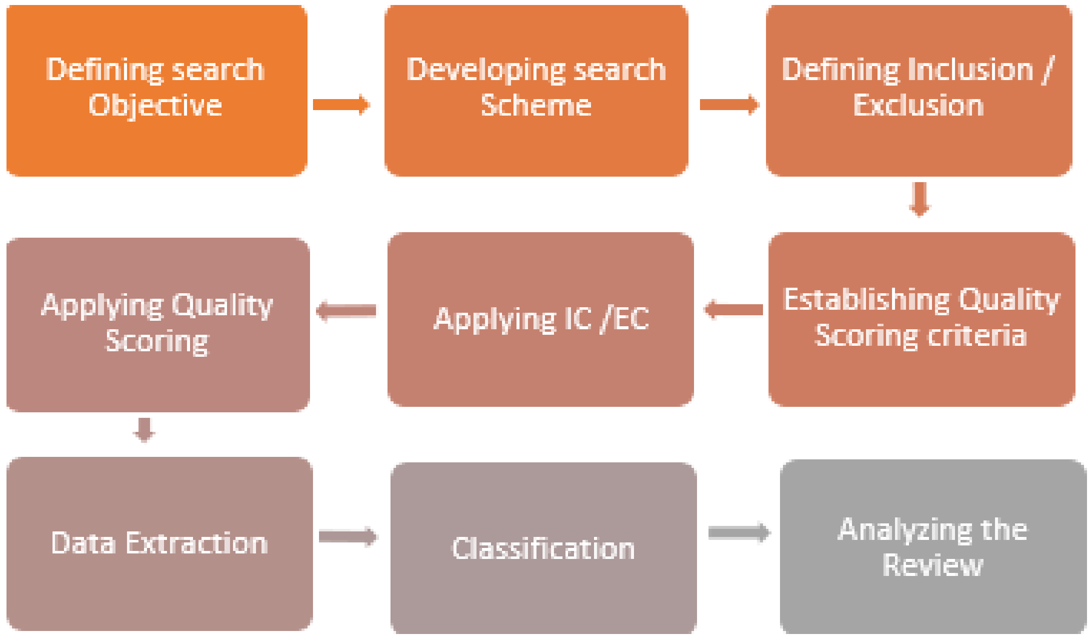

Figure 1. Research methodology.

RO3. To examine the impact and effectiveness of a decision support system (DSS) for the health management system of livestock.
RO4. To identify the challenges in prescribing the remedies for veterinary diseases.

Research Question (RQ)

Table 1 lists the research quest:ions formulated to investigate the livestock healthcare management domain and the motivation for development of each question is also stated.

Table 1. Research questions

S No	Question	Motivation
RQ1	How can the latest technologies be used in the healthcare of livestock?	To study how animal welfare be improved
RQ2	What tools and techniques can be used in identifying diseases in livestock?	Impact of AI on Livestock
RQ3	What is the impact and effectiveness of a decision support system for the health management system of livestock?	To ensure early disease detection.
RQ4	What are the challenges in prescribing the solutions to diseases in livestock?	To study the impact of diseases on various aspects of society

In the development of any robust research framework, collaboration with domain experts is instrumental in refining methodological aspects to ensure the accuracy and relevance of the study. In the context of the current research on the role of ML in livestock health monitoring systems, an integral step in the study's design involved extensive discussions with experts in the field. Specifically, the ROs and RQs were meticulously deliberated with these experts, drawing upon their profound knowledge and practical insights into precision livestock farming.

Search Scheme:

The formulation of a search plan to collect relevant and genuine information on the specific region is the most crucial stage in performing this SLR. Identifying resources to search the relevant literature, constructing search strings, and setting inclusion/ exclusion criteria are all part of this process. The articles included in this review have been sourced from reputable digital repositories such as IEEE, Springer Link, Elsevier, Research Gate, and ACM digital library. We also practiced the snow snowballing approach to hunt for papers that were missed in prior search cycles. All those journals that are connected to the topic and have better citation ratings were also consulted using a variety of keywords classified as primary, secondary, and tertiary. Table 2 lists the terms that were utilized to create the search string.

Table 2. Keywords used for searching.

Primary Keywords	Secondary Keywords	Tertiary Keywords
Machine Learning	Deep Learning	IoT / IoT Devices
Livestock	Cattle / Cow / Animal Farm	Animal Health / Livestock Health / Diseases
Precision Livestock	Smart Farming / Monitoring	Sensors / Computer Vision

Table 3 lists the search string applied to specific digital repositories and the count of articles extracted from repositories by applying the query mentioned against each.

Table 3. Specific search strings concerning digital repositories.

Repository	Query	Count
IEEE XPLORE	("All Metadata":": "Machine Learning" OR "All Metadata": "Deep Learning" OR "All Metadata": "IoT") AND ("All Metadata": "Livestock" OR "All Metadata": "Animal" OR "All Metadata": "Farm")	**162**
ACM Digital Library	[[All: "iot"] OR [All: "machine learning"] OR [All: "deep learning"]] AND [[All: "livestock"] OR [All: "cattle"] OR [All: "cow"]] AND [E-Publication Date: (01/01/2019 TO 12/31/2024)]	**645**
Science Direct	["Livestock"] AND ["Health" OR "Disease"] AND ["Machine Learning" OR "Deep Learning"]	**1202**
Springer Link	("iot-based" or "IoT" or "machine learning") and ("livestock")	**222**

Inclusion/Exclusion Criteria:

To shortlist the relevant literature from the a:rticles discovered by applying the search string to the digital repositories, inclusion criteria (IC) and exclusion criteria (EC) were carefully defined.

To incorporate the studies, the following criteria were created.

- **IC-1:** The study is primarily conducted for the health management of livestock.
- **IC-2:** The study targets the use of ML or deep learning in livestock health.
- **IC-3**: The study recorded some diseases in livestock.
- **EC-1:** Study is not written in English
- **EC-2:** The study is not focusing livestock
- **EC-3:** The study is published before 2018

Shortlisting Procedure:

Applying the search string to digital repositories resulted in the acquisition of a large volume of data, which had to be shortlisted by going through a multi-stage shortlisting process. This method begins with a search and examination of articles from databases presented in Table 4. After that duplicates were removed. Following that, the extracted papers were further scrutinized by reading abstracts. Articles having similar extracts have been added to this SLR after calculating the Kappa Coefficient and conclusions. The IC/EC criteria have been applied resulting in the identification of the most relevant articles to carry out the review process.

Kappa coefficient is a key metric for shortlisting articles by assessing agreement and disagreement between human observers. Given its ability to account for chance agreement and provide a more nuanced understanding of the reliability of the selection process. The Kappa coefficient has been applied to evaluate the concordance between expert recommendations and the outcomes of the shortlisting procedure.

This collaborative effort between the research team and domain experts underscores the importance of interdisciplinary cooperation in refining research methodologies. By incorporating expert recommendations and leveraging the Kappa coefficient, the research not only aims to establish a systematic and transparent shortlisting procedure but also seeks to enhance the overall credibility and reliability of the findings regarding the investigation of machine learning applications within the realm of livestock health monitoring. This synergy between expertise and statistical rigor positions the study to make meaningful contributions to the advancement of precision livestock farming practices.

Quality Scoring:

Quality evaluation is a crucial stage in SLR to evaluate the quality of included research. The quality of the shortlisted studies was determined using the criteria stated in **Table 4**.

Table 4. Quality scoring criteria.

Criteria	Description	Rank	Score
Internal Scoring			
a)	Did the study mention tools and technology?	Yes Partially No	1 0.5 0
b)	Did the study elaborate on data recording procedures?	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 sources?	JCR-Impact-Factor	2 1 0

For external scoring, the JCR impact factor was used in a way the impact score of JCR is more than 3 then we gave it 2 points and if it's above 2 and less than 3 then we gave it 1 and 0.5 for less than 2 and 0 if it has no score.

Table 5 shows the classification of research based on several investigative characteristics and quality assessments. The studies are classified according to the fields of investigation of this work, with the relevant study for a given area of the investigation indicated as none if-needed information is not explicitly presented in a study.

Table 5. Classification of shortlisted studies.

Ref No	Bibliography	Methodology						Internal Scoring				External Scoring	Total Score
	Channel	Year	Technology	Tools	Study Region	Livestock Type	Disease	1	2	3	4	JCR	
[5]	Journal	2018	ML, CV	DT	China	Cow	Lameness	1	1	1	.5	0	3.5
[6]	Journal	2023	ML	SVM, ANN	Iran	Chicken	Avian	1	1	1	1	2	6
[7]	Conference	2022	ML	NO	Global	Cow	Multiple	5	5	5	5	0	2
[8]	Journal	2019	ML	ANN	Global	Cow	FMD, Mastitis	5	1	0	5	0	2
[10]	Journal	2023	ML	RF	Bulgaria	Cow	Multiple	1	5	5	5	2	4.5
[9]	Conference	2020	ML	SVM, ANN	Global	Cattle	Lameness	1	1	5	5	0	3
[16]	Journal	2023	DL	NO	Global	Cattle	Multiple	1	5	5	5	2	4.5
[17]	Journal	2021	ML	ANN	Global	Cattle	Mastitis	1	0	5	5	2	4
[12]	Journal	2020	ML	KNN RF	Ireland	Cattle	Lameness	1	5	1	5	0	3
[11]	Journal	2023	ML	Reg	Global	Cattle	Bovine Respiratory	1	0	5	5	1	3
[18]	Conference	2021	ML	None	Global	Cattle	Multiple	5	5	0	5	0	1.5
[15]	Journal	2020	DL	F-RCNN	China	Goat	Multiple	1	1	5	5	0	3
[19]	Journal	2021	ML	None	USA	Cattle	Vesicular stomatitis	5	0	5	.	2	3.5
[14]	Journal	2023	ML	CNN	Italy	Cattle	Multiple	1	0	5	5	2	4
[13]	Journal	2018	ML	SVM	Germany	Cow	Lameness	5	1	1	5	0	3
[20]	Journal	2022	ML	None	Global	Dairy	Bovine	5	1	5	5	2	4.5
[8]	Journal	2022	ML	DT	Global	Cow	Mastitis	1	5	5	5	0	2.5
[21]	Journal	2021	ML	SVM KNN	Global	Cow	Mastitis	1	0	5	5	0	2
[22]	Journal	2022	ML	Fuzzy	Africa	Cow	FMD	1	5	5	5	0	2.5

[23]	Journal	2020	ML	RF	UK	Cow	Mastitis	1	0	5	5	2	4
[24]	Journal	2020	ML	KNN SVM	Global	Cattle	Multiple	1	0	5	0	2	3.5
[25]	Journal	2020	ML	KNN SVM	Global	Cattle	Multiple	1	5	5	5	0	2.5
[26]	Journal	2020	ML	SVM	France	Cow	Multiple	1	5	5	0	2	4
[27]	Journal	2023	DL	CNN	China	Cow	Multiple	1	5	0	5	2	4
[28]	Journal	2023	ML	RF SVM	China	Cow	Multiple	1	5	5	5	2	4.5
[29]	Conference	2021	DL	CNN	India	Cattle	FMD, LSD	1	1	1	1	0	4
[30]	Journal	2019	ML	RF SVM	UK	Cattle	Rumination	1	5	5	5	0	2.5
[31]	Journal	2023	DL	YOLO v5	South Korea	Cow	Multiple	5	0	5	5	2	3.5
[32]	Journal	2023	ML	-	Global	Cow	Mastitis Lameness	5	0	5	5	2	3.5
[33]	Journal	2021	DL	-	Global	Cow	Mastitis Lameness	5	0	5	5	2	3.5
[34]	Journal	2023	DL	CNN	Netherlands	Cow	Lameness	5	1	5	5	2	4.5
[35]	Journal	2023	DL	LSTM	Global	Cow	Lameness	5	0	5	5	2	3.5
[36]	Journal	2023	DL	CNN	Australia	Cattle	Multiple	5	5	5	5	2	4
[37]	Journal	2020	DL	CNN	Australia	Cattle	Multiple	5	5	5	5	2	4

Analysis and Findings:

This section discusses the conclusions and key findings acquired after the synthesis of the twenty publications selected in this review. The data extraction process and analysis of the selected publications have been carried out about livestock healthcare by processing papers published from 2018 to 2023. Figure 2 depicts the distributions of ML-based healthcare systems in cattle during the last five years. The trend to research about livestock healthcare has increased gradually from 2018 to 2023.

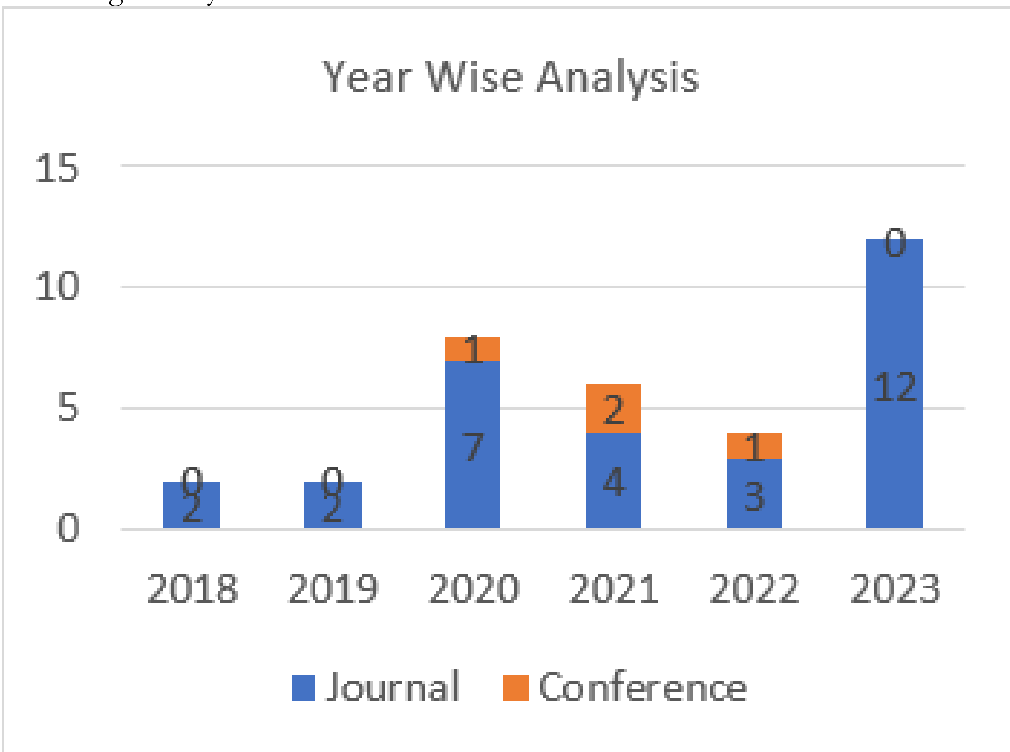

Figure 2. Distribution of selected studies over the years

Table 6 enlists the studies according to the total quality scores the studies obtained. It shows that 12% of studies are below average, 26% of studies have an average score, and 62% of papers have above-average scoring

Table 6. Quality assessment of selected papers.

Reference	Score	Total
[6]	6	1
[10],[16],[20],[28],[34]	4.5	5
[17],[14],[23],[26],[27],[29],[36],[37]	4	8
[5],[19],[24],[31],[32][33][35]	3.5	7
[9][12][11],[15][13]	3	5
[8][22][25][30]	2.5	4
[7][8][21]	2	3
[18]	1.5	1

Figure 3 depicts the quality evaluation findings according to scores obtained by these articles in Table 5 and Table 6.

Figure 3. Quality scoring classification analysis

Now all RQs are briefly discussed in order to clarify the respective exploring areas of the livestock healthcare domain.

RQ1: How Can The Latest Technologies Be Used In The Healthcare Of Livestock?:

The latest technologies can significantly enhance the healthcare of livestock, providing more efficient monitoring, early disease detection, and improved overall management. Scholarly investigation has explored the multifaceted application of cutting-edge technologies in livestock farming.

Research shows that ML has been a successful tool in identifying and predicting diseases in dairy livestock. **Figure 4** shows the list of diseases identified or predicted by ML algorithms.

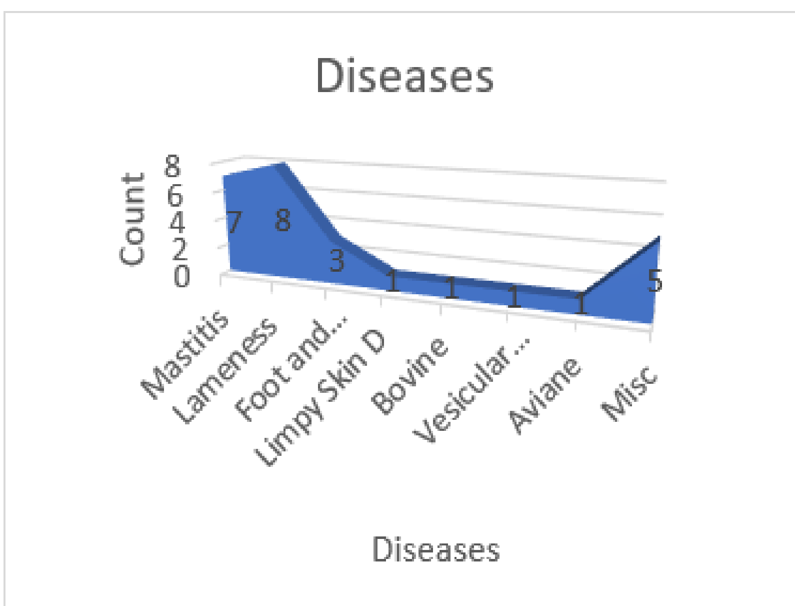

Figure 4. Predicted disease using ML

The review showed that the three major diseases predicted using ML were Lameness, Mastitis, and FMD. Lameness was detected in about 30% while mastitis was reported in about 26%. FMD was predicted or detected at about 11%.

RQ2: What Tools And Features Can Be Used In Identifying Diseases In Livestock?:

Identifying diseases in livestock involves a combination of tools and features, ranging from traditional diagnostic methods to modern technologies.

Attachable sensors on animals can monitor vital signs such as body temperature, heart rate, and activity levels [12][15][13]. Any abnormal readings could indicate the presence of a disease. Radio Frequency Identification (RFID) Tags and Global Positioning System (GPS) tracking can help monitor the movement patterns of livestock. Changes in behavior or location could be early indicators of health issues [38]. Analyzing historical data on disease outbreaks, weather patterns, and animal health can help predict the likelihood of disease occurrence [19]. ML algorithms can identify patterns and provide early warnings. Using data on known diseases and symptoms, models can be trained to recognize patterns associated with various illnesses. Aerial imagery can be used to monitor the overall health of livestock and identify potential issues such as malnutrition or disease spread [16]. This technology can detect changes in body temperature, which may be an early sign of illness. Integrating IoT devices such as environmental sensors and connected feeding systems can provide real-time data on the conditions within the livestock environment. Automated systems can continuously monitor food and water intake, flagging any anomalies that may indicate health issues.

Applying ML techniques comes with various challenges, spanning technical, ethical, and practical aspects. ML models often require large amounts of high-quality labeled data for effective training. Insufficient or poor-quality data can lead to biased models or inaccurate predictions. Imbalanced datasets, where one class significantly outnumbers others, can result in models that are biased towards the majority class, leading to poor performance in minority classes. Selecting a suitable ML algorithm is a crucial step in the model development process. The choice of algorithm depends on various factors related to the nature of the data and the problem at hand. **Figure** 5 shows the percentage of different ML models used in the selected research articles.

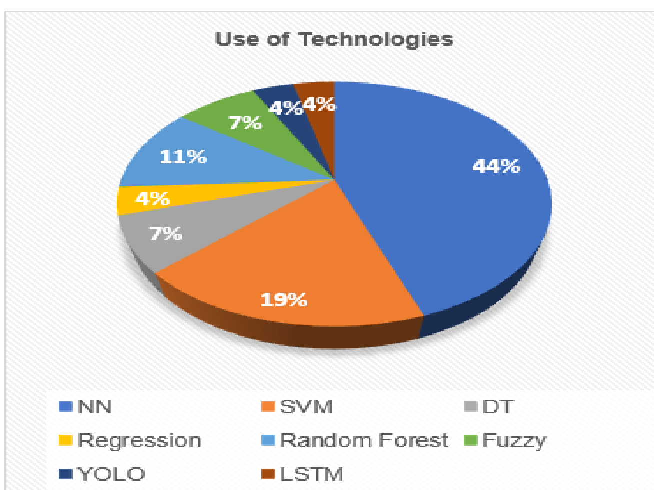

Figure 5. Technologies used in PLF

A review showed that three major algorithms of ML used to predict or detect livestock diseases were NN, SVM, and Random Forest. NN was used 44% while SVM was used 19%. Random Forest is the third most used algorithm to detect or predict livestock diseases with 11%. By integrating these technologies, farmers and livestock managers can create a comprehensive and proactive approach to disease detection and prevention, ultimately improving the overall health and well-being of their animals. Regular training and updates on these technologies are essential to ensure effective implementation.

RQ3: What Is The Impact And Effectiveness Of The Decision Support System (Dss) For Health Management System Of Livestock?:

The implementation of DSS in the health management system of livestock can have a significant impact on the effectiveness and efficiency of farm operations [6][10][16]. DSS can analyze data from various sources, including sensor readings, health records, and environmental factors, to detect subtle changes that may indicate early signs of diseases [10][28]. Early detection allows for prompt intervention, reducing the severity and spread of diseases [6][25]. It enhances the chances of successful treatment and minimizes economic losses for farmers [6]. DSS can leverage genetic and health data to provide personalized treatment plans based on individual animal characteristics and medical history [9]. Tailoring treatments to the specific needs of each animal can improve treatment efficacy, reduce the use of antibiotics, and minimize the development of drug resistance [9] [32].

DSS can assess the risk of disease outbreaks based on various factors, including weather conditions and historical data of the herd [10] [14]. By identifying high-risk periods or areas, farmers can implement targeted biosecurity measures, reducing the likelihood of disease introduction and transmission [10]. DSS allows for continuous monitoring of various parameters, adapting recommendations based on real-time data [5] [16]. This adaptability ensures that health management strategies remain relevant in dynamic environments, responding to changes in weather, disease patterns, and other factors [5].

While the impact and effectiveness of DSS in livestock health management are substantial, it's essential to consider factors such as data accuracy, system reliability, and the need for ongoing updates and training to maintain optimal performance [1] [4] [25]. Additionally, farmer education and user-friendly interfaces are critical for the successful adoption and utilization of decision-support tools in the agricultural sector [28] [29].

RQ4: What Are The Challenges In Prescribing The Solutions To Diseases In Livestock?:

Prescribing effective treatments for livestock diseases involves a variety of challenges, many of which stem from data, diagnostic, and practical constraints. Based on the reviewed literature, the key challenges can be grouped as follows:

Diagnostic Complexity:

Diseases often present with overlapping symptoms, making it hard to distinguish between different conditions.

Co-infections are common in livestock, further complicating accurate diagnosis.

Misdiagnosis can lead to ineffective treatments, increased costs, and further disease spread within the herd [3][12].

Data Quality and Availability:

Incomplete health records or lack of historical data limits the accuracy of predictive models and DSS [4][25].

Many farms, particularly in developing regions, do not have access to comprehensive, labeled datasets, undermining ML model performance.

Antibiotic Resistance:

Overprescription or misuse of antibiotics can contribute to drug-resistant bacteria, posing risks to both animal and human health [3][22].

Failure to follow the correct dosage or withdrawal periods exacerbates the resistance problem.

Financial Constraints:

Costs associated with diagnostics, treatments, and system implementation can be prohibitive for small or resource-limited farms [8][43].

Economic limitations may lead to delayed treatment or underutilization of available technologies.

Environmental and Climate Challenges:

fluctuations and changes in humidity or temperature can influence the prevalence of diseases and the efficacy of vaccines [17][40].

Climate variability can also impact disease vectors and animal immunity levels.

Education and Awareness:

Many farmers lack adequate training in early disease detection, preventive measures, and treatment protocols [10][30].

This knowledge gap can result in poor compliance with veterinary guidelines or delayed medical intervention.

Ethical and Regulatory Barriers:

The use of advanced technologies raises ethical concerns regarding data privacy, animal stress due to monitoring, and compliance with welfare laws [6][25][36].

The absence of regulatory frameworks or standardization complicates implementation across farms and regions [26][31].

Discussions:

This section contains a discussion and analysis of outcomes obtained from this review. A taxonomy of ML-based Livestock Health Management Systems (HMS) is proposed based on the findings analysis. The shortcomings and problems of existing systems are addressed, and a model is proposed as a guideline for practitioners and academics to design ML-based HMS for Livestock and implications as future directions of the underlying area are offered.

Taxonomy:

The designed taxonomy, shown in Figure 6, consists of four primary attributes. These are recording devices, sensors, identification of disease, and ML algorithms. Recording devices like video cameras and wearable sensors keep track of data which is further processed by ML algorithm to identify or predict the disease.

Video cameras are like the ones you use to record events or capture moments. They assist in monitoring animals in this instance. Certain cameras are designed to see in the dark, and there are high-quality ones that can capture excellent images. These cameras are positioned in areas where the animals feel at ease. They record the animal behavior as well as any physical indicators that may indicate an illness. These cameras send their data to a computer so it can be examined further.

Animals can wear wearable sensors, which are similar to fitness trackers for humans. These sensors are capable of measuring the animal's body temperature as well as its speed of movement. They are fastened to the animals in a variety of methods, such as leg bands or collars. The continuous data collection from the sensors helps farmers understand what's typical for each animal. However, we must ensure that these devices are accurate and do not cause undue stress to the animals.

Health Monitoring Sensors assess the animals' well-being [36]. Some are capable of measuring the animals' heart rates or blood pressure [35] [40]. They can be inserted inside the animal's body or adhered to its skin [35] [40]. To provide a complete picture of the animal's health, the data gathered by these sensors is integrated with the information obtained from video cameras [35] [36]. Environmental Sensors measure temperature and other environmental parameters in the animal's habitat. They also check to see if there is enough food for the animals to eat and the condition of the air. This aids farmers in providing their livestock with a healthy habitat. Even if there is something in the air that could make the animals ill, the sensors can detect it [35].

Since animals are unable to communicate with us when they are ill, we must check for physical or behavioral changes. We watch to see if they're eating or moving differently. We occasionally examine their skin or look for fever. Any of these alterations could indicate that the animal is not feeling well. Veterinarians assist us in determining whether an animal is ill or not. We consider the animal's past and apply standards to determine potential problems that are comparable to figuring out a problem. We must comprehend each type of illness that different animals may experience [38].

Regarding Health Management System Integration, the computer facilitates farmers in rapid decision-making to alert the farmer if it notices something unusual in the data [32] [42]. The underlying ML algorithm enables the computer to continuously learn and improve its ability to support animals' well-being [1] [14]. Farmers are assisted in caring for their livestock by this entire system of cameras, sensors, intelligent computer programs, and the ability to recognize symptoms of illness [32] [36] [42]. It's similar to having a group of assistants ensuring the well-being and happiness of the animals. We can guarantee that the animals receive the finest care possible by combining all of these factors [32] [36] [42].

Comparison with Existing Studies:

The current study reinforces the conclusions of prior reviews (e.g., García et al. [25], Roy et al. [26]) regarding the rising adoption of ML and IoT in precision livestock farming. However, our findings extend the existing literature in the following ways:

1. **Broader Disease Detection Scope**: While past studies largely concentrated on single diseases such as mastitis or lameness [24][5][19], our analysis shows that recent approaches increasingly support multi-disease detection capabilities through the integration of multiple sensor modalities and ML algorithms (e.g., [6][11][32][33]).
2. **Algorithm Preference Shift**: Earlier literature heavily favored Support Vector Machines (SVM) and Decision Trees (DT) due to their interpretability [24][19]. Our review, however, indicates a trend toward Neural Networks (NN), especially deep learning variants such as CNN and LSTM, used in over 44% of studies. This reflects a shift toward methods capable of handling complex data types like video and accelerometer data [18][36][39].
3. **Emphasis on Real-Time and Edge Analytics**: Unlike many previous reviews that focused on static or batch-processing approaches, our study found a growing emphasis on real-time monitoring enabled by edge and fog computing [13]. This highlights an evolution in system architecture toward latency-sensitive applications in livestock environments.
4. **Integration with Decision Support Systems (DSS)**: While DSS has been mentioned sporadically in earlier works, our study provides detailed evidence that DSS is not only used for early disease detection but also risk assessment, treatment personalization, and dynamic response adjustment [6][9][10][33]. This aligns with but goes beyond the findings of Niloofar et al. [29] who mainly emphasized DSS for welfare improvement.
5. **Geographic and Species Diversity**: Several earlier works have focused on limited regions or species. Our study included a broader geographic distribution (e.g., studies from China, Europe, Iran, and Australia) and species coverage (e.g., cows, goats, and chickens), providing a more comprehensive global picture.

Methodological Refinements Over Existing Reviews:

This SLR differs from earlier ones in its rigorous methodology:

- **Multi-tier Keyword Strategy**: Unlike some studies that used limited or overly general search terms, we employed a three-level keyword classification (primary, secondary, tertiary), increasing the specificity and comprehensiveness of the search.
- **Kappa Coefficient for Article Selection**: Few existing SLRs report inter-rater reliability. Our inclusion of the Kappa coefficient ensures objectivity and strengthens the validity of article selection.
- **Quality Scoring System**: Articles were not only evaluated based on methodological clarity and technological contribution but also on journal impact factors—yielding a nuanced quality map of the current research landscape.

Key Trends and Gaps:

From this synthesis and comparison, several key trends emerge:

- ML models with multi-modal sensor inputs are outperforming traditional single-modality approaches.

- Deep learning is gaining popularity but often at the cost of interpretability—a concern noted in explainable AI literature [1].
- There remains a significant implementation gap in lower-resource settings, echoing concerns raised by Sheham et al. [7] and Tawheed et al. [27].

Despite advancements, challenges such as data heterogeneity, high implementation costs, and lack of standardized protocols continue to limit the scalability and generalization of ML-based livestock health monitoring systems.

Advice For The Practitioners:

Based on the insights gathered from the referenced literature on health management systems for dairy livestock, practitioners can consider the following advice:

Embrace advanced technologies such as artificial intelligence, ML, and the Internet of Things for comprehensive health management systems. These technologies can provide real-time monitoring, early disease detection, and data-driven insights for better decision-making.
Explore multimodal approaches combining different technologies, such as image processing, thermography, and wearable sensors. Integrating various modalities can enhance the accuracy and effectiveness of health monitoring systems, capturing a more holistic view of livestock well-being.

Consider cloud-based solutions for data storage, analysis, and management. Cloud platforms, like AWS mentioned in [9], provide scalability and accessibility, allowing practitioners to process large datasets efficiently and access information remotely.

Implement edge computing, as discussed in [13], for real-time monitoring and decision-making. Edge computing brings computational capabilities closer to the data source, reducing latency and enabling quicker responses in detecting health issues.

Explore fog computing solutions, as mentioned in [13], to handle data processing tasks closer to the livestock, which can be especially valuable in large-scale farming operations. Fog computing enhances scalability and efficiency in managing data from distributed sensors.
Leverage wearable sensors, as highlighted in [18] and [19], to monitor livestock behavior. These sensors provide valuable insights into patterns that can indicate health issues, contributing to early detection and preventive measures.

Adopt the principles of precision livestock farming, as emphasized in [25]. Precision farming involves using technology to optimize management practices, including feeding, health monitoring, and overall well-being, leading to more efficient and sustainable farming operations.
Encourage collaboration between experts in agriculture, veterinary sciences, data science, and technology. Interdisciplinary collaboration can result in more comprehensive and effective health management solutions by combining domain knowledge with technical expertise.
Implement continuous monitoring and adaptability in health management systems. Livestock health is dynamic, and systems should be designed to evolve based on changing conditions, emerging diseases, and the evolving needs of the livestock.

Design user-friendly interfaces for practitioners to easily interpret and act upon the information provided by the health management system. Intuitive interfaces can enhance the adoption of technology among practitioners, making it more accessible and practical.
By integrating these pieces of advice, practitioners can create robust health management systems for dairy livestock, improving overall animal welfare, and optimizing farm productivity.

Limitations of this Study:

While the referenced literature on health management systems for dairy livestock provides valuable insights, it's important to acknowledge certain limitations and challenges identified across the studies:

Many studies rely on the availability and quality of data [1] [2]. Obtaining accurate and representative datasets for training ML models or validating system performance can be challenging [4] [6] [13] [25]. Incomplete or biased datasets may affect the reliability of the proposed health management systems [15] [25].

The accuracy and reliability of sensors, such as thermography cameras, wearable devices, and accelerometers, are crucial for the success of health management systems [6] [17] [18] [19] [21] [24] [28] [30] [34]. Issues related to sensor calibration, environmental conditions, and sensor drift can impact the precision of data collected [6] [17] [18] [21] [24].

Lack of standardization and interoperability between different devices and systems may hinder seamless integration [7] [27]. The diversity in technologies and protocols across studies can limit the scalability and practical implementation of health management solutions on a broader scale [7] [27].

Some studies may lack long-term evaluations of the proposed systems in real-world farm conditions [4] [12] [26] [33]. Long-term studies are essential to assess the sustainability, reliability, and effectiveness of health management solutions over extended periods [4] [12] [26] [33].

The implementation of advanced technologies, such as IoT and cloud computing, may involve high initial costs [7] [8] [9] [11] [27] [42]. Farms with limited financial resources or lacking the necessary infrastructure may find it challenging to adopt and maintain these systems [7] [8] [9] [11] [27] [42].

Ethical considerations related to data privacy, animal welfare, and the potential stress caused by continuous monitoring need careful attention [6] [8] [16] [19] [23] [25] [26] [31] [35] [36]. Balancing the benefits of health management systems with ethical considerations is crucial for the responsible deployment of these technologies [6] [8] [16] [19] [23] [25] [26] [31] [35] [36].

Some studies may focus on specific breeds or types of livestock, limiting the generalizability of findings to a broader range of dairy cattle [3] [4] [12] [13] [16] [20] [22] [25] [33]. The diversity in livestock genetics, behaviors, and farming practices should be considered for more universally applicable solutions [3] [4] [12] [13] [16] [20] [22] [25] [33].

Certain studies may not extensively explore external factors that could influence the health of livestock, such as environmental conditions, feed quality, and interactions with other animals [4] [6] [7] [18] [22] [23] [25] [26] [32] [34]. Understanding these external factors is essential for a holistic approach to health management [4] [6] [7] [18] [22] [23] [25] [26] [32] [34].

Compliance with regulatory standards and guidelines for animal welfare, data privacy, and technology usage may pose challenges [6] [8] [23] [26] [31] [35] [36] [38]. Health management systems need to align with existing regulations, and compliance issues could impact the practicality of widespread implementation [6] [8] [23] [26] [31] [35] [36] [38].

Adoption of advanced technologies may face resistance from practitioners due to factors such as lack of awareness, technological literacy, and concerns about system complexity [8] [10] [11] [26] [27] [42]. Addressing these barriers is crucial for the successful implementation of health management systems [8] [10] [11] [26] [27] [42].

By recognizing these limitations, researchers and practitioners can guide future developments in health management systems for dairy livestock, focusing on addressing these challenges to enhance the overall effectiveness and sustainability of these technologies in real-world agricultural settings.

Challenges and Future Work:

The future of ML in livestock health monitoring holds promising advancements that can significantly transform the way farmers manage their herds.

As wearable technology advances, it will be possible to monitor individual animals in real-time and record a wider range of health parameters. Early health issue detection will be made easier by wearable technology, which will provide more in-depth information about the behavior, physiological responses, and general well-being of livestock. A greater reliance on edge computing will make it possible to process data on-device, enabling real-time analysis and decision-making independent of cloud-based solutions. Latency will be decreased, responsiveness will be improved, and prompt interventions in animal health management will be supported by real-time analysis at the edge.

The interpretability of ML algorithms will be addressed by concentrating on the development of explainable AI models. Farmers, veterinarians, and other stakeholders will be more trusting in transparent and comprehensible models, which will promote a broader usage of ML technology in livestock health monitoring.

ML advances will allow for automated treatment planning based on genomic information and individual animal health histories. Treatment efficacy will increase, drug usage will be optimized, and the risk of antibiotic resistance will be decreased with the help of automated treatment programs. Increased adoption of blockchain technology will enhance data security and traceability in livestock health monitoring systems. Blockchain will provide immutable records of health data, ensuring data integrity, and supporting transparent traceability throughout the supply chain.

Robust ML models will be easier to construct if farmers, academics, and organizations throughout the world collaborate more and share more data. Models that can effectively generalize across various locations and livestock populations will be able to be created with the help of shared data sets and cooperative efforts. Creation of cutting-edge, AI-driven decision support tools intended to help vets with diagnostic and treatment planning. Improved diagnosis and customized treatment plans will result from increased veterinarian-AI system collaboration.

Predicting disease outbreaks and other health problems in cattle will become more accurate with continued advancements in predictive modeling. By enabling farmers to take proactive preventive action, early alerts can lessen the effects of illnesses and enhance the general health of their herd. A more thorough understanding of livestock health will be possible with increased integration of various data sources, including genetic, environmental, and sensor data. The accuracy of health evaluations will be improved by holistic data integration, enabling better-informed decision-making and individualized health management plans.

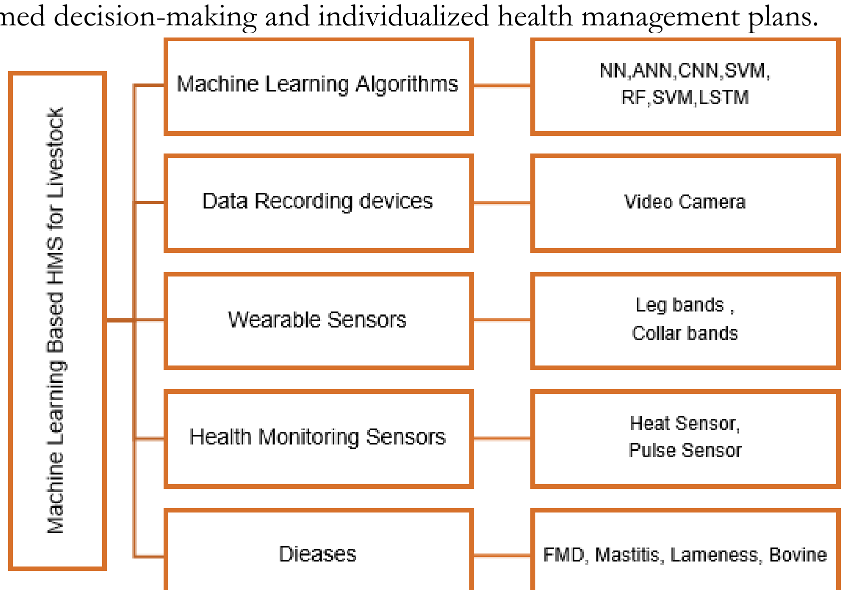

Figure 6. Taxonomy of ML based health management system for livestock.

Conclusion:

This study reports a systematic literature review of the ML-based health management system of livestock to predict and identify diseases like mastitis, FMD, and Lameness in dairy animals. It was conducted by reviewing 43 research articles gathered through eminent publication sources. Articles for reviewing the ML-based health management system of livestock are gathered by considering some primary and secondary keywords. Though a number of the keywords are used to search the relevant literature, there exists the possibility that some studies used other words and their synonyms in their work which could affect the final results. This risk was mitigated by carefully considering various keywords and classifying these keywords as primary, secondary, and tertiary to form the search string and apply different Boolean operators to combine the specified classification of keywords.

Livestock Health Monitoring System allows the monitoring of livestock and evaluation of animal welfare by using data from an increasing number of sensors and IoT devices. The use of ML can revolutionize how livestock is managed and monitored. This will improve livestock production and management. ML algorithms are an integral part of precision livestock farming. A lot of work has been done over the last 20 years but a lot more is to be done. Identification of disease is a huge task that will lead to the detection of diseases. However, a health monitoring system must also be capable of prescribing suitable veterinary medicine to cut down the expenses of veterinary doctors. As technology continues to advance, the potential for transformative impacts on animal welfare, farm sustainability, and global food production is substantial.

A comprehensive review has been conducted by formulating ROs, RQs, Searching criteria, and Inclusion / Exclusion criteria. Search is also supported by snowballing. Moreover, the Kappa coefficient has also been calculated to ensure the fair inclusion of articles.

References:

[1] Q. An, S. Rahman, J. Zhou, and J. J. Kang, "A Comprehensive Review on Machine Learning in Healthcare Industry: Classification, Restrictions, Opportunities and Challenges," *Sensors*, vol. 23, no. 9, May 2023, doi: 10.3390/S23094178,.

[2] R. R. von Kaufmann and H. Fitzhugh, "The Importance of Livestock for the World's Poor," *Perspect. World Food Agric. 2004*, pp. 137–160, Sep. 2003, doi: 10.1002/9780470290187.CH9.

[3] S. J. Wells, S. L. Ott, and A. Hillberg Seitzinger, "Key Health Issues for Dairy Cattle—New and Old," *J. Dairy Sci.*, vol. 81, no. 11, pp. 3029–3035, Nov. 1998, doi: 10.3168/JDS.S0022-0302(98)75867-9.

[4] P. Shine and M. D. Murphy, "Over 20 Years of Machine Learning Applications on Dairy Farms: A Comprehensive Mapping Study," *Sensors 2022, Vol. 22, Page 52*, vol. 22, no. 1, p. 52, Dec. 2021, doi: 10.3390/S22010052.

[5] K. Zhao, J. M. Bewley, D. He, and X. Jin, "Automatic lameness detection in dairy cattle based on leg swing analysis with an image processing technique," *Comput. Electron. Agric.*, vol. 148, pp. 226–236, May 2018, doi: 10.1016/J.COMPAG.2018.03.014.

[6] M. Sadeghi, A. Banakar, S. Minaei, M. Orooji, A. Shoushtari, and G. Li, "Early Detection of Avian Diseases Based on Thermography and Artificial Intelligence," *Animals*, vol. 13, no. 14, Jul. 2023, doi: 10.3390/ANI13142348,.

[7] N. H. Sheham, M. T. Hassan, A. Imran, T. F. Ahmed, M. S. Parvez, and A. Ahmed, "Design of an IoT-based Smart Farming System," *ACM Int. Conf. Proceeding Ser.*, pp. 284–293, Mar. 2022, doi: 10.1145/3542954.3542996/SUPPL_FILE/P284-SHEHAM-SUPPLEMENT.PPTX.

[8] S. Vyas, V. Shukla, and N. Doshi, "FMD and Mastitis Disease Detection in Cows Using Internet of Things (IOT)," *Procedia Comput. Sci.*, vol. 160, pp. 728–733, Jan. 2019, doi: 10.1016/J.PROCS.2019.11.019.

[9] A. A. Chaudhry, R. Mumtaz, S. M. Hassan Zaidi, M. A. Tahir, and S. H. Muzammil School, "Internet of Things (IoT) and Machine Learning (ML) enabled Livestock Monitoring," *HONET 2020 - IEEE 17th Int. Conf. Smart Communities Improv. Qual. Life using ICT, IoT AI*, pp. 151–155, Dec. 2020, doi: 10.1109/HONET50430.2020.9322666.

[10] K. Dineva and T. Atanasova, "Health Status Classification for Cows Using Machine Learning and Data Management on AWS Cloud," *Anim. 2023, Vol. 13, Page 3254*, vol. 13, no. 20, p. 3254, Oct. 2023, doi: 10.3390/ANI13203254.

[11] J. K. Gwaka *et al.*, "Machine-Learning Approach for Risk Estimation and Risk Prediction of the Effect of Climate on Bovine Respiratory Disease," *Math. 2023, Vol. 11, Page 1354*, vol. 11, no. 6, p. 1354, Mar. 2023, doi: 10.3390/MATH11061354.

[12] M. Taneja, J. Byabazaire, N. Jalodia, A. Davy, C. Olariu, and P. Malone, "Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle," *Comput. Electron. Agric.*, vol. 171, p. 105286, Apr. 2020, doi: 10.1016/J.COMPAG.2020.105286.

[13] J. Haladjian, J. Haug, S. Nüske, and B. Bruegge, "A Wearable Sensor System for Lameness Detection in Dairy Cattle," *Multimodal Technol. Interact. 2018, Vol. 2, Page 27*, vol. 2, no. 2, p. 27, May 2018, doi: 10.3390/MTI2020027.

[14] P. Balasso, C. Taccioli, L. Serva, L. Magrin, I. Andrighetto, and G. Marchesini, "Uncovering Patterns in Dairy Cow Behaviour: A Deep Learning Approach with Tri-Axial Accelerometer Data," *Anim. 2023, Vol. 13, Page 1886*, vol. 13, no. 11, p. 1886, Jun. 2023, doi: 10.3390/ANI13111886.

[15] Y. Rao, M. Jiang, W. Wang, W. Zhang, and R. Wang, "On-farm welfare monitoring system for goats based on Internet of Things and machine learning," *Int. J. Distrib. Sens. Networks*, vol. 16, no. 7, Jul. 2020, doi: 10.1177/1550147720944030/ASSET/F6D9C9F7-8E12-42B2-91F6-C9B63C1A7E16/ASSETS/IMAGES/LARGE/10.1177_1550147720944030-FIG12.JPG.

[16] S. Mishra, "Internet of things enabled deep learning methods using unmanned aerial vehicles enabled integrated farm management," *Heliyon*, vol. 9, no. 8, p. e18659, Aug. 2023, doi: 10.1016/J.HELIYON.2023.E18659.

[17] M. van der Voort, D. Jensen, C. Kamphuis, I. N. Athanasiadis, A. De Vries, and H. Hogeveen, "Invited review: Toward a common language in data-driven mastitis detection research," *J. Dairy Sci.*, vol. 104, no. 10, pp. 10449–10461, Oct. 2021, doi: 10.3168/JDS.2021-20311.

[18] P. Niloofar, S. Lazarova-Molnar, D. P. Francis, A. Vulpe, G. Suciu, and M. Balanescu, "Modeling and Simulation for Decision Support in Precision Livestock Farming," *Proc. - Winter Simul. Conf.*, vol. 2020-December, pp. 2601–2612, Dec. 2020, doi: 10.1109/WSC48552.2020.9383975.

[19] D. Burruss *et al.*, "Predicting the Geographic Range of an Invasive Livestock Disease across the Contiguous USA under Current and Future Climate Conditions," *Clim. 2021, Vol. 9, Page 159*, vol. 9, no. 11, p. 159, Oct. 2021, doi: 10.3390/CLI9110159.

[20] A. Puig, M. Ruiz, M. Bassols, L. Fraile, and R. Armengol, "Technological Tools for the Early Detection of Bovine Respiratory Disease in Farms," *Anim. 2022, Vol. 12, Page 2623*, vol. 12, no. 19, p. 2623, Sep. 2022, doi: 10.3390/ANI12192623.

[21] N. A. Ghafoor and B. Sitkowska, "MasPA: A Machine Learning Application to Predict Risk of Mastitis in Cattle from AMS Sensor Data," *AgriEngineering*, vol. 3, no. 3, pp. 575–583, Sep. 2021, doi: 10.3390/AGRIENGINEERING3030037/S1.

[22] NIRERE Gaudence; Kayalvizhi Jayavel; MASABO Emmanuel, "Fuzzy Logic Applied to Smart Cow's Wearable Device for Early Detection of Foot and Mouth Disease in Rwanda," *Int. J. Innov. Sci. Res. Technol.*, vol. 7, no. 6, 2022, [Online]. Available: https://ijisrt.com/fuzzy-logic-applied-to-smart-cows-wearable-device-for-early-detection-of-foot-and-mouth-disease-in-rwanda

[23] R. M. Hyde *et al.*, "Automated prediction of mastitis infection patterns in dairy herds using machine learning," *Sci. Rep.*, vol. 10, no. 1, pp. 1–8, Dec. 2020, doi: 10.1038/S41598-020-61126-8;SUBJMETA=114,308,631,692,699;KWRD=COMPUTATIONAL+BIOLOGY+AND+BIOINFORMATICS,DISEASES,MEDICAL+RESEARCH.

[24] P. Niloofar et al., "Data-driven decision support in livestock farming for improved animal health, welfare and greenhouse gas emissions: Overview and challenges," *Comput. Electron. Agric.*, vol. 190, p. 106406, 2021.

[25] S. Neethirajan, "The role of sensors, big data and machine learning in modern animal farming," *Sens. Bio-Sensing Res.*, vol. 29, p. 100367, Aug. 2020, doi: 10.1016/J.SBSR.2020.100367.

[26] L. Riaboff *et al.*, "Development of a methodological framework for a robust prediction of the

main behaviours of dairy cows using a combination of machine learning algorithms on accelerometer data," *Comput. Electron. Agric.*, vol. 169, p. 105179, Feb. 2020, doi: 10.1016/J.COMPAG.2019.105179.
[27] H. Wang *et al.*, "Diagnosis of dairy cow diseases by knowledge-driven deep learning based on the text reports of illness state," *CEAgr*, vol. 205, p. 107564, Feb. 2023, doi: 10.1016/J.COMPAG.2022.107564.
[28] X. Zhou *et al.*, "The Early Prediction of Common Disorders in Dairy Cows Monitored by Automatic Systems with Machine Learning Algorithms," *Animals*, vol. 12, no. 10, May 2022, doi: 10.3390/ANI12101251,.
[29] M. Rony, D. Barai, Riad, and M. Z. Hasan, "Cattle External Disease Classification Using Deep Learning Techniques," *2021 12th Int. Conf. Comput. Commun. Netw. Technol. ICCCNT 2021*, 2021, doi: 10.1109/ICCCNT51525.2021.9579662.
[30] A. W. Hamilton *et al.*, "Identification of the Rumination in Cattle Using Support Vector Machines with Motion-Sensitive Bolus Sensors," *Sensors 2019, Vol. 19, Page 1165*, vol. 19, no. 5, p. 1165, Mar. 2019, doi: 10.3390/S19051165.
[31] A. Fuentes, S. Han, M. F. Nasir, J. Park, S. Yoon, and D. S. Park, "Multiview Monitoring of Individual Cattle Behavior Based on Action Recognition in Closed Barns Using Deep Learning," *Anim. 2023, Vol. 13, Page 2020*, vol. 13, no. 12, p. 2020, Jun. 2023, doi: 10.3390/ANI13122020.
[32] "(PDF) Lameness detection and scoring." Accessed: Jun. 05, 2025. [Online]. Available: https://www.researchgate.net/publication/350835786_Lameness_detection_and_scoring
[33] S. R. Silva, J. P. Araujo, C. Guedes, F. Silva, M. Almeida, and J. L. Cerqueira, "Precision Technologies to Address Dairy Cattle Welfare: Focus on Lameness, Mastitis and Body Condition," *Anim. 2021, Vol. 11, Page 2253*, vol. 11, no. 8, p. 2253, Jul. 2021, doi: 10.3390/ANI11082253.
[34] M. Taghavi, H. Russello, W. Ouweltjes, C. Kamphuis, and I. Adriaens, "Cow key point detection in indoor housing conditions with a deep learning model," *J. Dairy Sci.*, vol. 107, no. 4, pp. 2374–2389, Apr. 2024, doi: 10.3168/JDS.2023-23680.
[35] K. Zhang *et al.*, "Early lameness detection in dairy cattle based on wearable gait analysis using semi-supervised LSTM-Autoencoder," *Comput. Electron. Agric.*, vol. 213, p. 108252, Oct. 2023, doi: 10.1016/J.COMPAG.2023.108252.
[36] R. Arablouei, L. Wang, L. Currie, J. Yates, F. A. P. Alvarenga, and G. J. Bishop-Hurley, "Animal behavior classification via deep learning on embedded systems," *Comput. Electron. Agric.*, vol. 207, p. 107707, Apr. 2023, doi: 10.1016/J.COMPAG.2023.107707.
[37] E. A. Eckelkamp and J. M. Bewley, "On-farm use of disease alerts generated by precision dairy technology," *J. Dairy Sci.*, vol. 103, no. 2, pp. 1566–1582, Feb. 2020, doi: 10.3168/JDS.2019-16888.
[38] C. Carslake, J. A. Vázquez-Diosdado, and J. Kaler, "Machine Learning Algorithms to Classify and Quantify Multiple Behaviours in Dairy Calves Using a Sensor: Moving beyond Classification in Precision Livestock," *Sensors 2021, Vol. 21, Page 88*, vol. 21, no. 1, p. 88, Dec. 2020, doi: 10.3390/S21010088.