SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I1P109

Volume 12 Issue 1, 94-103, January 2025

Original Article

Sensor and Computer Vision Based Cattle Health Monitoring and Management

Devendra Singh[1], Rajesh Singh[2], Anita Gehlot[3], Gaurav Bhandari[4], Atulya Verma[5], Pavan Gangwar[6], Purnendu Shekhar Pandey[7]

[1,2,3]*UIT, Uttaranchal University, Uttarakhand, India.*
[4]*ICFAI Tech School, The ICFAI University, Uttarakhand, India.*
[5]*ICFAI Education School, The ICFAI University, Uttarakhand, India.*
[6]*United College of Engineering and Research, Uttar Pradesh, India.*
[7]*GL Bajaj Institute of Technology and Management, Uttar Pradesh, India.*

[1]*Corresponding Author : devendra0503@gmail.com*

Received: 06 November 2024 Revised: 08 December 2024 Accepted: 09 January 2025 Published: 25 January 2025

Abstract *- As part of its efforts to achieve the Sustainable Development Goals by 2030, the United Nations promotes sustainable farming. Though there are complications with real-world deployment, autonomous farming is being explored within the context of edge computing. Automation and smart farming practices could boost farmer efficiency, sustainability, and the well-being of livestock. These advancements minimize costs, eliminate laborious processes, and elevate product quality. Wearable sensors gauge animal behavior, emphasizing the significance of impeccable remote data sharing in this expanding business. Global population growth is driving an evolution toward intelligent farming to address food security and resource constraints. IoT and data analytics optimize farming productivity by substituting outdated wireless sensor networks. IoT effortlessly incorporates technologies like WSN, RFID, and cloud computing. ZigBee technology finds application in livestock health monitoring systems, where sensors measuring heart rate, temperature, pulse rate, and respiration are included. These sensors have connectivity to a Graphical User Interface (GUI) to improve livestock wellness tracking. The advantages of cloud computing encompass exceptionally low latency, bandwidth optimization, assurance, and real-time analytics. This article examines Computer Vision and sensor-based technologies in intelligent agriculture.*

Keywords *- Sustainable development, Intelligent agribusiness, Livestock management, Wearable sensors, Computer Vision.*

1. Introduction

Conventional techniques for assessing the well-being of cattle in large herds are both ineffective and expensive, delivering only fragmentary data and generating substantial expenses in terms of manpower and technological advances [1]. The United Nations promotes sustainable development in the context of intelligent agribusiness by confronting technological, social, and economic issues. The organization strongly supports greater adoption of innovative agricultural technologies [2]. An efficient reporting mechanism facilitates agencies in planning for and promoting perception regarding livestock ailments, minimizing economic losses, and boosting productivity in the farming and processing of eggs, meat, and dairy products [3].

The integration of IoT and cognitive computing technologies in farming marked the start of the era of Agriculture 4.0, with an elevated focus on intelligence and automation [4]. The Internet of Things (IoT) will undoubtedly revolutionize livestock management by allowing dispersed farmers to obtain biological and ecological data. This breakthrough has the potential to boost production effectiveness and minimize labour expenses [5]. IoT improves real-time monitoring and automation of farming operations, leading to a reduction in manpower and the encouragement of sustainability through the integration of cutting-edge technology [6]. IoT technology captures, evaluates, and interprets real-time data on rumen acidification in livestock, which is imperative to livestock and herd health, guaranteeing legitimate pH measurement [7].

Farm automation and nanotechnology, for instance, serve a significant role in the effective and affordable administration of livestock on farms, minimizing the necessity for a substantial workforce [8]. In the past, researchers evaluated rumen conditions employing wireless sensor nodes equipped with pH monitoring tools. The limited capacity of the reference electrode, however, contributes to these nodes' limited life span [9]. The incorporation of sensors and computing algorithms in farming for real-time uninterrupted control and surveillance systems facilitates farmers to gain a greater understanding of the specific requirements of individual cattle and identify concerns at an early stage [10]. The emergence of on-farm and point-of-care technology is altering livestock operations, facilitating the early detection of transmissible diseases, eliminating economic losses, diminishing antimicrobial treatment infringement, and promoting overall livestock well-being [11].

The amalgamation of sensor technology with computer vision in cattle health surveillance has demonstrated considerable potential in improving livestock management. A key problem in employing computer vision for cattle monitoring is the precise identification of individual animals, particularly in dynamic and intricate surroundings. Despite substantial advancements in cattle health monitoring through sensors and computer vision, these technologies remain in a state of evolution. Addressing the recognized research deficiencies will necessitate interdisciplinary collaboration and sustained innovation. The study analyses a sensor and vision-based ecosystem for agriculture, focussing on technology, the internet, communication, and data storage. It includes positive aspects, challenges, future developments, and opportunities. The paper is presented in the following order of contents.

Section 2 discusses various innovative technological techniques for cattle health surveillance. Section 3 provides an overview of existing sensor-based cattle health technologies. Section 4 examines the methodology employed for cattle health management. Detailed information regarding the outcomes of the cattle health monitoring is provided in Section 5. Section 6 finally concludes this research article.

2. Innovative Technological Cattle Health Surveillance

Livestock farming is a valuable business globally; however, it confronts barriers such as health monitoring, livestock theft, and early ailments identification to minimize the possibility of both mortality and financial loss [12]. Precision agriculture integrates information, algorithms, engineering, livestock and veterinary sciences, and physiological functions to diligently track real-time livestock growth, behavior, well-being, and productivity. This enables farmers to make well-informed choices promptly [13]. The accessibility of real-time, trustworthy, and farm-specific information is essential for sustaining productivity. However, this expertise is often dispersed and delivered one-on-one. As a consequence, employing automated, specific, and cost-effective approaches becomes essential for accurate data gathering and transmission. [14].

In livestock ailments tracking, novel techniques such as Restriction Fragment Length Polymorphism (RFLP), DNA analysis, and real-time PCR are employed. These procedures necessitate expertise and access to contemporary laboratory facilities to perform accurate diagnosis and supervision [15]. An innovative approach that integrates an Inertial Measurement Unit with a Machine Learning (ML) model leverages a time-driven embedded sensor to reliably monitor and classify the activity of dairy cattle [16]. The latest studies explore avoiding infection by employing Internet of Things (IoT) sensors that capture real-time data and store it in cloud-based storage units. Users receive alerts via screening and statistical analysis, with their identities derived from the information being gathered [17].

In the livestock industry, the incorporation of IoT and data analytics possesses the potential to radically transform the business by discovering abnormalities in animal behavior associated with ailments such as lameness [18]. The establishment of a health diagnosis algorithm designed for livestock utilizes the capabilities of an intelligent harness to precisely evaluate the well-being of the livestock, offering valuable information for farmers in their decision-making processes [19].

Accurate identification of cattle individuals is vital for farming, disease prevention, authenticating meat products, and minimizing fraudulent insurance claims. This requires employing computational imaging technologies for identifying livestock faces and recognizing facial emotions [20]. Smart Farming promotes farming operations by minimizing costs, eliminating waste products, and reducing the demand for workforce. It makes utilization of sensor and ICT data to accelerate the implementation of technological innovations like ML and big data [21]. As a successor to cloud computing, fog and edge computing are attracting popularity for farming applications [22].

3. Sensor-Based Cattle Health Technologies

The integration of the Internet of Things (IoT) entails merging technologies such as wireless sensors, big data, and cloud computing, which will revolutionize agribusiness [23]. Sensor technology advancements are boosting the productivity and profitability of dairy livestock through tracking performance and physiological indicators. This encompasses heat detection alternatives, which leads to enhanced identification percentages [24]. Biosensors have become increasingly prevalent in epidemics, providing quick, economical, and user-friendly diagnostic outcomes in the actual environment. Their increasing popularity is attributed to their affordable prices [25]. Livestock activity, nutrition, body temperature, rumination, and rumen pH may all be monitored by employing wearable sensors. Responsive biosensors deliver significant distant data transfer, which is necessary for the rapidly developing business [26].

In the real world of livestock administration, nano-biosensors are essential for gauging animal health. They are beneficial for determining infectious ailments, reproductive cycles, dietary patterns, adverse reactions to medication, and evaluating livestock habitat [27]. The accessibility of off-the-shelf sensors, more substantial documenting capacity, enhanced data storage and computational power, and increasing focus on sustainable dairy farming are all driving the development of supervisory technological advances [28]. ZigBee Technology is connected to a Graphical User Interface (GUI) for digital data interpreting, coupled with a versatile sensor operational in an array of environments facilitating animal well-being surveillance [29]. A Wireless Sensor Network system (WSN) is developed by combining RFID, Zigbee modules, and additional sensors for monitoring and tracking livestock activity, including consuming food and water, weakness, heart rate, and body temperature [30].

Integration of technologies such as WSN, RFID, cloud computing and middleware systems in agribusiness leverages the potential of IoT and data analytics to boost operational effectiveness and output [31]. Agribusiness is experiencing an evolution as an impact of Artificial Intelligence (AI) and Machine Learning (ML) as extremely important innovations for monitoring the welfare of livestock, including hyperspectral imagery and 3D laser scanning [32]. Based on the input variables, an AI module has been designed to identify ailments in livestock and determine their state of wellness by diagnosing deep body temperature in real-world scenarios [33]. The adoption of emerging innovations such as AI and ML can lead to revolutionary improvements in animal husbandry optimization, cost reduction, and enhanced supervision of livestock welfare and health spanning numerous industries [34].

Innovative technology utilized in livestock operations can support early illness detection through real-time data analysis. This entails combining big data with ML and utilizing metabolomics as ailments indicators [35]. According to the latest research, Edge Computing, which uses IoT devices at network edges, delivers excellent solutions to minimize latency, strengthen privacy, and limit bandwidth costs in IoT applications [36]. AI-driven systems encompassing machine learning, deep learning, and swarm intelligence have shown significant promise in intelligent cognitive sensing, network administration, big data analytics, and boosting privacy for intelligent applications at the edge [37].

The application of AI in every aspect of the farming ecology includes livestock management, postharvest administration, processing, dispersion, utilization, and waste management [38]. Due to the expensive setup costs, complex machinery requirements, and the absence of connectivity among multiple vendors in present mechanisms, identifying lameness in dairy cattle renders a substantial economic barrier [39]. An approach for monitoring cattle health employing UAVs and IoT devices intends to promote consumer consciousness about food quality. It also promises to supply vital information to the national ecosystem for livestock marketing [40].

A revolutionary supervision methodology utilizes deep learning models based on Convolutional Neural Networks (CNNs) to classify cattle postures into two categories: ruminating and other. This approach represents long-term oscillations in understandable 2D imagery [41]. Based on the literature review, Figure 1 illustrates how farmers can monitor the health of their cattle on a mobile app. Or a personal computer assisted by various sensors like humidity and temperature sensors, motion sensors, pH sensors and others, the data is stored in the cloud, which can be accessed by the farmer anytime, anywhere.

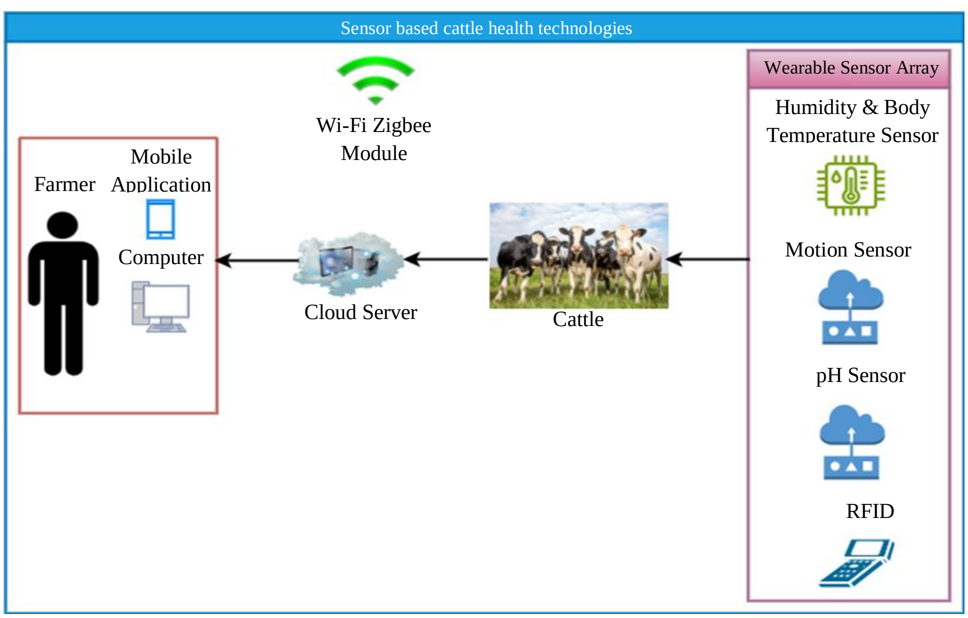

Fig. 1 Sensor-based cattle health monitoring

4. Methodology

We have implemented two approaches to assess cattle health. The first method involves collecting real-time data on cattle using sensors, while the second method uses a vision-based solution to assess cattle health.

4.1. Monitoring the Well-being of Cattle Using Computer Vision

The integration of technology in animal husbandry has facilitated improved monitoring of cattle health. Therefore, we demonstrate the development of a machine learning model for cow welfare that would provide real-time automated monitoring of several aspects of animal health and behaviour.

Fig. 2 Vision apparatus for observing the health of livestock

A Visual device for assessing the well-being of cattle is shown in Figure 2. The Raspberry Pi, an affordable portable computing system, can be utilized by farmers as it allows for inexpensive expansion without requiring extensive infrastructure, providing continuous surveillance. It integrates computer vision and machine learning methodologies for evaluating photos or videos of livestock, facilitating precise assessment of their welfare and physical condition at any moment. The Algorithmic approach of Computer Vision is shown in Figure 3.

The image data is categorized into 7 classes: Grazing, Sitting, Standing, Healthy, Unhealthy, Human, and unlabeled, each indicating distinct clusters within the dataset. Subsequently, the dataset for each relevant class will be manually annotated. Subsequent to the annotation, conduct pre-processing of the dataset by resizing it to 360x360 pixels, followed by doing augmentation on the resized photos. Execute augmentation on the resized images: flip, shear, greyscale, saturation, and brightness.

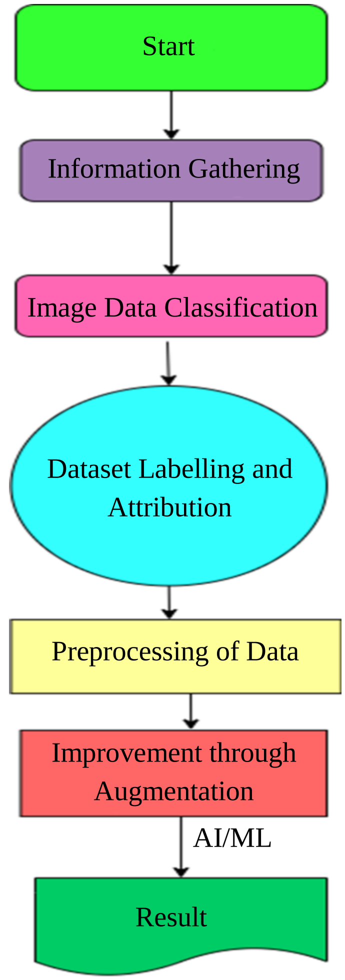

Fig. 3 Computer vision from an algorithmic point of view

Table 1 presents a comprehensive overview of the quantity of annotations relevant to each classification within the dataset.

Table 1. Comprehensive overview of the quantity of annotations relevant to each classification within the dataset

Class Name	Total Count	Training Count	Validation Count	Test Count
Unhealthy	1434	988	310	136
Healthy	1256	891	233	132
standing	217	164	29	24
Grazing	143	115	13	15
sitting	49	31	6	12
Human	9	6	2	1
Unlabeled	1	1	0	0

4.2. Monitoring the Well-being of Cattle Using SENSORS

Figure 4 depicts the architecture for monitoring cattle health through the utilization of sensors. Sensors systematically gather data at specified intervals. The Temperature sensor provides quantifications of bodily temperature. The heart rate sensor collects information related to pulse rate. The accelerometer records patterns of activity and movement.

The ESP32 processes raw sensor data, implements filtering techniques to reduce noise, and computes relevant metrics such as the average heart rate or motion indices. The data is thereafter transmitted to the Thing Speak/Blynk server. The data from the ThingSpeak/Blynk server is analyzed using algorithms to detect irregularities in the cattle's health.

Upon detection of any anomalies, notifications are dispatched to the farmer's mobile device. An extensive amount of data generated by sensing devices is directed to the cloud owing to the introduction of IoT-enabled sensor nodes. If the collected data is extensive, local processing of such data is impractical.

The local server experiences obstacles in its function to receive, store, manage, and process the extensive amount of data arising from IoT-connected devices. A cloud server is an online server that utilizes a cloud computing platform for its operations. It is a software-based representation of a physical server that can be constructed, configured, and managed using software tools rather than hardware components.

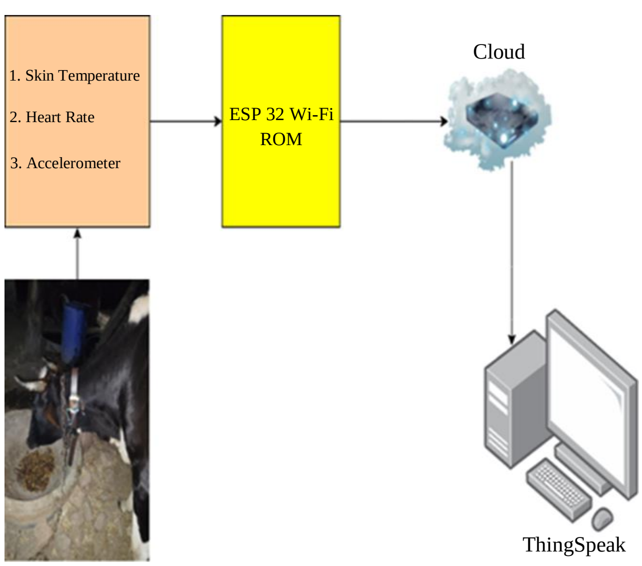

Fig. 4 Architecture for cattle health monitoring

Figure 5 illustrates IoT equipment, including skin temperature sensors, heart rate monitors, and accelerometers, which provide the monitoring of bovine health through these three metrics. Corporal temperature, cardiac frequency, activity level of exertion.

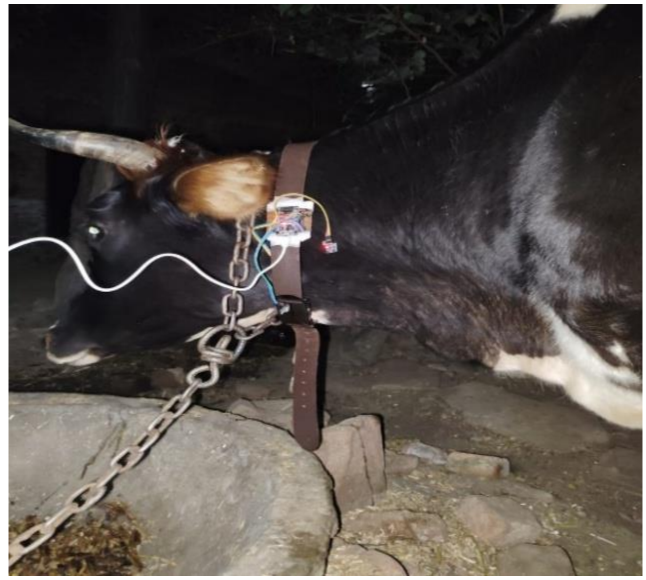

Fig. 5 Real-time execution of intelligent collar device

5. Results

Figure 6 illustrates the results obtained from the Computer Vision model pertaining to Grazing cattle. Figure 7 illustrates the results obtained from the Computer Vision model pertaining to Healthy Cattle, specifically through the examination of eye characteristics. The validation accuracy of the model trained using COCO v12 is 96.7% in this study. The real-time data is systematically gathered from cattle equipped with smart collar gadgets in the Firozabad district of Uttar Pradesh, spanning the period from June 1, 2023, to June 1, 2024, at two-hour intervals.

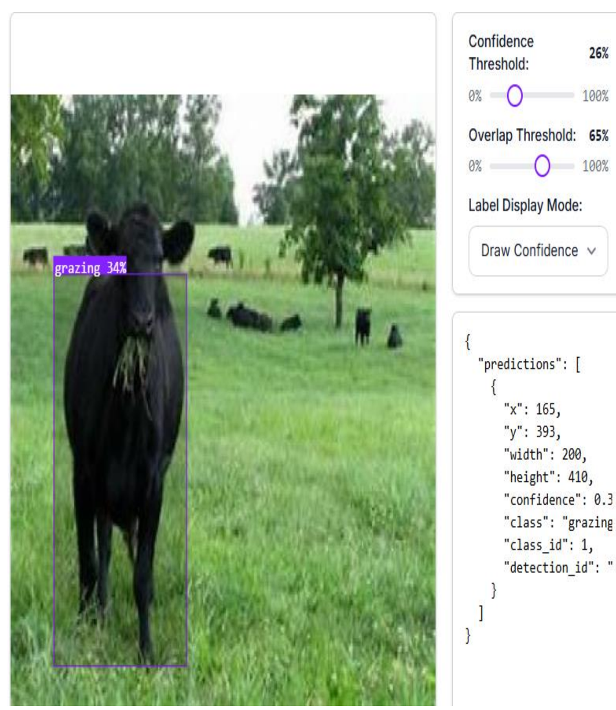

Fig. 6 Model output utilizing computer vision

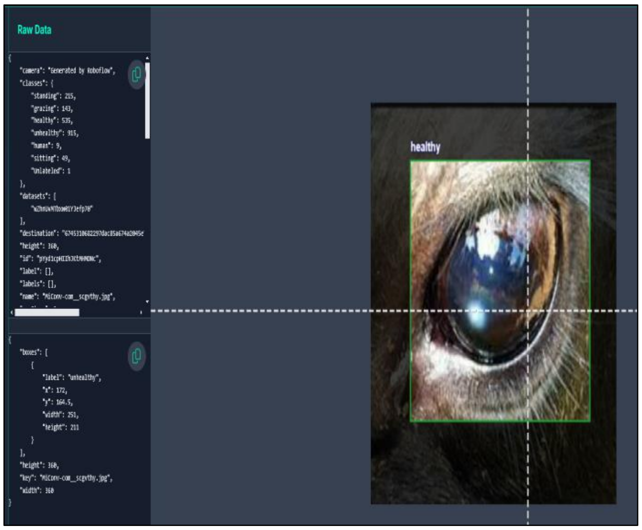

Fig. 7 Model output utilizing computer vision

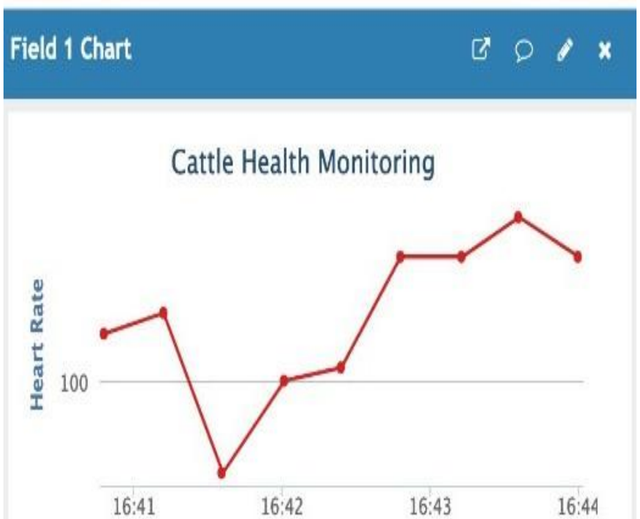

Fig. 8 Cattle hear rate monitoring on Thing Speak

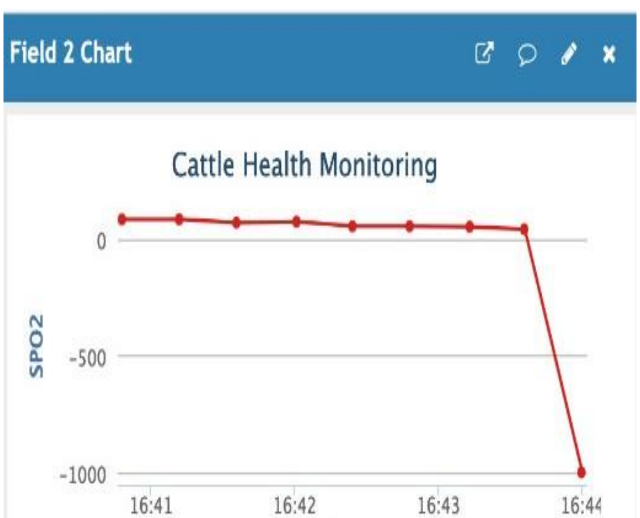

Fig. 9 Cattle SPO2 monitoring on Thing Speak

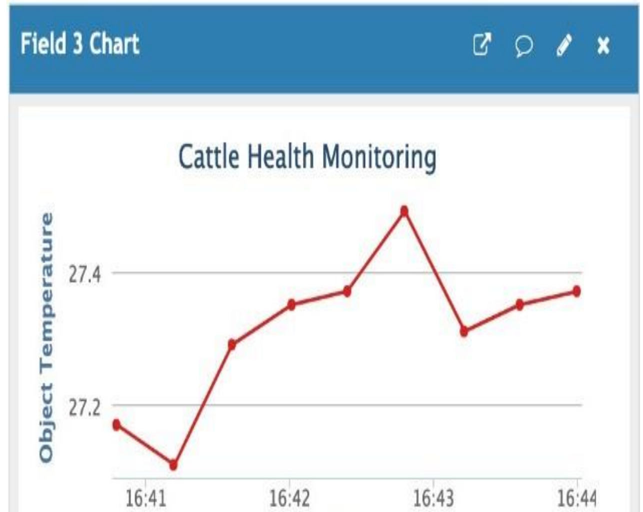

Fig. 10 Cattle temperature monitoring on Thing Speak

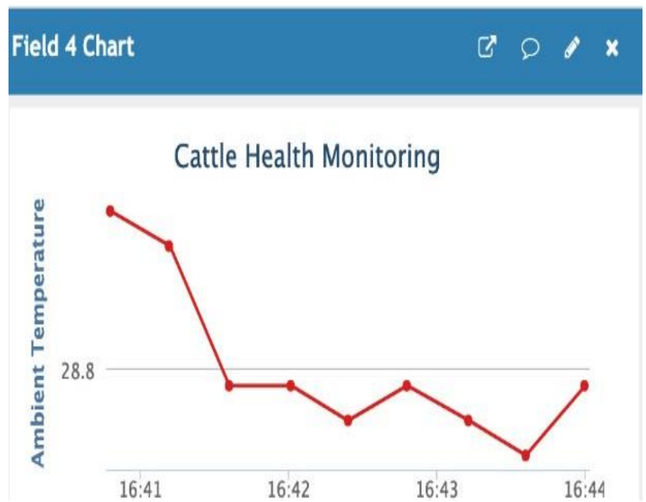

Fig. 11 Ambient temperature surveillance employing the ThingSpeak framework

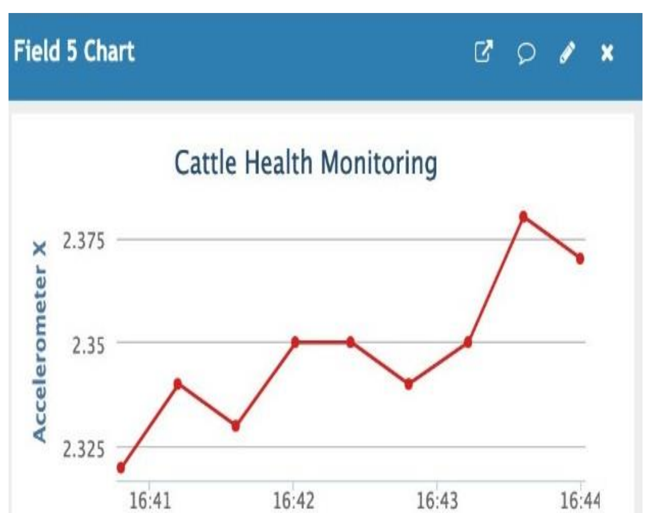

Fig. 12 Monitoring the forward or backward locomotion of cattle using Thing Speak

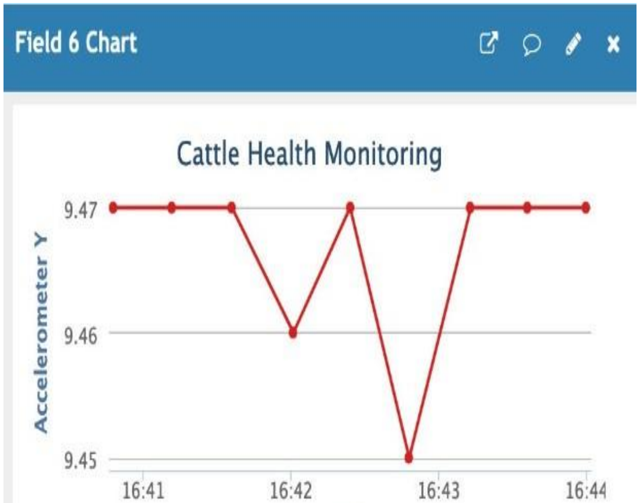

Fig. 13 Monitoring lateral movements of cattle utilizing Thing Speak

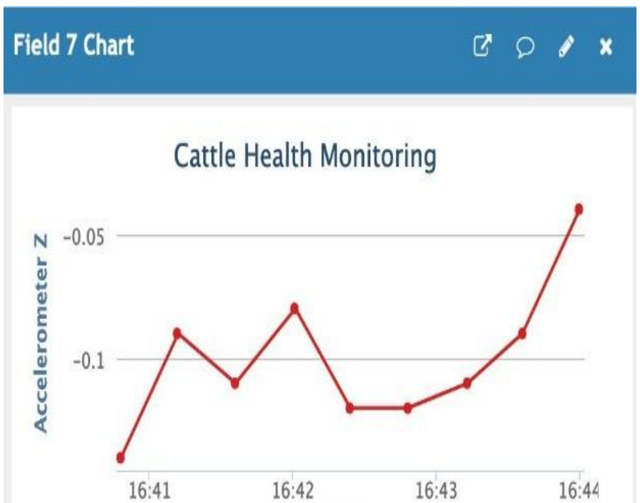

Fig. 14 Monitoring the vertical movement of cattle as a result of steps or alterations in body posture utilizing Thing Speak

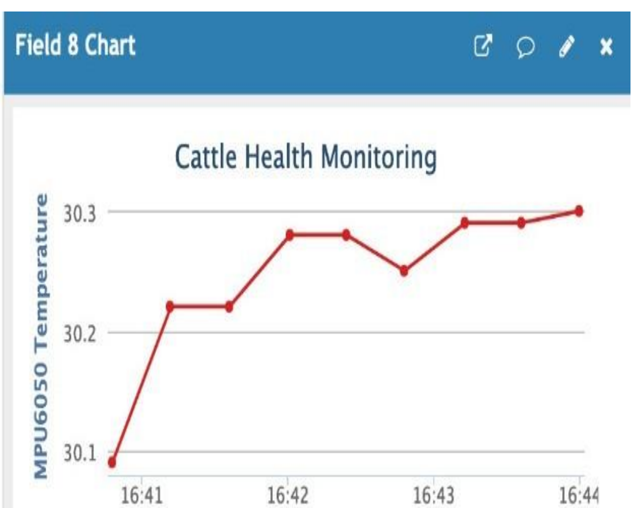

Fig. 15 Assessing the internal thermal parameters of the sensor chip through the utilization of the ThingSpeak platform

The dedicated gateway and sensor node are interconnected and communicate with the Thing Speak server via Wi-Fi and the API. Analysis of the authentic data connection facilitated by the embedded sensor nodes was conducted. For the efficient and precise prediction of meteorological variables, a machine learning approach is implemented on real data collected through nodes.

In order to implement machine learning on real-time data acquired from collar neckbands, it is imperative to first engage in data pre-processing, which consists of data cleaning, feature extraction, data synchronization, and normalization/scaling. Data visualization is a key component of exploratory data analysis, which aims to find correlations between sensor readings and health outcomes and spot anomalies and outliers to reveal patterns and trends.

Import all requisite libraries for data analysis and machine learning jobs, subsequently loading the ‘Cattle Health.csv’ dataset utilizing Pandas. The subsequent phase entails the manipulation of the data for the purpose of modeling, which includes the rectification of absent values as well as the encoding of categorical variables. Ultimately, the methodology segments the dataset into training and testing subsets while employing Standard Scaler to normalize the numerical attributes.

Table 2 showcases the conclusive dataset employed in analytical procedures, modelling frameworks, or decision-making processes (Shown in Appendix).

6. Conclusion

The livestock business is rapidly embracing innovative applications that leverage cloud-based sensors and technological devices. However, persistent challenges in this sector, such as privacy, security, mobility assistance, data processing, energy efficiency, escalating hardware prices, and internet connectivity inaccuracies, highlight the relevance of continued research and integration endeavours. There is a requirement for an innovative framework that incorporates livestock health monitoring and mobility tracking, integrating together components from diverse platforms into one platform to enable thorough analysis of ailments.

The article covers how IoT and data analytics are being employed in farming, emphasizing limitations and unresolved research in optimizing production and efficiency in operations. The objective of the research is to identify the potential advantages of IoT adoption in agriculture. The study established an approach for tracking cattle well-being and whereabouts, featuring feedback broadcast on online and mobile applications. This technology monitors cattle’ dietary habits, regions, and physiological conditions by placing sensors in headgear. The livestock head-strap sensors monitor eating habits, inhabiting settings, and the cattle’s physiological state. These data are cautiously transferred to applications, with potential improvements such as integrating cardiovascular and humidity sensors. The adoption of IoT solutions in intelligent farming is essential since it promotes efficiency, guarantees the production of nutritious and sustainable food, and facilitates food traceability. Exciting future research possibilities include investigating breakthroughs in guarantee and communication technology.

References

[1] Mohamed Gameil, and Tarek Gaber, "Wireless Sensor Networks-Based Solutions for Cattle Health Monitoring: A Survey," *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics*, pp. 779-788, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[2] M.J. O'Grady, D. Langton, and G.M.P. O'Hare, "Edge Computing: A Tractable Model for Smart Agriculture?," *Artificial Intelligence in Agriculture*, vol. 3, pp. 42-51, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[3] K.P. Suresh et al., "Livestock Disease Risk Forewarning Methodology-March 2023," *ICAR-NIVEDI*, vol. 11, no. 2, pp. 1-51, 2023. [Google Scholar] [Publisher Link]

[4] Sasmita Padhy et al., "AgriSecure: A Fog Computing-Based Security Framework for Agriculture 4.0 via Blockchain," *Processes*, vol. 11, no. 3, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Wataru Iwasaki, Nobutomo Morita, and Maria Portia Briones Nagata, "IoT Sensors for Smart Livestock Management," *Chemical, Gas, and Biosensors for Internet of Things and Related Applications*, pp. 207-221, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[6] Syed Anas Ansar et al., "A Step towards Smart Farming: Unified Role of AI and IoT," *Computer Vision and Robotics*, pp. 557-578, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Fatih Başçiftçi, and Kamil Aykutalp Gündüz, "Identification of Acidosis Disease in Cattle Using IoT," *2019 4th International Conference on Computer Science and Engineering (UBMK)*, Samsun, Turkey, pp. 58-62, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[8] Navaneethan Renuga Devi et al., "Animal Health Monitoring Using Nanosensor Networks," *Nanosensors for Smart Agriculture*, pp. 573-608, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Hirofumi Nogami et al., "Minimized Bolus-Type Wireless Sensor Node with a Built-in Three-Axis Acceleration Meter for Monitoring a Cow's Rumen Conditions," *Sensors*, vol. 17, no. 4, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[10] Deepika Sharma, Jayati Mishra, and Nibedita Talukdar, "Application of Precision Livestock Farming for Improved Goat Management and Production," *Revista Electronica de Veterinaria*, vol. 24, no. 2, pp. 461-470, 2023. [Google Scholar] [Publisher Link]

[11] Mohamed Zeineldin et al., "On-Farm Point-of-Care Diagnostic Technologies for Monitoring Health, Welfare, and Performance in Livestock Production Systems," *Sustainable Agriculture Reviews 54*, pp. 209-232, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Kennedy Okokpujie et al., "Development of a Sustainable Internet of Things-Based System for Monitoring Cattle Health and Location with Web and Mobile Application Feedback," *Mathematical Modelling of Engineering Problems*, vol. 10, no. 3, pp. 740-748, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Shyamasree Ghosh, and Rathi Dasgupta, *Machine Learning in Biological Sciences: Updates and Future Prospects*, 1st ed., Springer Singapore, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Amsale Zelalem Bayih et al., "Utilization of Internet of Things and Wireless Sensor Networks for Sustainable Smallholder Agriculture," *Sensors*, vol. 22, no. 9, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[15] Anuj Tewari et al., "Biosensors: Modern Tools for Disease Diagnosis and Animal Health Monitoring," *Biosensors in Agriculture: Recent Trends and Future Perspectives*, pp. 387-414, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Brahim Achour et al., "Classification of Dairy Cows' Behavior by Energy-Efficient Sensor," *Journal of Reliable Intelligent Environments*, vol. 8, no. 2, pp. 165-182, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Mohammad Meraj et al., "A Critical Review of Detection and Prediction of Infectious Disease Using IoT Sensors," *2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Coimbatore, India, pp. 679-684, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mohit Taneja et al., "Connected Cows: Utilizing Fog and Cloud Analytics toward Data-Driven Decisions for Smart Dairy Farming," *IEEE Internet of Things Magazine*, vol. 2, no. 4, pp. 32-37, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[19] Chaowei Jia, and Fei Dong, "Research on Intelligent Collar Animal Husbandry Health Diagnosis Service Platform Based on Cloud Computing," *2022 World Automation Congress (WAC)*, San Antonio, TX, USA, pp. 489-493, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[20] Beibei Xu et al., "Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle," *Agriculture*, vol. 11, no. 11, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[21] Sargam Yadav et al., "Disruptive Technologies in Smart Farming: An Expanded View with Sentiment Analysis," *Agri Engineering*, vol. 4, no. 2, pp. 424-460, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Yogeswaranathan Kalyani, and Rem Collier, "A Systematic Survey on the Role of Cloud, Fog, and Edge Computing Combination in Smart Agriculture," *Sensors*, vol. 21, no. 17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Vu Khanh Quy et al., "IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges," *Applied Sciences*, vol. 12, no. 7, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Serap Göncü, and Nazan Koluman, "The Sensor Technologies for More Efficient Cow Reproduction Systems," *MOJ Ecology & Environmental Sciences*, vol. 4, no. 3, pp. 128-131, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[25] Shesh Asopa, and Ashish Joshi, "Biosensors: Advanced Tools for Disease Diagnosis and Animal Health Monitoring," *Current Advances in Agriculture, Animal Husbandry and Allied Sciences (CAAAS)*, pp. 45-49, 2023. [Google Scholar]

[26] Karina Džermeikaitė, Dovilė Bačėninaitė, and Ramūnas Antanaitis, "Innovations in Cattle Farming: Application of Innovative Technologies and Sensors in the Diagnosis of Diseases," *Animals*, vol. 13, no. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[27] Sumaira Younis et al., "Nanosensors for Animal Health Monitoring," *Nanosensors for Smart Agriculture*, pp. 509-529, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Ephraim Maltz, "Individual Dairy Cow Management: Achievements, Obstacles and Prospects," *Journal of Dairy Research*, vol. 87, no. 2, pp. 145-157, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[29] P. Keertana, B. Vanathi, and K. Shanmugam, "A Survey on Various Animal Health Monitoring and Tracking Techniques," *International Research Journal of Engineering and Technology*, vol. 4, no. 2, pp. 533-536, 2017. [Google Scholar] [Publisher Link]

[30] AftabAhmed Isak Mulla et al., "Continuous Health Surveillance System for Cattle," *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, pp. 1192-1195, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[31] Olakunle Elijah et al., "An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3758-3773, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[32] Mohd Javaid et al., "Understanding the Potential Applications of Artificial Intelligence in Agriculture Sector," *Advanced Agrochem*, vol. 2, no. 1, pp. 15-30, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] Sai Ma et al., "Development of Noncontact Body Temperature Monitoring and Prediction System for Livestock Cattle," *IEEE Sensors Journal*, vol. 21, no. 7, pp. 9367-9376, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[34] Manisha Malhotra et al., "Application of AI/ML Approaches for Livestock Improvement and Management," *Biotechnological Interventions Augmenting Livestock Health and Production*, pp. 377-394, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[35] Andrea Puig et al., "Technological Tools for the Early Detection of Bovine Respiratory Disease in Farms," *Animals*, vol. 12, no. 19, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[36] Inés Sittón-Candanedo et al., "A Review of Edge Computing Reference Architectures and a New Global Edge Proposal," *Future Generation Computer Systems*, vol. 99, pp. 278-294, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[37] Amira Bourechak et al., "At the Confluence of Artificial Intelligence and Edge Computing in IoT-Based Applications: A Review and New Perspectives," *Sensors*, vol. 23, no. 3, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[38] Innocent Kutyauripo, Munyaradzi Rushambwa, and Lyndah Chiwazi, "Artificial Intelligence Applications in the Agrifood Sectors," *Journal of Agriculture and Food Research*, vol. 11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[39] Mohit Taneja et al., "Machine Learning Based Fog Computing Assisted Data-Driven Approach for Early Lameness Detection in Dairy Cattle," *Computers and Electronics in Agriculture*, vol. 171, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[40] Khouloud Hwerbi et al., "Veterinary Drone: Blockchain-Based System for Cattle Health Monitoring," *2023 International Wireless Communications and Mobile Computing (IWCMC)*, Marrakesh, Morocco, pp. 1613-1618, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[41] Safa Ayadi et al., "Dairy Cow Rumination Detection: A Deep Learning Approach," *Distributed Computing for Emerging Smart Networks*, pp. 123-139, 2021. [CrossRef] [Google Scholar] [Publisher Link]

Appendix:

Table 2. Conclusive dataset

Data	X	Y	Z	Body Temperature	Heart Rate	Activity	Health Status
01-06-2023 00:00	2.09	-1.36	0.7	38.1	89	Walking	Unhealthy
01-06-2023 02:00	2.32	-0.15	1.34	38.3	52	Walking	Unhealthy
01-06-2023 04:00	0.86	2.36	1.61	38.4	73	Walking	Healthy
01-06-2023 06:00	1.54	2.51	1.82	38.4	54	Walking	Unhealthy
01-06-2023 08:00	2.25	2.11	0.52	39.2	82	Walking	Unhealthy
01-06-2023 10:00	1.3	-0.7	-0.94	38.5	85	Walking	Unhealthy
01-06-2023 12:00	1.58	2.14	0.7	39	85	Walking	Unhealthy
01-06-2023 14:00	2.79	-0.3	0.74	38.8	85	Walking	Unhealthy
01-06-2023 16:00	1.33	1.95	-0.39	39.3	64	Walking	Healthy
01-06-2023 18:00	0.39	-1.69	0.52	39.1	58	Walking	Unhealthy
01-06-2023 20:00	1.68	-0.63	1.61	38	73	Walking	Healthy
01-06-2023 22:00	1.02	-1.94	0.56	39.3	51	Walking	Unhealthy
02-06-2023 00:00	0.1	0.62	0.43	37.8	81	Walking	Unhealthy
02-06-2023 02:00	1.64	0.27	0.52	39.2	50	Walking	Unhealthy
02-06-2023 04:00	1.63	-0.15	0.35	39.5	74	Walking	Healthy
02-06-2023 06:00	0.76	-0.68	-0.79	39.6	60	Walking	Unhealthy
02-06-2023 08:00	0.84	-1.87	-0.2	38.3	66	Walking	Healthy
02-06-2023 10:00	1.96	1.01	-0.31	39.3	89	Walking	Unhealthy
02-06-2023 12:00	2.2	0.05	1.41	39.8	85	Walking	Unhealthy
02-06-2023 14:00	0.38	-0.76	-1.07	39.9	77	Walking	Unhealthy
02-06-2023 16:00	1.7	1.04	-0.7	37.8	56	Walking	Unhealthy
02-06-2023 18:00	2.05	0.35	0.69	38.9	55	Walking	Unhealthy
02-06-2023 20:00	1.74	-1.32	1.36	39.4	60	Walking	Healthy
02-06-2023 22:00	1.74	1.25	0.22	38.7	81	Walking	Unhealthy
03-06-2023 00:00	1.56	1.73	-0.64	38.7	60	Walking	Healthy
03-06-2023 02:00	2.82	-0.18	1.53	38.1	61	Walking	Healthy