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Review

An Imperative Role of Digitalization in Monitoring Cattle Health for Sustainability

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Abstract: In the current context, monitoring cattle health is critical for producing abundant milk to satisfy population growth demand and also for attaining sustainability. Traditional methods associated with cattle health must be strengthened in order to overcome the concern of detecting diseases based on the health condition. This problem has moved attention toward digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, edge/fog computing, big data, blockchain, drones, robotics, and augmented reality (AR)/virtual reality (VR), as these technologies have proved for real-time monitoring, intelligent analytics, secure data distribution, and real-time visual experience. The purpose of this study is to examine and discuss many cattle health disorders, as well as to address the fundamental notion of digital technologies, as well as the significance of these technologies for cattle health. Furthermore, the article addressed the different devices that integrated IoT and AI for cattle health monitoring, in which the previous architecture of cattle health monitoring is presented. Based on the review, the article discusses the challenges and suggests recommendations that can be implemented for the future work

Keywords: IoT; AI; animal health monitoring; cattle; digital technology

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1. Introduction

Agriculture is the primary source of income in rural areas. Farmers must therefore use efficient and technical methods to increase productivity while reducing animal husbandry and crop-related problems. The agriculture industry is currently facing several issues, including demography, food waste, and natural resource constraint. According to the FAO, humans would need to generate 70% more food by 2050 [1] Dairies are encouraging farmers in South Asian countries such as India, Bangladesh, and Bhutan to use artificial insemination to increase the number of cattle. In recent times, livestock farmers all over the world have faced cattle health issues as a result of the continuous rise in air pollution. The tropospheric temperature, Temperature fluctuations on animal health has a negative impact, leading to diseases such as swine fever, foot, and mouth disease, bovine spongiform disease encephalopathy, polioencephalomalacia, bovine rhinotracheitis, hypomagnesemia, clostridia polioencephalomalacia, clostridia disease, warts, web tear, necrotic pododermatitis, squamous cell carcinoma and hypoglycemia [2]. Animal diseases can reason significant economic, social, and environmental harm, and in a few cases, they can endanger human well-being. Various threats ascending from the livestock sector and various zoonotic contagious illnesses have global-scale features, depending on the effects of global change.

The World Organization for Animal Health encourages members in high-risk areas to launch immunization efforts ahead of the arrival of animal diseases and to continue timely reporting of all outbreaks [3]. Cattle activity patterns, such as decreased or increased activity over compound days in average daily activity levels, are linked to the animal's health and welfare and can be a display of illness [4]. When animals are unwell, their entire physical activity is reduced, including water and food intake, sexual behavior, aggression, and social performance [5]. Declined activity quantities in cattle can indicate infected cattle. Rumination monitoring is one of the most effective methods for assessing and maintaining your cattle's health [6]. A rumination rate of 500 (+100) min per day suggests healthy and happy cows, whereas lower rumination levels imply rumen function or health issues. The main contribution of the research is:

- We discussed the different diseases that affect the cattle animal on the dairy farm.
- The fundamental notion of digital technologies, as well as the significance of these technologies for cattle health, are presented in detail.
- A detailed discussion on hardware devices and prototypes that are implemented in the previous studies for monitoring cattle health.
- Finally, the article presents a detailed discussion and suggested significant recommendations that can be applied in the future.

The organization of the study is: Section 2 delivers an overview of diseases in cattle; Section 3 provides a discussion on different existing technologies for real-time monitoring of animal health; Section 4 discusses the devices and prototypesforcattle health monitoring; Section 5 provides the discussion and recommendations.

2. Overview of Diseases in Cattle

Cattle health is one of the primary concerns of most farmers concerned with growth and cultivation, as cattle wellbeing has a direct influence on output [7]. Physically monitoring the health of cattle can be difficult, especially when the population is large. Various categories of diseases arise in cattle. One of the most serious issues affecting cattle and buffalo calves is parasitism. Protozoa and helminths, which include trematodes, cestodes, and nematodes, are examples of endoparasites. These parasites have an impact on animal health and productivity [8]. Ectoparasitic plagues such as pediculosis, scabies, tungiasis, myiasis, and cutaneous larva migrans are common but often overlooked disorders [9]. Mastitis is the most expensive disease of dairy cows, with lower milk output causing the greatest economic loss [10]. Mycoplasma Bovis is a significant and emerging cause of respiratory disease and arthritis in feedlot cattle and it occurs when an illness affects the lung's air sacs to fill up with liquid or pus [11].

Clostridium chauvoe infectious disease is distinguished by skeletal muscle inflammation, gaseous oedema, and severe toxaemia [12]. Bovine ephemeral fever is a viral disease that affects cattle and buffaloes, as well as ruminant species in the subclinical stage and it causes milk production losses, and recumbency [13]. Foot-and-mouth disease is a costly viral illness impacting cattle around the world [14]. The rabies virus infects mammals' central nervous systems, resulting in brain disease and death [15]. Dipterous larvae in mammals can feed on the host's living, and swallow food liquid body material, resulting in a wide range of infestations depending on the body location and the larvae's connection with the host [16]. Acidosis is caused by a build of carbon dioxide in the blood caused by poor lung function or slow breathing, or by an excess of acid in the blood or an excessive loss of bicarbonate from the blood [17].

Anestrus is a broad term that refers to the absence of estrous expression even though effective estrus exposure. Anestrus is typically defined by a decrease in ovarian progesterone production [18]. Retaining the placenta (RP) is also known as retaining the fetal membrane or retaining the cleansing. When the fetal membranes on the calf's side of the placenta fail to separate from the mother's side, RP occurs [19]. An injury is a wound. Wounds in domestic animals can occur as a result of fighting injuries, animal/insect bites, barbed wire injuries while grazing, accidents, and blows [20]. LSD is a destructive infection of cattle affected by the capripox virus. The symports of LSD are on the skin around the head, neck, genitals, and limbs raised nodules to 50 mm in diameter form these nodules can appear anywhere on the body. In this disease scabs form in the center of the nodules and fall off, creating huge, potentially infected wounds [21]. Table 1 addresses the different diseases in cattle with percentages. This clearly defines the type of diseases and the number of cases that have been registered to date.

Table 1. Different diseases in cattle with percentages.

S. No	Disease and Disorder	Cattle No. of Cases	Percentage
1	FMD	8	8.89%
2	Dermatitis	3	3.33%
3	Rabies	2	2.22%
4	Pneumonia	2	2.22%
5	Infectious bovine keratoconjunctivitis	1	1.11%
6	Mastitis	4	4.44%
7	Black quarter	1	1.11%
8	Endoparasitic infestation	14	15.56%
9	Bovine ephemeral fever	7	7.78%
10	Myiasis	3	3.33%
11	Babesiosis	1	1.11%
12	Ectoparasitic infestation	5	5.56%
13	Indigestion	4	4.44%
14	Bloat	6	6.67 %
15	Acidosis	4	4.44%
16	Retention of placenta	2	2.22%
17	Milk fever	1	1.11%
18	Diarrhea/Enteritis	7	7.78%
19	Wound	2	2.22%
20	Anestrous	4	4.44%
21	Alopecia	3	3.33%
22	Pyometra	1	1.11%
23	Papillomatosis	1	1.11%
24	Dermatophytosis	2	2.22%
25	Poisoning	2	2.22%
	Total	90	100%

The identification of all these diseases in cattle by a normal person is a challenging task. Every disease has comprised of its symptoms, and the characterization of diseases by the symptoms requires a trained and skilled person. However, there is a requirement for a real-time monitoring system, that detects the disease based on input data, i.e., sensor and visual data. Currently, there are different technologies including IoT, AI, DL, ML, blockchain, and robotics that can deliver a digital solution with real-time analytics and also with advanced security. IoT sensors embedded in the cattle obtain sensory data, and the vision-based device obtains visionary data. Pre-trained AI/DL/ML model can be applied to this data, based on input attributes the model will detect the diseases and send the disease detected to the vision device. Robotics also assists to collect vision data during the feeding process. Drones are used for tracking and capturing the visuals of the cattle in an outdoor environment. All these data can log into the cloud and also for better visualization on the digital platform. In addition to this, blockchain empowers to enhance the security of the data and also distributed in peer-2-peer network for better treatment and diagnosis to the cattle from any location.

3. Overview of Digital Technologies

Effective animal health observation techniques need consistent, high-quality, and sensible data for decision-making. Various Technologies are used to monitor Animal health.

Integrating information from several sources can assist in early disease identification and response through animals as well as early outbreak control. In this section, we will discuss the different digital technologies that empower the delivery of the digital network for real-time monitoring and prediction.

(a) Internet of Things (IoT)

IoT is a modern concept that allows electronic appliances and sensors to connect via the internet to improve our lives [22]. Overall, IoT is an innovation that brings altogether a broad variety of sensors, intelligent devices, and smart systems. Additionally, it makes use of quantum and nanotechnology to achieve previously unimaginable levels of storage, sensing, and computing speed. Figure 1 shows the different wireless technologies implemented for IoT Applications [23].

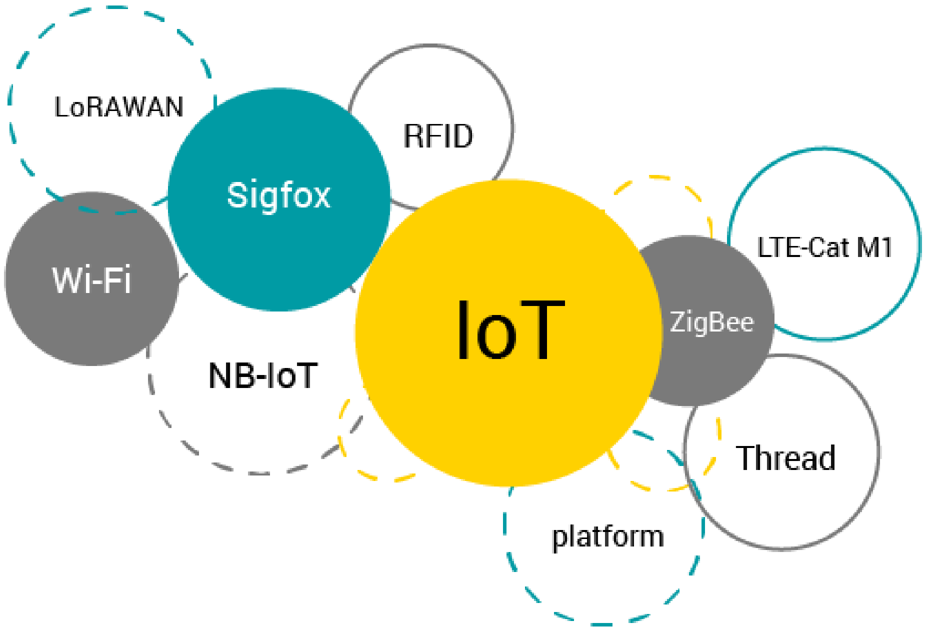

Figure 1. The technology behind the Internet of Things.

ZigBee has proven to be a reliable communication protocol for IoT networks. It can support a large number of nodes and has a range of up to 900 feet. The benefits of ZigBee include high scalability, low power consumption, strong security, and durability [2]. Long Range (LoRa) is a wide area network technology with a transmission range of up to 10 miles [24]. Narrow Band IoT (NB-IoT) is developed exclusively for networks that require low bandwidth to support high connection density with low latency. Transmission range of NB- IoT communication protocol is up to 20 miles (indoors and underground) [25]. Wireless Fidelity (Wi-Fi) is the most widely used IoT communication protocol for wireless local area networks based on the IEEE 802.11 standard, allowing for reliable communication between connected devices within a range of 115–230 ft [26].

Thread is a low-power wireless mesh networking protocol that was created to address the IoT's unique interoperability, security, power, and architecture challenges. The communication protocol, which is based on IEEE 802.15.4 radio standards, can self-heal and reconfigure when devices are added or removed. The range of Thread Communication Protocol is up to 115–230 ft [27]. SigFox has adopted a novel approach to the IoT concept and transformed it into a typical network operator's business model. The LPWAN family of technologies, which includes SigFox technology, is used primarily for the development of IoT networks when the volume of data supplied is minimal. The operational range is very long (tens of kilometers), and the current consumption is extremely low [28]. LTE CAT M1, commonly referred to as LTE-M, is a cellular LPWAN technology that excels at sending low to medium data rates (200–400 kbps) over a large geographic area. However, because it operates with a greater frequency bandwidth of 1 MHz, it can transmit data at a rate of up to 1 Mbps. The specifications state that Cat-M1 has lower latency than NB-IoT [29].

Table 2 illustrates the comparison of various wireless technologies. In the table, the technical specifications of the different communication protocols have been discussed with advantages and disadvantages. The implementation of the thread, Zigbee communication limits the data transmission to short-range; Wi-Fi consume high power for data transmission and interference problem. Currently, LPWAN technologies such as LoRaWAN, SigFox, and NB-IoT has gained significant attention in the data transmission of IoT network.

Table 2. Comparison of Various Wireless Technology [30].

Attribute	Wi-Fi	ZigBee	Thread	NB-IoT	SigFox	LoRaWAN	LTE-Cat M1
Frequency Bands	2.4 GHz and 5 GHz	2.4 GHz ISM Band	2.4 GHz ISM Band	800–900 Mhz	962–928 MHz	865–867 MHz	1.08 MHz
Range	15–100 m	10–100 m	20–30 m	1–10 km	10–50 km	2–20 km	1–10 km
Data Rate	600 Mbps	250 KbPS	250 Kbps	230 Kbps	100 Bps	10 kbps–0 Kbps	Up to 1 Mbps
Power Consumption	Medium	Low	Low	Low	Low	Low	Medium
Topology	Star	Star, Tree, Mesh	Mesh	Star	Mesh	Mesh	Mesh
Advantages	Large-scale data transfers, with voice calls and video streaming, enabled via high-speed wireless connectivity	The node support for Zigbee technology is high. One network can accommodate thousands of nodes	Multiple tasks from an application can be run simultaneously and reduce a large application's complexity	Under licensed frequency ranges, it achieves excellent coexistence performance with GSM and LTE	With SigFox, you may have long-distance communications that are inexpensive, simple to connect to, use little power, and emit little electromagnetic radiation	Due to its simple architecture, a single LoRa Gateway device is intended to manage thousands of end devices or nodes	Provide better coverage even in challenging environments such aa basements, and because it is a P2P technology, it works well in rural areas with lower meter densities.
Disadvantages	There could be significant co-channel interference.	Zigbee has a low bit rate, which also affects how quickly data is transmitted using this technology.	The developers have to spend more time on thread synchronization, which increases the risk of data inconsistency or thread sync problems.	Due to NB-limited IoT's downlink capacity, reliability is a problem because only half of the messages are acknowledged, which is inconvenient.	Due to the low receiving power used, the SigFox network can be jammed by any nearby device, which poses a reliability concern.	For real-time applications demanding lower latency and bounded jitter constraints, it is not the best choice.	LTE Cat-M1 is still an emerging technology with limited global coverage.

Biological Effect: Animal health is affected by radiofrequency radiation (RFR) exposure via wireless technologies such as Wi-Fi. RFR can be hazardous to animals because it can affect their reproductive health, circadian rhythms, circadian rhythms, healing, hormone balance, and immunological, allergy, and inflammatory responses. RF emissions from Wi-Fi devices have an impact on the entire body. As a result of full-body exposure, it is challenging to estimate vulnerable organs during Wi-Fi exposure. The oxidative stress is increased by wireless devices [31].

(b) Artificial Intelligence

The general term "AI" describes the use of a computer to simulate intelligent behavior with the least amount of human involvement. It is a modern method of utilizing machines to perform muscle operations and illustrate complex problems in a "cognitive" manner. AI is very important in exhibiting intelligent behavior, learning, demonstrating, and advising the user. The combination of training, perception, problem solving, and tailoring new solutions to the system is a larger definition of artificial intelligence [32]. Figure 2 illustrates the different AI models such as support vector machines, artificial neural networks, natural language processing, machine learning, and heuristics analysis.

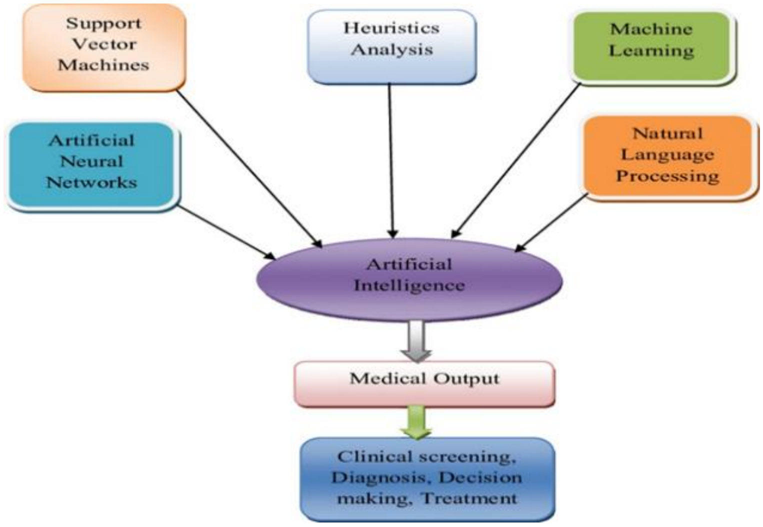

Figure 2. Process chart of artificial intelligence in the medical field.

(c) Machine learning

Machine learning (ML) is a modern AI application that encourages the existence of giving machines entrance to data for more to improve the human design and simply learning them for themselves [33]. When big data, data science, and analysis are mentioned, intelligence and ML are frequently combined. ML is a very efficient solution for dealing with such large amounts of data in multinational industries.

One of the most important technological approaches to AI is ML, which has served as the foundation for many recent developments and commercial applications [34,35]. Figure 3 illustrates the flowchart of the ML model, in which the gathered data is pre-processed, and wrangled. After that, the data is analyzed and further, the model is trained and tested. The deployment of the model will be carried out after the training and testing.

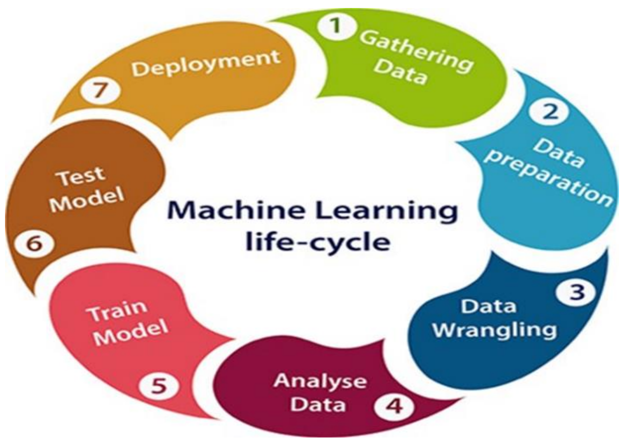

Figure 3. Life Cycle of Machine Learning.

(d) Cloud Computing

Cloud computing has arisen from the distributed software architecture intending to provide hosted services over the internet, and it can be an efficient alternative to owning and managing computer resources and applications for many enterprises [36]. The four major cloud models are infrastructure as a service (IaaS), container as a service (CaaS), software as a service (SaaS), and platform as a service (PaaS), It also improves data security, data and application access efficiency, Quality of Service (QoS), lowers operating costs.

(e) Edge Computing

Edge computing provides restricted and decentralized infrastructure, creating essential resources edge to data sources and avoiding the need to transport data to a centralized cloud [37]. Edge Computing allows data created by various IoT items to be processed at the network's edge rather than being transmitted to a remote centralized or distributed Cloud platform. Edge computing decreases latency, and load on a network core and enhances protection through storage data in infrastructure.

(f) Fog Computing

Fog Computing (FC) facilitates filtering, analysis, and data handling, at the edge of a network, pushing resources down to IoT devices. Depending on the desired QoS, FC enables computation and storage resources to disperse along the pathway between cloud computing and IoT devices [38]. Fog computing architecture encompasses of cloud in the upper, devices with extremely minimal intensity at the bottom, and fog nodes servers in the center.

(g) Robotics

The utilization of mobile robots has grown dramatically in recent years. They can now be found in a variety of locations, including industrial, domestic, educational, and healthcare setting [39]. The robot should be capable of creating an environment model, evaluating its present location and orientation inside the environment using this model, and navigating throughout the environment to reach the goal spots.

(h) Drones

Drones are the airborne vehicle that encompasses unmanned aerial vehicles (UAVs) able to commute thousands of kilometers and small drones [40]. Drones are aerial vehicles that do not fly autonomously, by human operators, and can deliver harmful or safe payloads. In recent years, the most interest has been focused on flying robots for planetary exploration, military surveillance, and search-and-rescue missions. Drones benefit from the ability to operate a broad range of missions such as patrolling, reconnaissance, protection, and aerology.

(i) Bigdata

Big data refers to big data collections with large, diversified, and complicated structures that are challenging to store, analyze, and visualize for subsequent processes or results [41]. Big data analytics refers to the technique of researching huge amounts of data in order to uncover hidden patterns and hidden relationships. This important information for businesses or organizations can assist them to obtain richer and deeper insights and gain a competitive advantage.

(j) Blockchain

Blockchain is a novel technology that is built on a distributed data structure that is shared over a decentralized network [42]. Blockchain provides excellent protection against information manipulation. The blockchain serves as a distributed ledger system. It works in tandem with IoT to allow machine-to-machine interactions. It employs a database containing a collection of transactions. These transactions are verified and recorded in a centralized ledger [43].

(k) Robotic Process Automation

Robotic Process Automation (RPA), such as AI and ML, is a technology that automates jobs. The use of software to automate corporate operations such as application processing, transaction processing, data management, and even email response is known as robotic process automation (RPA). RPA automates repetitive tasks that were previously performed by humans [44].

4. Devices and Prototype for Cattle Health Monitoring

Anuj et al. [2] have designed and constructed an animal health monitoring system (AHMS) prototype to monitor cattle physiological parameters with a sensor module based on Zigbee and a PIC18F4550 microcontroller. Wietryzk al. [4] have proposed a smart health monitoring procedure for animals utilizing Zigbee sensor modules. In this system, various sensor modules have been used for continuous monitoring of rumination, heart rate, body temperature, and environmental temperature. Wietrzyk and Radenkovic et al. [4,35] defined the animal health surveillance system based on an adhoc wireless sensor network and determined that livestock farmers can take preventive measures at the initial stage to reduce the propagation of diseases with the help of measured data. Chao et al. [44] presented and developed an animal monitoring algorithm for providing a better environment and healthcare to strays as well as enhancing their adoption rate. They used Arduino to build a wireless sensor network, Radio Frequency Identification (RFID) to distinguish strays, and IoT for connectivity to the internet.

Nadimi et al. [45–47] presented a ZigBee-based mobile ad hoc network (MANET) for the classification and surveillance of livestock behavior. They demonstrated some advantages such as energy efficiency, better communication reliability, and the least rate of packet loss. The study also include two techniques for monitoring stress in cattle. They used a polar spot tester (PST) and electrocardiograph (ECG) to propose the system and also provided the output of their study. They have realized that "PST" is an appropriate methodology for the heartbeat measurement of cattle and assessed that the opposite factor for the animal behavioral study is heart rate. Hugo et al. [48] designed a system to identify animals in the livestock with the following specifications such a slow cost, energy efficiency, and robustness. Jacky et al. [49] developed a Mobile Monitoring System based on RFID to handle the cattle efficiently with the help of location identification, dynamic information retrieval, and behavior analysis over a wireless network. Ji-De et al. [50] presented the technique with an embedded system utilizing IoT sensors. The system consists of a smart infrastructure that measures different parameters and communicates among themselves. Huircan et al. [51] presented cattle monitoring in cropping fields based on a Zigbee and utilized the scheme of localization in WSN. Lovett et al. [52] presented a measurement technique using infrared thermography for detecting foot- and mouth disease in livestock. Their study was focused on estimating infrared thermography as a screening technique for FMDV-infected animals and its attainable usage in the identification of suspected cattle for sampling and confirmatory diagnostic testing during FMD outbreaks.

Nielsen et al. [53] presented an algorithm for detecting walking and standing in dairy cows based on the output of a three-dimensional acceleration measuring electronic device. Janzekovic et al. [54] presented a polar sport tester (PST) based heart rate monitoring technique for cattle. The parameters which are used for the detection of disease for different animals are body temperature and heartbeat rate. Ariff et al. [55,56] proposed and developed a livestock information system (LIS) on android smartphones for real-time monitoring of the state of health of animals. In the developed device, Smart mobiles use Bluetooth technology for communicating and processing the data of sensors. It also demonstrates the physiological parameter such as the heartbeat and temperature of the animals in real-time.

The real-world application of the presented system has not been conducted yet despite all these improvements in research. At present we do not find any animal health monitoring device in the Indian market which can monitor on the go. The physical factors of animals are examined by veterinary doctors most of the time manually. Currently, livestock farmers face numerous challenges in monitoring animal health, necessitating the conversion of theoretical information into practical methods. At present systems to measure the health parameter of animals mainly concentrate on measuring heartbeats to predict the status of the fitness of cattle. The survey of literature discloses that the vital technique to gather precise data on animal health can be a setup of hardware and software that can be mounted on the body of the animal and can be remotely accessed [8].

Figure 4 demonstrates a framework that is inspired by previous studies for the health monitoring of animals through IoT devices with automation. The architecture comprises the edge-based vision node, mobile robot, and cloud server. The edge-based vision node is the integration of a camera module, AI model, high computational computing unit, wireless communication module, and battery power supply. This vision node will be positioned before every cattle to obtain real-time visual data. Based on visual data, the pre-trained AI model which is available in the computing unit enables the process and analyze the data for health condition monitoring. Every vision node will convey the output of the visual data processed with identity whenever the mobile robot comes to monitor the cattle. The information received with identity will be communicated to the cloud server through internet connectivity which is possible with a Wi-Fi module. In the cloud server, the user can visualize each cattle's health on the digital network.

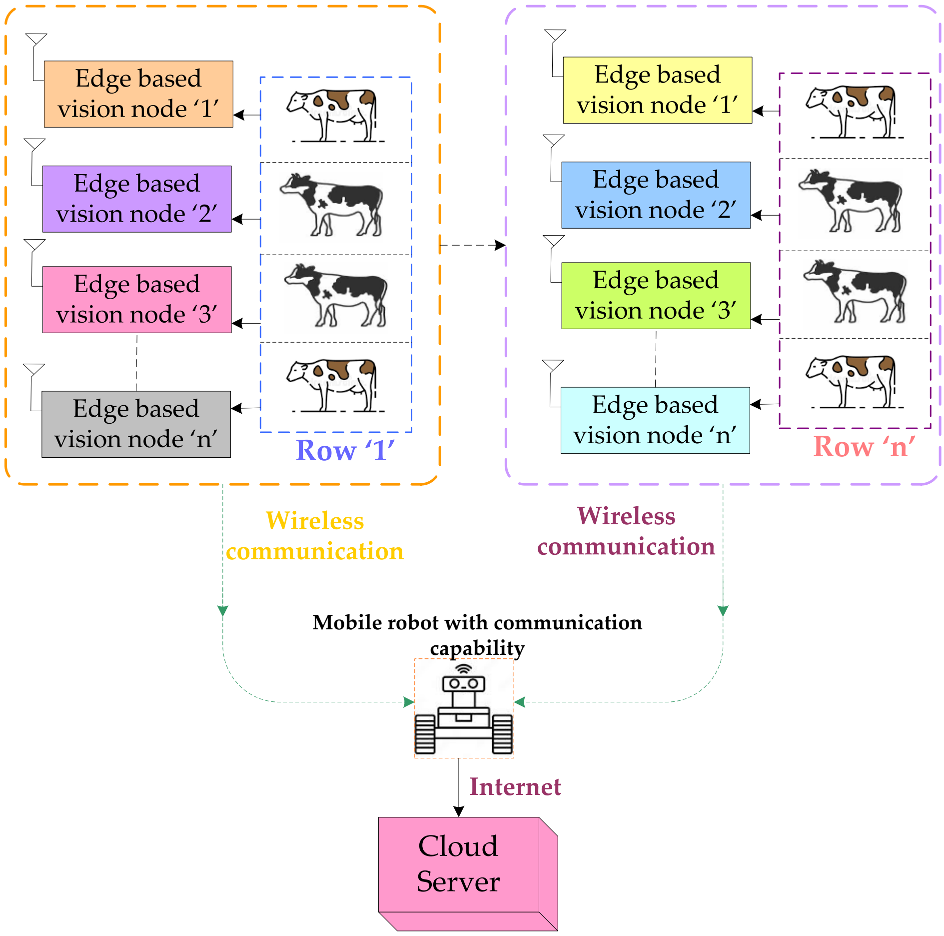

Figure 4. Architecture implemented in previous studies for animal health monitoring.

Table 3 presents the comparative analysis with previous studies and the review on cattle health monitoring. It has been observed that the studies have implemented WSN, deep learning, and IoT technologies individually. No study has discussed the multiple technologies' significance and implementation for cattle health monitoring. In addition to this, this study has discussed the recommendations for the future scope with the assistance of digital technologies.

Table 3. Comparison of the previous studies of cattle health monitoring.

Ref	Objective	Findings
[57]	Automatic health monitoring systems for dairy cattle based on wireless sensor networks (WSNs)	WSN is a low-cost technique that is used to detect infections in dairy cattle.
[58]	Deep learning applications in precision cow farming, particularly health and identity.	ResNet is the most commonly used of the 19 training networks identified.
[59]	Precision cattle farming, with a focus on live weight calculation, and body condition score assessment.	intelligent perception for precision Cattle farming will evolve through non-contact, high precision methods.
[60]	Techniques for identifying cattle lameness and recognizing automatic animal behavior.	Precision livestock farming (PLF) would develop in an autonomous, and real-time manner.
[61]	Remote monitoring and calving prediction using automatic devices and technologies	Non-optimal local tolerability and cow welfare issues have been noted.

5. Discussion& Recommendations

In this study, we have discussed the significance of digital technology integration in the cattle sector for real-time cattle health monitoring. From the perspective of cattle health, the data obtained from the sensors, and vision-based devices are crucial in concluding which kind of disease the cattle animal is facing. Based upon the observation, below we will discuss the challenges and suggest the recommendations that can be employed for future enhancement also it will assist the researchers to carry out the real-time implementation:

- The health monitoring platform based on the IoT and AI techniques is implemented in previous studies. For real-time monitoring of physiological parameters such as heart rate, body temperature, and rumination with surrounding temperature [62]. Various sensors mounted on the bodies of animals provide information about their health status, which users can easily access via the internet. This will aid in analyzing the cattle movement and determining whether the cattle are infected or not based on their average daily motion.
- The researchers must emphasize building a hybrid model capable of detecting multiple diseases based on real-time data because for every type of disease, the trained dataset, and input attributes are different. In addition to this, the real-time data from the IoT sensors need to be carried out for building the real-time dataset. This indeed assists to increase the accuracy of the model for applying the AI model to real-time data.
- The widespread adoption of sensors and IoT communication protocols is required to accelerate the implementation of digital networks in cattle for real-time monitoring and visualization [63]. Furthermore, prediction and intelligent analytics are only attainable when there is a sufficient volume of real-time data available via IoT.
- Using AI techniques in animal health enables researchers to solve extremely complicated topics such as forecast and statistical epidemiological, animal/human personalized treatment, and host-parasite interaction [64]. AI could help (i) To disease detection and diagnosis, (ii) more realistically represent complex biological systems, and (iii) To accelerating decisions and improving risk analysis accuracy.
- Figure 5 shows the proposed architecture for the wearable gadget with an edge gateway. The proposed architecture can be implemented in the scalable network. Here the wearable gadget comprises multiple biological sensors that can be used to sense various biological parameters of animals [65]. A biosensor is a sensing device composed of a particular biological constituent and a transducer. The term "biosensor" denotes that the device is made up of two parts: bio-element and sensor-element. Electric current, electric potential, the intensity and phase of electromagnetic radiations, mass, conductance, impedance, temperature, viscosity, and so on are examples of sensor elements. Specific "bio" element recognizes a specific analyte, and the "sensor" element converts the biomolecule's change into an electrical signal [66]. All these wearable gadgets are interconnected to the edge gateway through long-range communication. For long-range communication usethe LoRa module. Lora is a wide area network technology, and Lora WAN is a LoRa-based low power, wide area networking (LPWAN) protocol. Long Range Wide Area Network is intended primarily

for long-range, battery-powered wireless IoT devices. It is well-known for its ability to communicate over long distances with minimal power consumption and detect signals at low-to-high signal levels. It is specially designed to support low-cost mobile secure communication in IoT while also accommodating millions of devices [54]. A pre-trained DL model will be loaded in the computing unit of the edge gateway, so that based on received sensor data, the edge gateway predicts health variations in the animal and generates warnings on the cloud server via internet communication with the Wi-Fi module. Edge gateway also comprises of LoRa and Wi-Fi modules for the establishment of the connection with wearable gadgets and cloud servers.

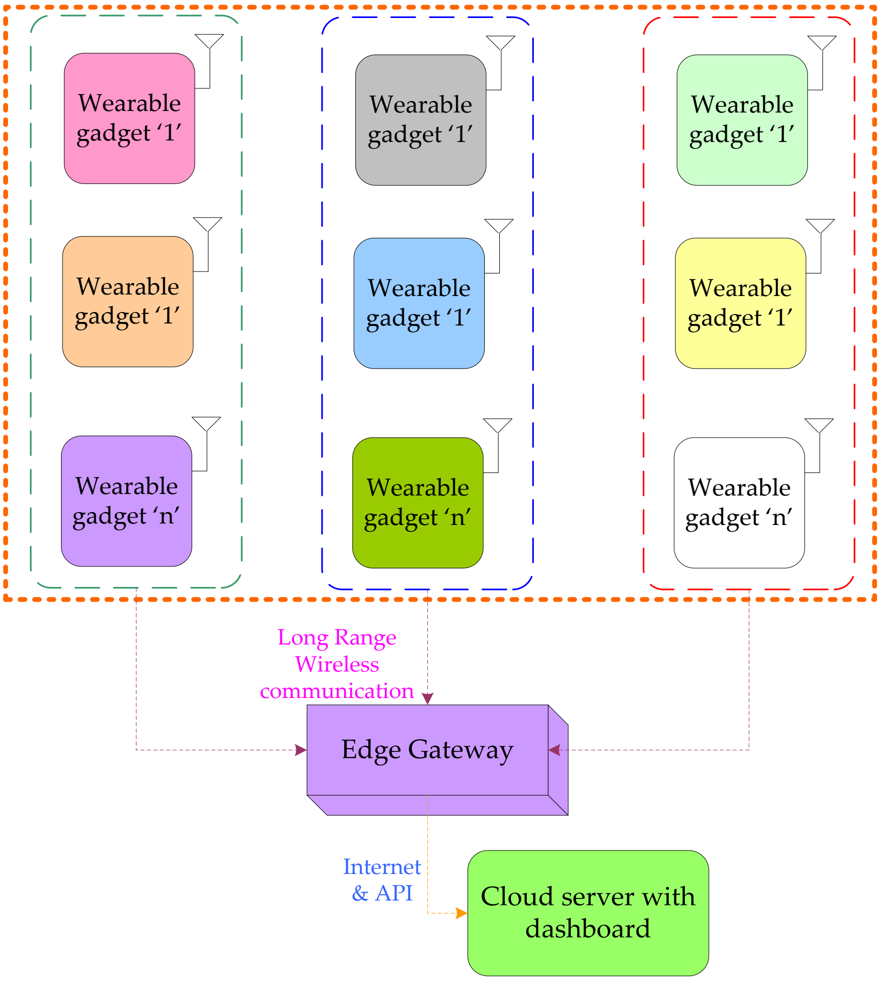

Figure 5. Wearable Gadget with edge gateway.

6. Conclusions

Cattle health monitoring is critical for ensuring the health of cattle for milk production. Digital technologies also gained wide attention in every area, where it realizes real-time monitoring and real-time prediction. Inadequate cattle health monitoring results in lower quality milk production. Traditional methods connected to cattle health must be improved in order to overcome the barrier of time required for illness detection based on the health condition. This article is focused on studying digital technology's significant role in cattle health. In this study, we have discussed the different real-time monitoring systems in the field of cattle health. The article discussed numerous cattle diseases, followed by a discussion of various digital technologies and their relevance to cattle health. Finally, the article suggests recommendations that can be implemented in future work for ensuring cattle's health effectively.

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