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Dairy 4.0: Intelligent Communication Ecosystem for the Cattle Animal Welfare with Blockchain and IoT Enabled Technologies

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Abstract: An intelligent ecosystem with real-time wireless technology is now playing a key role in meeting the sustainability requirements set by the United Nations. Dairy cattle are a major source of milk production all over the world. To meet the food demand of the growing population with maximum productivity, it is necessary for dairy farmers to adopt real-time monitoring technologies. In this study, we will be exploring and assimilating the limitless possibilities for technological interventions in dairy cattle to drastically improve their ecosystem. Intelligent systems for sensing, monitoring, and methods for analysis to be used in applications such as animal health monitoring, animal location tracking, milk quality, and supply chain, feed monitoring and safety, etc., have been discussed briefly. Furthermore, generalized architecture has been proposed that can be directly applied in the future for breakthroughs in research and development linked to data gathering and the processing of applications through edge devices, robots, drones, and blockchain for building intelligent ecosystems. In addition, the article discusses the possibilities and challenges of implementing previous techniques for different activities in dairy cattle. High computing power-based wearable devices, renewable energy harvesting, drone-based furious animal attack detection, and blockchain with IoT assisted systems for the milk supply chain are the vital recommendations addressed in this study for the effective implementation of the intelligent ecosystem in dairy cattle.

Keywords: animal health; block chain; dairy cattle; IoT; ML; sustainability

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Citation: Gehlot, A.; Malik, P.K.; Singh, R.; Akram, S.V.; Alsuwian, T. Dairy 4.0: Intelligent Communication Ecosystem for the Cattle Animal Welfare with Blockchain and IoT Enabled Technologies. *Appl. Sci.* **2022**, *12*, 7316. https://doi.org/10.3390/app12147316

Academic Editors: Ying-Ren Chien, Mu Zhou, Liang-Hung Wang and Xun Zhang

Received: 5 July 2022
Accepted: 19 July 2022
Published: 21 July 2022

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1. Introduction

The United Nations adopted the Sustainable Development Goals (SDGs) in 2015 as a universal declaration to take action to combat poverty, protect the environment and ensure peace and prosperity for all by 2030 [1]. The 17 SDGs are interconnected to each other, where the actions in one area influence the outputs in another area and the development must stabilize the social, economic, and environmental sustainability. Dairy cattle are the most significant area that empowers to support and achieve the following SDGs such as *No poverty (goal 1); Zero hunger (goal 2); Good health and well-being (goal 3) and Gender equality (goal 5)* [2]. Milk and dairy products help to improve the health of the world's population because they contain proteins, vitamins, and minerals that are beneficial to both children and adults' growth and development [3]. According to the food and agriculture organization (FAO) estimates [4], India will account for 54% of the increase in global demand for milk and fresh dairy products. To meet the rising demand, India's dairy producers will need to produce an additional 56 million tons of milk per year by 2026, representing a 40% increase in output from 2014. However, the milk productivity of India is very low when compared to the

United States (US) in the same year. Figure 1 clearly illustrate that India is a pinnacle with inside milk production, however, the productivity of India is very low as the US produce 93 million tons of milk with 9.2 million dairy animals, where India produces 140 million tons of milk with 90 million diary animals [5]. Concerning milk productivity, there is also the issue of high methane emissions from milk production due to poor feed quality, and the FAO concludes that the region is responsible for 23% of global methane emissions from dairy production [6].

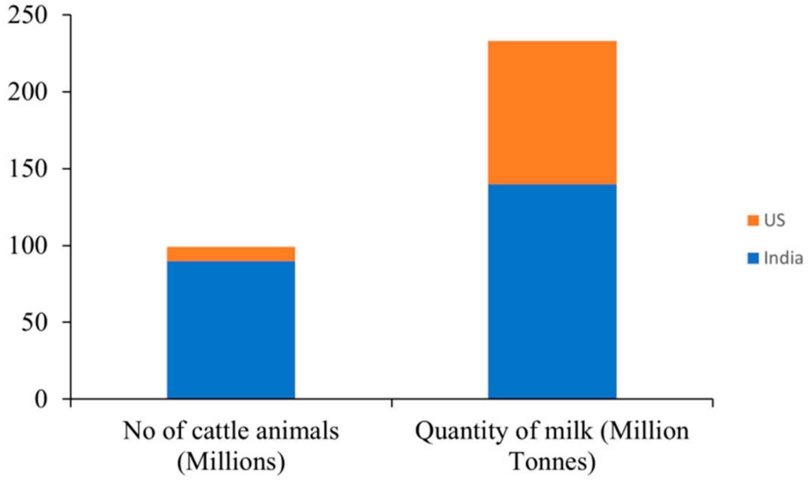

Figure 1. Statistics of Milk Productivity.

In any case, if the milk productivity is not enhanced, and the farmers follow the practice of using more dairy animals to meet demand, this indeed will have serious implications for the environmental sustainability of milk production in India. Concerning this, dairy cattle need to ensure the safety and quality of raw milk to satisfy the demand of industries and consumers. Furthermore, farm practices should ensure that milk is produced by healthy cattle in economic, social, and environmental conditions that are sustainable [7]. To achieve it, the FAO has suggested six best daily cattle practices such as *animal health; animal welfare; milking hygiene; nutrition (water and feed); environment, and social-economic management* (Figure 2) [8].

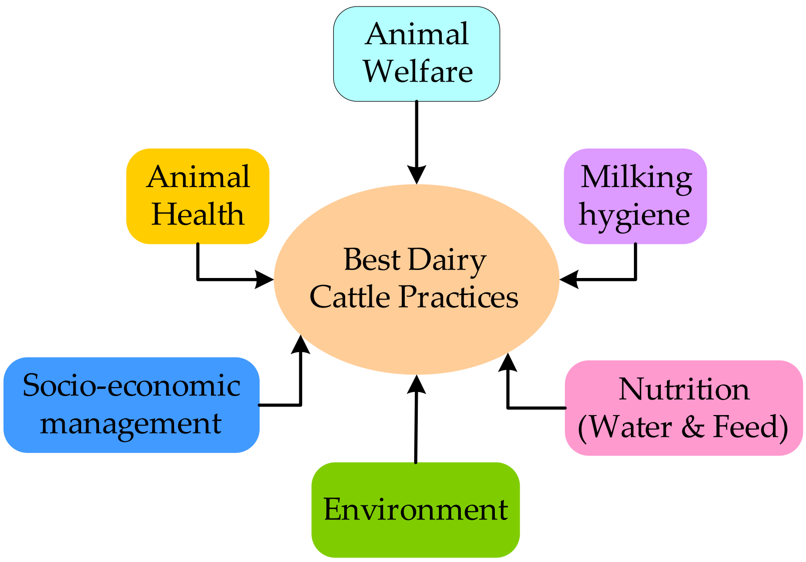

Figure 2. Best Dairy Cattle Practices.

The detailed description of the six best practices are discussed as follows [8]: (i) establishing disease resistance in the herd; effective herd health management; and preventing disease entry onto the farm by using all chemicals and veterinary medicines as directed; (ii) assuring that milking routines do not harm the animals or introduce contaminants into the milk; (iii) ensuring a sufficient supply of feed and water of appropriate quantity and quality; controlling feed storage conditions; and ensuring the traceability of feedstuffs brought onto the farm; (iv) the goal is to keep animals free of thirst, hunger, and malnutrition, as well as pain, injury, disease, discomfort, and fear, and to allow them to engage in relatively normal patterns of animal behaviour; (v) environmentally sustainable farming practices; an appropriate waste management system; and assure that dairy farming practices have no negative impact on the local environment; (vi) human resource management that is both efficient and fully accountable; ensuring that farm tasks are completed safely and competently; and managing the business to ensure its financial viability.

Technology integration enables the dairy best practices to be implemented with digitally connected infrastructure, resulting in overall increased sustainability [9]. Emerging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), machine learning (ML), edge computing, and fog computing have had a significant impact on every application in terms of real-time monitoring, analyzing, and prediction [10]. In addition, the evolution of distinct kinds of biosensors and advanced communication protocols has empowered to implementation of emerging technologies to optimize dairy cattle through remote monitoring and data-driven decision making [11]. The emerging technologies implementation in dairy cattle enables to achieve real-time health monitoring, real-time tracking, real-time disease detection, real-time nutrition monitoring, real-time animal welfare, real-time monitoring of milk hygiene, and vision node-based furious animal attack detection. This work is motivated by the above aspects and explores the significance of emerging technology implementation in dairy cattle for various applications from an architectural and communication perspective as well as a future perspective to empower dairy cattle for achieving sustainability. The contribution of the study is as follows:

- The study discusses the significance of implementing an intelligent ecosystem with emerging technologies for dairy cattle.
- Hybrid architecture with ML-based edge device is detailed explained for physical and mental health monitoring of dairy cattle.
- The integration of drones and long-range communication for animal tracking in real-time is discussed in detail.
- The implementation of IoT-based devices and blockchain for milk quality monitoring and supply chain is presented.
- Feed monitoring of the dairy cattle with real-time behavior and health through edge devices and robots are presented in this study.

The organization of the study is as follows: Section 2 covers the overview and description of emerging technologies; Section 3 covers the animal health monitoring; Section 4 covers the animal location tracking and safety of animals; Section 5 covers the milk monitoring and supply chain; Section 6 covers the feed monitoring of the dairy cattle; Section 7 covers the discussion and recommendations.

2. Overview of Emerging Technologies

In the current world, the proliferation of internet access has significantly increased to its peak, and the International Telecommunication Union (ITU) estimates that 4.9 billion people were connected to the internet in 2020 [12]. The Internet plays a crucial role to enhance the digital infrastructure for realizing digitalization, smart and real-time monitoring in every field. Governments in various developing countries are under an initiative to improve digital infrastructure to accelerate digitalization [13]. Parallel to the proliferation of Internet access, advancements in embedded systems, system on chip (SoC), and wireless communication protocols have enabled the widespread adoption of IoT devices in a variety of fields to support digitalization and real-time monitoring through the internet [14].

Currently, 10 billion IoT devices are deployed, and it is also predicted that the number of IoT devices will rise to 75 billion by 2025 [15]. The integration of sensors, communication protocols, and computing capability of SoC enabled the implementation of low-cost IoT devices in a variety of applications to collect real-time data and apply AI and ML models to it to achieve insightful information [16]. Intelligent things in smart cities can automatically, intelligently, and collaboratively enhance life quality, the standard of living and act as a sustainable resource ecosystem. To achieve this, advanced collaborative technologies such as IoT, AI, drones, and robotics are required to intensify the smartness of smart cities by enhancing energy efficiency, connectivity, and quality of service (QoS) [17].

Figure 3 illustrates the framework of implementing technologies such as IoT, AI, ML, edge computing, robotics, drones, and cloud collaboratively for an intelligent ecosystem. IoT refers to the billions of physical devices around the world that are now connected to the internet, all collecting and sharing data [18]. The sensing layer (perception layer), gateway layer (transport layer) and cloud layer (application layer) are the basic three components of IoT [19]. The sensing layer is the layer where the real-time sensor data of the physical things are obtained. With the communication protocol, the data is processed locally at the edge layer and sends the results to the gateway layer through the communication protocol.

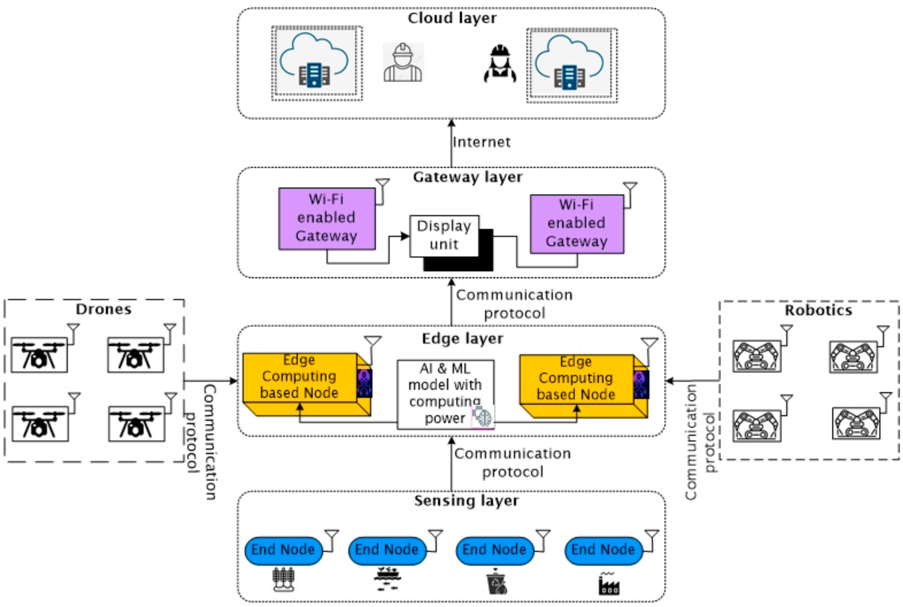

Figure 3. Hybrid framework with the integration of multiple emerging technologies.

The gateway layer supports multiple communication protocols, and the received results from the edge layer are logged on the cloud server through internet connectivity in internet protocol (IP) [20]. AI is an area of computer science that specializes in developing and managing technology that can train to make decisions and take acts on behalf of humankind [21–23]. As discussed earlier, the number of active IoT devices is 10 billion and the amount of data from those IoT devices is large. The IoT devices are made more intelligent by the assistance of AI, especially ML which can be utilized to identify the different patterns in the data [24]. Data analysis using ML automates the creation of analytical models and it is a subset of artificial intelligence predicated on the premise that machines can learn from data, recognize patterns, and make decisions with little or no human intervention [25]. Edge computing is the processing of sensor data away from centralized nodes and near to the network's logical edge, toward individual data sources [26].

ML and DL models are currently being created and deployed using edge computing powered hardware to train on real-time data and make decisions at the edge device itself [27]. Drones are autonomous robots that fly in the sky and are associated with different applications such as disaster mitigation, communication, surveillance, transportation, safety and security, environmental protection, and intelligence gathering [28]. Drones can move autonomously toward IoT devices to collect data, establish a real-time connection, process the data, and send it to collect nodes or other devices [29]. Robots are used widely in hazardous environments, to perform the repetitive tasks of humans and these robots are made intelligent to do complex tasks by integrating with sensing, computation, and communication capability in it [30]. Indeed, IoT technology would greatly enhance these characteristics to meet the demands of sophisticated applications in pervasive and distributed contexts, particularly those with a high level of criticality [31].

3. Animal Health Monitoring

According to the FAO, one of the characteristics of best dairy cattle production is animal health monitoring. Dairy farms and sustainable milk production are dependent on the health and well-being of the animals. The identification of a specific animal within a herd is a critical activity since it optimizes better health outcomes, especially in large-scale dairy cattle. Both physical health and mental health are crucial for monitoring the health of the animal, so in this section, we discussed both the physical and mental health of the animal in detail.

3.1. Physical Health

An infectious disease epidemic in dairy cattle, where thousands of animals are kept together, can result in substantial losses, and in such a circumstance, a contagious disease outbreak will be difficult to prevent unless the farmer gets involved immediately. When symptoms show, it is generally too late to intervene. The advancement of biosensors enables them to spot disease in its early stages and, with the help of a communication protocol, inform dairy cattle farmers. Sensors and wearable technologies are implanted in dairy cattle to measure body temperature [32,33], sweat constituents [34–36], detect stress [37], observe behaviour and movement [38,39], detect pH [40], analyse sound [41], prevent disease [42], detect analytes, and detect the presence of viruses and pathogens [43,44]. Wearable sensors aid farmers in detecting illness early and preventing animal deaths. Sensors, AI, and ML are used to continuously monitor important animal health aspects e.g., movement, air quality, and food and fluid consumption, rather than reacting to problems as they arise or using the services of doctors. Farmers may now identify, forecast, and prevent disease outbreaks even before they occur on a wide scale by continuously collecting data and applying modern AI and ML algorithms to predict deviations or abnormalities. This type of system has two major advantages. One advantage of such a system is that it allows fewer farmers to care for many more animals, lessening production costs. Two, such a system can alert farmers to the possibility of a disease, even if it is still in the pre-clinical stage. This, in turn, will assist farmers in taking timely action to avoid catastrophic losses.

3.2. Mental Health Monitoring

The aspects/pillars of the three-circles model of animal welfare [45] include natural living, basic health and functioning, and affective states. Maintaining pleasant emotional states can result in significantly increased happiness and health in domestic and farmed animals [46]. Facial expressions and sounds are two behavioral indications of emotion that are relevant for sensor technology in farm animals. Because most farm animals are mammals capable of changing their facial expression to some extent, the ability to connect an animal's face and sounds to an emotional state is vital for many practical uses. Animals may feel and exhibit a wide spectrum of emotions, both positive and negative [47], and the most prevalent emotional states observed in dairy cattle animals by researchers are illustrated in Table 1.

Table 1. The emotional state of dairy cattle animal (Cow).

Ref.	Indicators		Emotional State
[48]	Longer upright ear posture		Excitement
	Ears pointing forward		Frustration
[48]	Backward ears and half-closed eyes		Relaxed State
	White eyes are visible and ears are facing forward		Excited State
[49]	Decreased nasal temperature and peripheral changes		Positive experience or increase in arousal
[50]	Vocal	A higher number of vocal units per sequence and open mouth calls	alert and stress escalation
		Closed mouth calls	Positive emotional state
[51]	Maximum eye temperature and visible eye white		Stress

Pain expression is challenging in animals, and research on the utilization of facial alterations in reaction to pain or stress is still in its early stages [51]. Animals' emotional states can also be conveyed through sound and many animal vocalizations are involuntary, especially those conveying a negative feeling. As a result, noises may frequently imply fundamental emotional responses as a first reaction [52]. Direct measuring of emotion is currently impossible, even for humans and Indirect emotional measures are time-sensitive and difficult to perform manually. However, modern technology, on the other hand, is making animal behavior and physiology observation and analysis faster and more effective. Sensors, facial expression analysis, sound analysis, and multimodal integrated technology techniques are discussed as tools for monitoring farm animal emotions.

Visual sensors (cameras) and biosensors are important components of the system to automate farm animal monitoring [53]. Sensors and biosensors, in this context, are devices that collect data on a physical, chemical, biological, or biochemical property, which can subsequently be measured and analyzed [54]. While wearable sensors are often more precise in terms of the parameter they measure, they also necessitate a large number of individual sensors to gather enough data to assess the emotional condition of all individual animals. There are various types of sensors that are commercially available or in development, each of which measures a different characteristic and has its own set of advantages and disadvantages (Table 2).

Table 2. Sensors for animal health [55].

Sensor	Advantages	Disadvantages
Electrocardiograph	Heart rate monitoring is a likely trustworthy sign of positive affect.	Motion artifacts cause deployment difficulties; It's not feasible to monitor in real-time or on-site.
Global Positioning System	Global Positioning System (GPS) Noninvasive, long-lasting system Expensive at first, poor battery life, and other concerns	Costly at first, battery life, accuracy difficulties, and noise
Electroencephalography	Measurement of brain activity that is accurate regardless of subject movement	EEG states and emotional valences are not linked; real-time non-invasive sensors are not yet accessible.
Thermal Infrared Imaging	Accurate temperature gauge.	External heat sources may cause interference.
Electromyogram	Particularly beneficial for diagnostic purposes and animals with particular breathing habits.	It's difficult to put into practice, because it's influenced by a variety of things, including mobility.
Olfactory and chemical sensors	Deeply associated with feelings	Do not utilize the animal's data directly; There are no verified benchmarks for indirect measuring.

Facial expression technology is already widely employed in human applications [56], and it has the potential to be used in animal emotion studies. Even though the facial traits of farm animals are not fully understood or linked to emotional states, this is an emerging subject of research. Each minor movement in a farm animal's eyes, ears, nose, cheeks, and jaws could indicate a different feeling. Changes in ear position, in addition to changes in eye size, may be symptomatic of certain emotions in farm animals. Pain management is crucial for improving animal wellbeing, and facial expressions are now thought to be a viable method for assessing pain in farm animals. The current grimace scale scoring systems, which analyze many sorts of so-called facial action units in determining pain levels, incorporated body function, physiological reactions, and behavior observation [57]. In addition, in recent years, facial action coding systems (FACS) for many animals have been developed, providing an objective approach for identifying all potential facial emotions in an animal and doing species comparisons [57]. Correlations between physiological factors such as heart rate variability, skin conductance (electrodermal activity), skin temperature fluctuations (infrared data), and facial-emotional reactions described using multi-sensor complex data would necessitate a substantial amount of computational capacity [58]. Distinguishing expressive qualities of animals from sensor data based on a plethora of physiological processes, as well as the dynamic changes in their emotional states over time, necessitates the ability to systematically extract information from huge data.

Data collected from sensors is solely one component of the process of interpreting animal emotions and another aspect of the process is algorithms that can be used to examine the collected data [59]. In general, these methods rely on modern computer ML capabilities. ML refers to the ability of computer algorithms to learn and change as more data is introduced into the system. The systems are all capable of taking in all available information (facial expressions, temperature readings, vocalizations, etc.) and establishing standards, then comparing these benchmarks to fresh information to sort out discordant results. ML approaches are required to forecast and frequently estimate an individual's affective states based on physiological functions and behavior. ML algorithms are helpful because of the vast volume of data and in the feature selection and optimization of emotional factors such as valence, duration, and activation [58].

Figure 4 illustrates an architecture that is capable of monitoring the physical and mental health parameters of the dairy cattle with sensor mote and vision mote. The sensor mote attached to the body of the dairy cattle provides information related to body temperature, position (lying, standing), and heart rate. The sensor for muscle strength and behavior analysis can only be used during critical conditions and rare conditions. All the sensors are interfaced with the controller of the sensor mote. In this architecture, a long-range radio module is preferred as it is the communication protocol that is capable of transmitting to long-range up to 10 km with low power consumption. Every individual sensor mote of dairy cattle is identified with an ID provided in the controller through programming. Based upon ID, the edge gateway identifies the identity of the sensor mote and processes the data. An edge gateway is powered with edge computing and a pre-trained ML model, where it analyzes the received data and provides insights from it. In case, if it identifies that the particular dairy cattle are unwell, then it immediately transmits the information to the farmer/user on the cloud server. The vision mote is placed inside the cattle shelter, before the cattle and the visuals captured are transmitted to the edge gateway for analyzing the physical and mental behavior of the cattle. The computing of the data is processed at the edge gateway, and it sends the insights or data related to the condition of dairy cattle on a cloud server. To enhance the computing power of the edge gateway, it is powered with a co-processor and is charged with a dual power supply. Transfer learning and domain adaption approaches can be employed in collaboration with deep neural networks at the edge gateway to improve cross-domain image recognition generalisation [60,61]. Furthermore, transfer learning ensures that deep-learned features become more domain-invariant when carrying discriminative representations for cross-domain visual recognition. Edge gateway also enhances the latency and provides insights in real-time within a minimum duration.

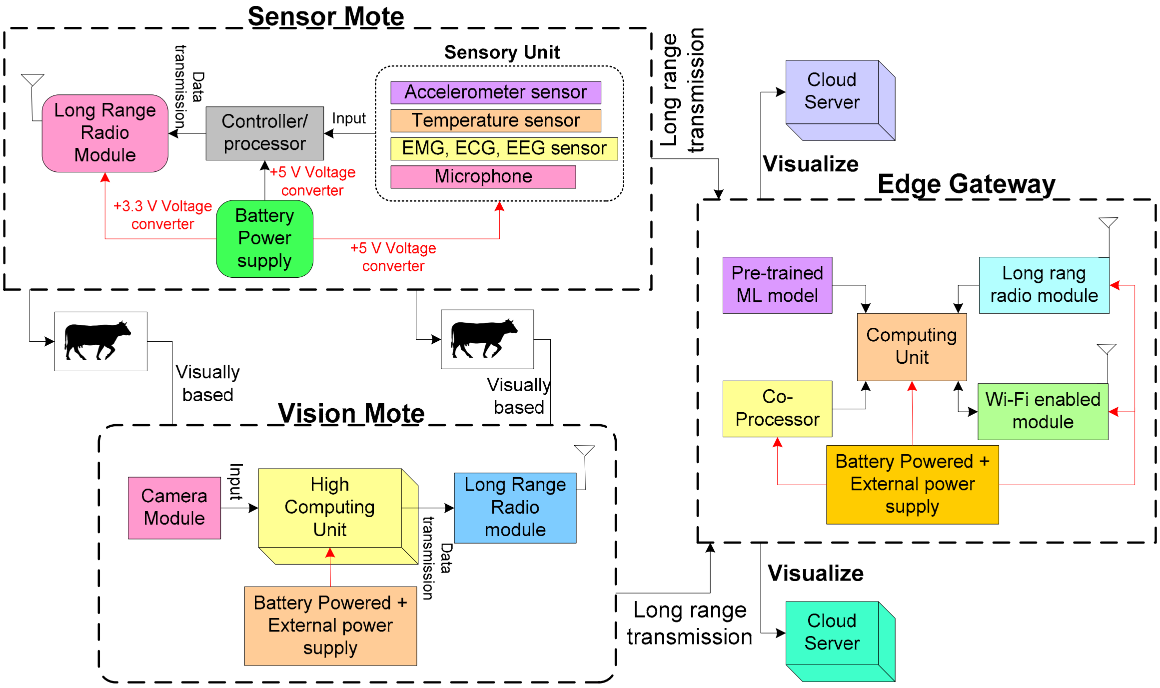

Figure 4. Architecture of Real-time animal health tracking.

4. Animal Tracking and Safety

In this section, we have discussed the animal tracking and safety of animals in the cattle shelter. Initially, we discuss the significance of animal tracking, and later on, the enhancement of the safety of the animals will be addressed.

4.1. Animal Location Tracking

The importance of tracking in combination with an identification task and counting the number of animals entering after grazing outside plays a crucial role in animal welfare, and improves husbandry techniques [62]. Animal behavior data can help with husbandry system optimization, resulting in more efficient and sustainable animal production and animal handling that is conducted correctly, which leads to better animal health and welfare [63]. Monitoring and recording individual animal behavior has now played an important role in providing high-quality research and effective farm management. Basic dairy cattle behavior often refers to feeding, standing, and laying activity, with groups exhibiting coordinated resting and activity patterns [63]. In animal husbandry, decreased resting behavior can be utilized to detect social stress. Dairy cattle that spend too much time lying down may be unwell, a dairy cow that has difficulty walking may be lame, and a dairy cow that spends too little time feeding may have difficulties with its mouth, teeth, or digestive system.

There is growing interest in installing sensors and electrical systems to monitor animal activities and detect behavioral aberrations automatically. In several farms for animal supervision, direct observation and video monitoring are both time-consuming tasks [64]. In animal research, additional wearable sensors are added to record animal behavior. Tri-axial accelerometers, for example, are utilized to monitor lying time and heat events. Human inspectors have been replaced by computer vision-based systems that track animal movement using image segmentation and feature extraction from a single camera [65]. Few studies used dual cameras to examine cow standing and lying behavior based on the cow's position, with the resting area referring to lying and the feeding alley referring to standing.

Furthermore, simply employing the RGB camera in a barn with low illumination, a complicated background, and a dusty atmosphere can impair the performance of computer vision analysis [66]. The use of a computer vision system allows for the regular monitoring of animal behavior, and in order to maximize the contribution of each animal, the system must be able to identify and locate individual animals in the herd.

Vision-based systems have difficulty identifying the location of cows; however, ML-based vision-based systems can help identify the location of cows, but they require additional infrastructure to monitor dairy animals in big areas such as barns [67]. So, in dairy farms, identifying technology such as passive radio-frequency identifications (RFIDs) are used to register food intake, and this technology has traditionally been utilised to determine the position and identity of animals in a barn. The drawback of this approach is that the antennae are sensitive to disruptions, and the system only indicates where the animals are in relation to an antenna. A real-time positioning system based on ultra-wideband (UWB) provides new potential for determining the position of animals in real-time with high precision [68]. An existing system (Ubisense, Cambridge, UK) determines the location of moving objects in a variety of situations, with the system's accuracy ranging between 30 and 100 cm [69]. Although these tests demonstrated the capability of tracking individual animals on-farm, the location information was derived using the barn's position along the *x*- and *y*-axes. However, without evaluating the cow's location along the *z*-axis, the system cannot determine whether the cow is lying or staying in the resting region. As a result, a sensor fusion back system capable of automatically detecting and reporting the standing and lying behaviors of individuals in larger barns would be extremely beneficial and in high demand [70]. To support the animal tracking with real-time monitoring capability, architecture is illustrated in the Figure 5. As discussed above, regarding the limitations of previous system, here a system is demonstrated for the real-time monitoring of cattle animals with the assistance of drones. In general, humans find it difficult to enter restricted areas, thus drones are capable of entering restricted areas via the air and perform necessary inspection.

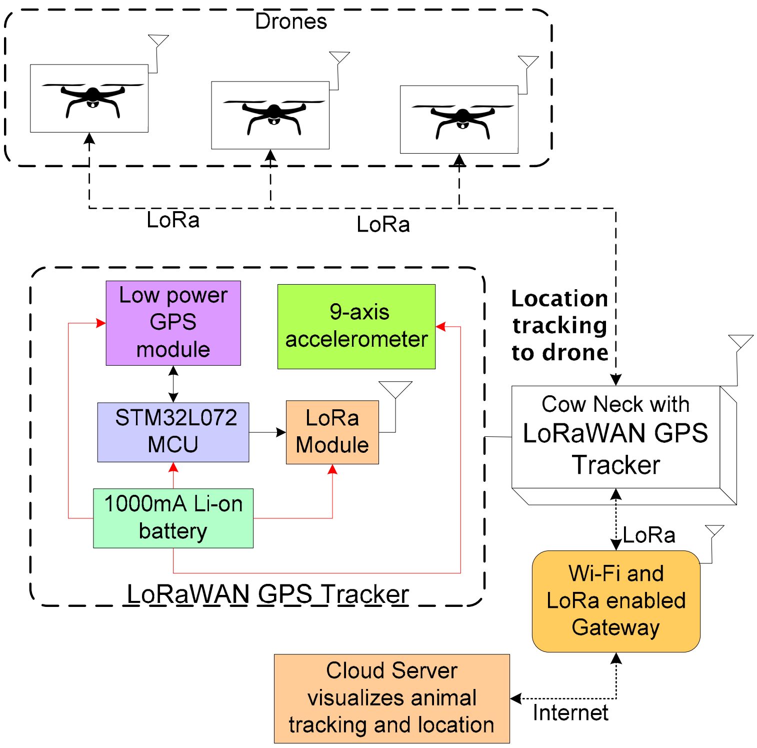

Figure 5. LoRa based Architecture of animal location tracking and identification.

A LoRaWAN GPS tracker [71] interfaced to the cow neck, is capable of providing the GPS location and motion of a cow. This tracker comprises of a low power GPS module and 9-axis accelerometer, and these two components are interfaced to the STM32L072 MCU along with LoRa module and 1000 ma Li-on battery. The ID provided in the GPS tracker assists the drone to categorize the identification of particular dairy cattle in the grazing field. The drone is equipped with a LoRa module that allows it to communicate with cattle for knowing the location and tracking during emergency state. In addition to this, the LoRaWAN GPS tracker communicates the location and motion information of dairy cattle to the farmer/user upon request from the cloud server through the gateway. The gateway is linked to LoRa and Wi-Fi in order to transmit and receive sensor data via LoRa and the internet. The cloud server provides feasibility to the farmer/user to visualize position and motion of each dairy cattle and it enables to realize the digitalization of the animal tracking. Moreover, the geo-fencing can be added to this system, as it also triggers the events if any dairy cattle move away from the fencing of the premises. Geo-fencing relies on GPS, Wi-Fi, RFID, and cellular data, and it is achievable with the existing system because GPS is available in the cow neck.

4.2. Vision Inspired Cattle Shelter for the Safety of Animals

In general, livestock in shelters are vulnerable to nighttime attacks by ferocious animals and theft by suspicious individuals, and as a result, a system should be installed at the cattle shelter to warn the owner of the cattle shelter in real time of any suspicious activity [72]. Solar-powered electricity generation on a shelter improves animal protection and safety. The structure must protect the animals from inclement weather and provide enough ventilation.

A vision mote and a ML-enabled system is proposed to protect cattle from attack by ferocious animals and theft by unknown individuals. The architecture presented in Figure 6, comprises of an edge powered vision mote, and this vision mote is installed on the roof top of the cattle shelter to ensure the safety of the cattle. The edge powered vision mote is fed with a pre-trained ML model, which aids the vision mote in precisely classifying the enraged animals and suspicious person. If the vision mote detects a ferocious animal or a suspicious person, it quickly sends an alert to the owner of the cow shelter via LoRa-based gateway.

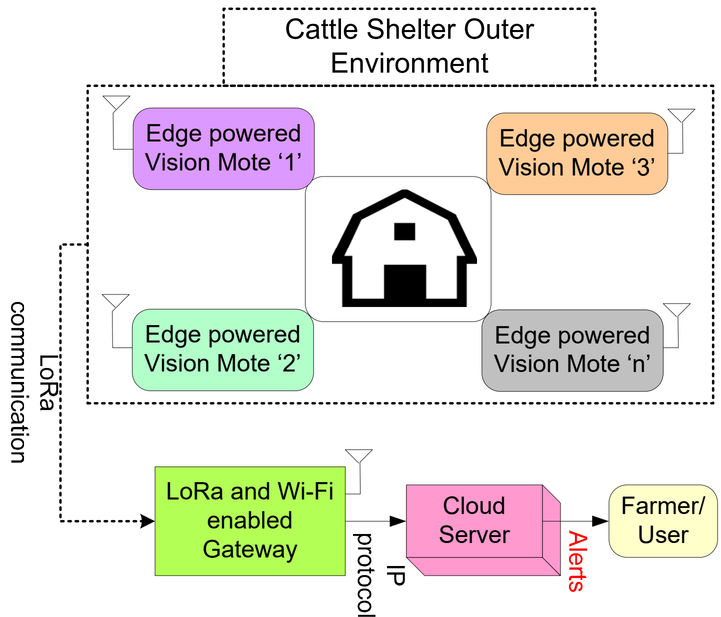

Figure 6. Edge computing and IoT enabled system for the safety of cattle.

The owner is able to receive the alerts on the Alert based GUI unit and smartphone through the internet. Edge computing-based vision mote is the primary node that monitors and identifies the furious animals and suspicious person through camera visuals. The computing unit interfaced with ML model and co-processor analyzes the real-time visuals provided by the camera module to identify the suspicious and furious activities. The LoRa module assists to transmit the alerts to the owner. The solar power supply is preferred as the node is placed in the outdoor environment. A solar based power supply is provided to the mote. Real-time suspicious activities near the cattle shelter are informed to the owner in short interval of time. Edges computing in the vision mote enables the identification of the attack on the cattle at the edge device.

5. Milk Monitoring and Supply Chain

Connecting to the different entities that require milk, where the quality, quantity, and the ID complete information about the entities. The existing process in the milk business for measuring the percentage of milk solids is based on collecting samples when picking up milk at the farm [73]. The milk samples are sent to laboratories for investigation of milk quality and determination of the percentage of solids in the inbound milk. Furthermore, because the varied quality milks cannot be separated once they are mixed during pick-up, a mixture of high and low-quality milk is sent to the processing plants [74]. IoT has the ability to improve the milk sector by providing real-time monitoring of milk quality through the use of suitable sensors capable of assessing and separating between milk with distinct characteristics [75].

Monitoring, decision making, and automation offered by IoT will be used to deal with the complexity of cyber-physical production and supply chain logistics, resulting in improved productivity, product quality, and supply chain efficiency. Real-time monitoring of the milk supply and the conditions that affect milk production will aid in reducing milk rejection at processing plants, allowing for the identification and separate pickup of high-quality milk for premium products, improving milk supply forecasting, and allowing for better production planning [76]. Live monitoring of the milk supply and pickup events will also provide farmers with milk and pickup alerts, allowing them to cope with inappropriate milk chilling and pickup difficulties such as trucks arriving late, the driver forgetting to wash the vat, etc. This data will also help suppliers forecast their production [77].

Various research investigations have shown that spectroscopy based on visible light, Near Infra-Redlight (NIR), or IR (Infra-Red) are suitable techniques for assessing milk-quality characteristics [78]. According to research on NIR and visible-NIR spectroscopy, the commercial success of milk quality detection is based on the NIR spectroscopy concept [79]. Existing NIR milk quality sensors are considered to be highly expensive, as they need the use of complex instrumentation, and so are unlikely to be practical to install on a broad scale on farms [80]. Furthermore, recent improvements in low-cost biosensors and electro-chemical sensors have been found to be successful in laboratory-based milk quality assessment [81,82]. With this background knowledge, the requirement for a low-cost milk quality sensing technology for inbound milk quality monitoring becomes clear.

To enhance the milk quality monitoring in the dairy cattle, a framework is illustrated in the Figure 7 and it is based on IoT and blockchain technology. Basically, the manipulation of information and records are the current events that are possible to hide the wrong events and information. In the area of dairy cattle, it is necessary to maintain data transparency and data security for enhancing the business relationship and trust. With current emerging technology, it is possible with blockchain technology. Blockchain technology is distributed ledger technology, where ledgers are distributed in a peer-to-peer format among the entities, and moreover, the ledgers are secured with a hash algorithm and private key cryptography [83]. Milk monitoring mote is the main component of the framework, where it comprises of different components that are required for checking the quality and quantity of milk.

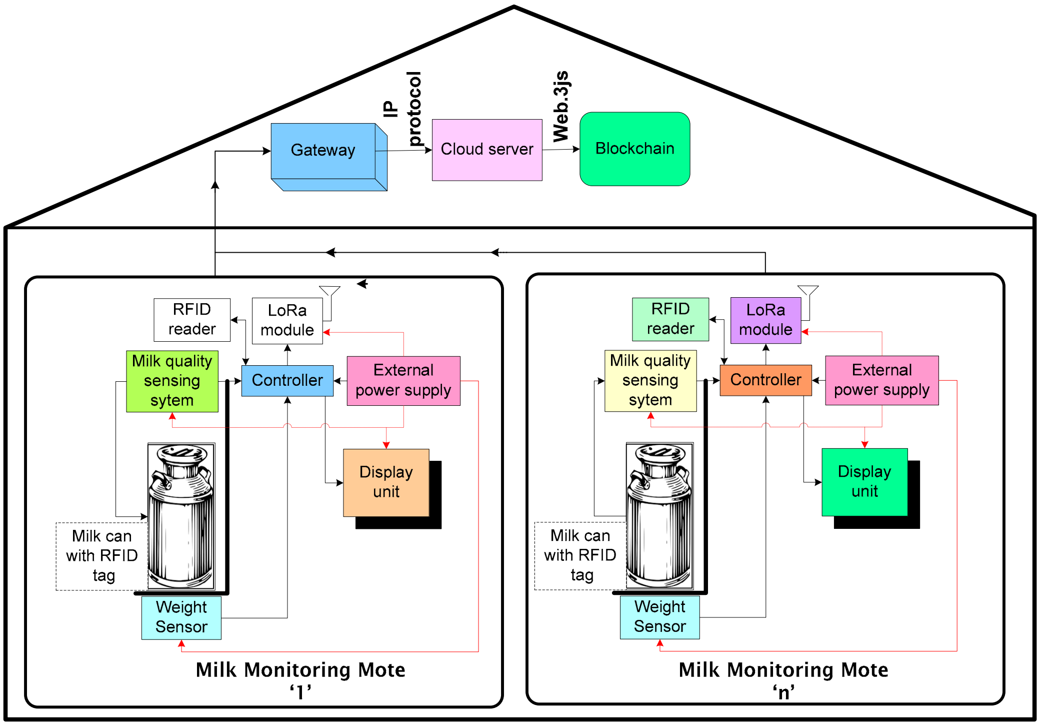

Figure 7. IoT enabled system for monitoring milk quality and supply chain.

A sensing system is utilized for checking the milk quantity, and a weight sensor is used for the measurement of weight of the milk vessel. In addition to this, an RFID reader interfaced to the milk monitoring mote recognizes the identification of the milk vessel through the RFID tag attached to it. This framework assists to establish communication when 'n' number of milk monitoring mote are deployed in dairy farm in a scalable manner. To connect 'n' number of the milk monitoring mote to the blockchain, first it needs to connect to the cloud server. To connect to the cloud server, it should establish communication with a gateway, so the LoRa module embedded in the milk monitoring mote empowers it to connect to the gateway. The LoRa module in the gateway serves as a receiver unit, and the Wi-Fi module allows it to connect to the internet and log data to a cloud server. Here the cloud server is interfaced to the blockchain web3.js interface, and this interface is utilized to connect the cloud server and blockchain locally or remotely through HTTP, IPC or WebSocket. Blockchain enables the provision of real-time data of milk with transparency and security. Moreover, the trust and collaboration with different business entities will be enhanced further for digitalized real-time information.

6. Feed Monitoring

Food is essential for animal nutrition since it determines the amount of nutrients available to the animal for health and productivity. Actual or valued food reduces nutrient under- or over-feeding and promotes optimal nutrient utilization [84]. Nutrient deficiency reduces productivity and may have a negative impact on animal health, and overfeeding nutrients raises feed costs, increases environmental nutritional load, and can be harmful or dangerous to one's health [85]. The high-yielding cow breeds of today demand a constant supply of feed and fodder.

While most bovine feeds for conventional dairy production are purchased from the market, sustainable dairy feed must be grown or purchased locally. Dry fodder can be purchased locally, but green fodder must be farmed on the property. Guinea grass may be produced in desolate rain-fed ground, while high yielding Bajra Napier hybrids can be grown in fertile and well-irrigated land [86]. While poultry and dairy farms are growing across the country, their long-term viability is still a concern.

Dairy production, in particular, necessitates a huge amount of cattle feed, meal supplements, antibiotics, and other inputs. In the previous few decades, India's dairy farming business has exploded, resulting in the world's largest animal population [87]. After years of consistent success in milk and cattle production, the business is now confronted with a number of obstacles. A chronic scarcity of cattle feed, along with inadequate fodder quality, has become the most significant limitation in Indian dairy farming. The current intensive animal production system places a great emphasis on concentrate feeding, which has raised the cost of milk production and significantly reduced farmer income [87]. The increasing cost of feed ingredients and its seasonal variability also adds to the gravity of the situation.

The architecture illustrated in Figure 8 empowers the implementation of the edge device with robots for planning a healthy diet and feeding the cattle with respect to the health conditions. The edge mote is placed in the position of the cow where the image captured by the camera module is analyzed by the pre-trained model embedded in it. Further, the results of analytics are communicated to the robots in the premise of dairy cattle through LoRa. Based up on received health information, the robots prepare the food to the dairy cattle. This food is placed in the chamber of mobile robot, that carry the food to the particular cattle position. Mobile robot identifies the ID of the particular cattle that is provided during firmware development in both mobile robot and edge mote. The implementation of robots also ensures the health environment to the cattle, as it is difficult for the cattle, if the farmer/user are unhealthy. The co-processor in the edge mote provides the computing power for analyzing the data with the ML model. Moreover, the information is logged on the digital platform i.e., cloud server through gateway. The integration of robots, ML, IoT and edge devices has facilitated the implementation of intelligent systems to ensure a healthy diet for dairy cows.

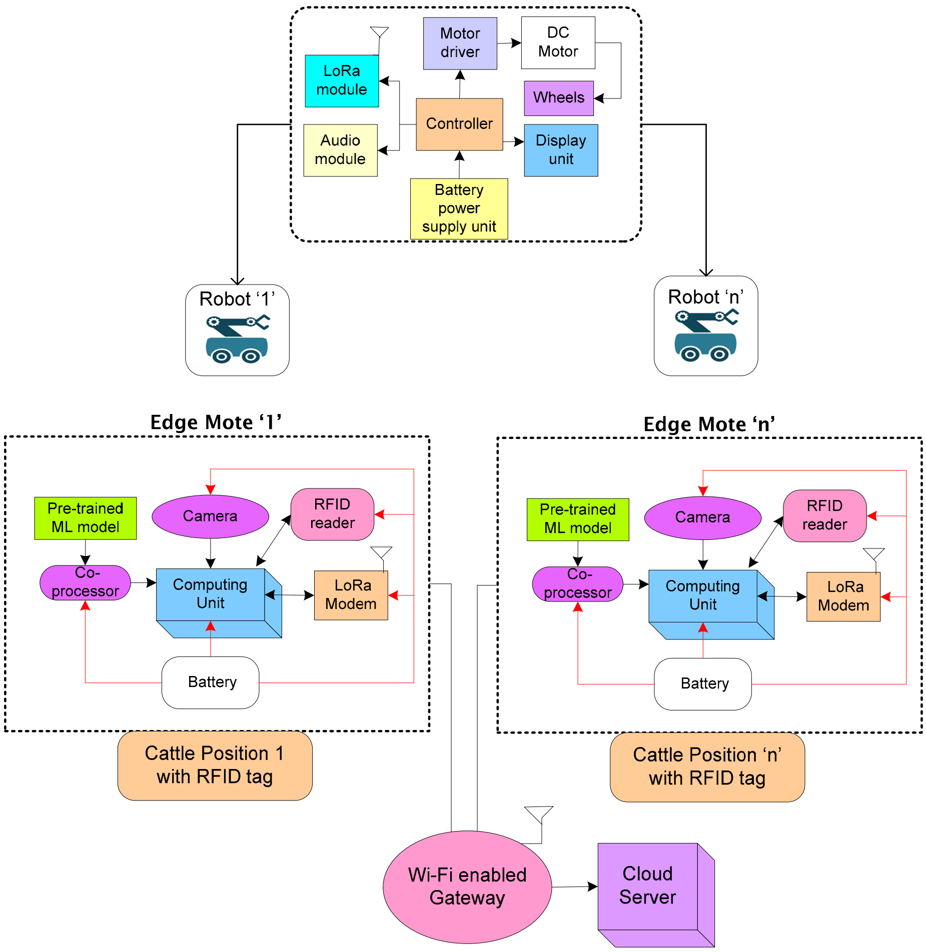

Figure 8. IoT and Robotics Inspired architecture for diet planning and feeding.

7. Discussion and Recommendations

Dairy cattle represent a significant sector which is responsible for milk production all over the world. The rise in population growth demands the production of milk for health and well-being. To meet this demand, farmers adopted different methods to produce milk in a larger amount. However, the methods followed by the farmers minimize milk productivity and rise in methane gases in the environment. Correspondingly, the UN SDG goal is towards sustainability in all aspects to achieve a clean and green environment. To support SDG, the dairy cattle must undergo a transition to establish an intelligent ecosystem with emerging technologies such as IoT, AI, ML, robotics, drones, edge computing, and blockchain. With this motivation, this study explored the different studies on different aspects of dairy cattle such as animal health monitoring, animal location tracking, milk quality monitoring, feed planning, and the safety of animals in the shelter. From our exploration, the following findings and suggestions are addressed below:

- Wearable technology has recently attracted widespread attention for its application in the field of human health monitoring, and it is now being used in animals to monitor their health status in real-time [88]. It has been determined that the wearable devices for dairy cattle must be enhanced with advanced wireless connectivity, and the controller in the wearable devices must be capable of doing intelligent analytics using real-time series sensor data. Intelligent analytics is achieved by designing a computing unit for the wearable device that is powered by ML, and results obtained from the analytics can be useful for the researchers to further process the research [89]. Deep learning models can also be embedded for the identification of real-time emotional behavior of animals precisely [90].
- Milk quality and quantity monitoring are critical in the dairy industry, as tiny flaws cause supply chain losses. The embedded devices used to assess milk quality must be precisely calibrated to provide accurate findings. From the exploration, it is identified that the blockchain implementation in the milk supply chain for dairy cattle is limited. Moreover, the IoT-enabled hardware with blockchain implementation is necessary for the milk supply chain to obtain real-time tracking data for all the entities connected on the respective blockchain network [91].
- In dairy cattle, robots play a significant and intelligent role in executing tasks intelligently and precisely [92]. In small dairy cattle, mobile robots can be deployed to study the behavior and eating patterns of the cattle precisely. In addition to this, the mobile robot needs to be equipped with different sensors on it for monitoring the environmental conditions inside the cattle [93]. Data on environmental conditions, as well as data on cattle feeding and eating analyses, must be analyzed collaboratively in order to generate valuable insights for improving the inner ecosystem with a cattle-friendly atmosphere. In addition to this, the mobile robot needs to customize with a reliable, fast, and secure communication protocol in it [94].
- Drones that track cattle are used to locate and count the animals on a farm. Drones must be equipped with high computing power in order to detect any abnormal activity in real-time, such as a ferocious animal approaching the farm or an unknown human [95]. Drones must also be equipped with an energy-efficient communication protocol as well as a computing unit for analyzing real-time visual data using deep learning models [96].
- In the study, it is also observed that the real-time empowered IoT devices with low cost, energy-efficient, fast transmission, and intelligent computing are to be customized for dairy cattle for enhancing with intelligent ecosystem [97]. The customization of IoT devices allows the farmers/users to design the device according to their farming requirements [98]. This indeed minimizes the cost and also enhances to implementation of precise IoT devices for real-time monitoring.
- The IoT devices installed in dairy cattle should use a renewable energy harvesting approach to improve energy efficiency and provide continuous power to the IoT devices for real-time application [99]. Renewable energy sources, such as solar and

wind energy, can be used to generate electricity for the cattle shelter, and it will also be advantageous to deploy high computational edge devices in the interior environment of the cattle shelter for real-time behavior, feeding, and eating analysis of cattle.

8. Conclusions

Dairy cattle comprise the most significant area that empowers the support and achievement of the SDGs for good health and well-being in a sustainable approach. Milk and dairy products from dairy cattle serve to promote the health of the world's population because they are beneficial to the growth and development of both children and adults. Emerging technologies such as IoT, AI, ML, robots, drones, and blockchain will play a key role in improving the productivity and sustainability of dairy cattle. The possibilities and problems of implementing prior strategies for various activities in dairy cattle were examined in this study. In addition to this, generalized architecture for animal health, animal location tracking, milk quality monitoring and supply chain, feed monitoring, and safety of dairy cattle are detailed presented in this study. Finally, we have suggested some significant recommendations for further enhancement of technologies in dairy cattle for meeting sustainability. High computing power-based wearable devices, renewable energy harvesting, drone-based furious animal attack detection, and blockchain with IoT assisted systems for milk supply chain analysis are the vital recommendations addressed in this study for the effective implementation of the intelligent ecosystem in dairy cattle.

Author Contributions: Conceptualization, P.K.M.; Formal analysis, A.G.; Investigation, R.S.; Resources, T.A.; Writing—original draft, S.V.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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