sustainability

MDPI

Systematic Review

Systematic Review on Internet of Things in Smart Livestock Management Systems

Sebastian Terence [1], Jude Immaculate [2,*], Anishin Raj [3] and Jeba Nadarajan [4]

[1] Department of Artificial Intelligence and Machine Learning, Karunya Institute of Technology and Sciences, Coimbatore 641114, India; sebastian@karunya.edu
[2] Department of Mathematics, Karunya Institute of Technology and Sciences, Coimbatore 641114, India
[3] Department of Computer Science and Engineering, Muthoot Institute of Technology and Science, Varikoli 682308, India; anishinrajmm@mgits.ac.in
[4] Department of Computer Science and Engineering, Kumaraguru College of Technology, Coimbatore 641049, India; jeba.n.cse@kct.ac.in
* Correspondence: judeimmaculate@karunya.edu

Abstract: The advent of the Internet of Things (IoT) has sparked the creation of numerous improved and new applications across numerous industries. Data collection from remote locations and remote object control are made possible by Internet of Things technology. The IoT has numerous applications in fields such as education, healthcare, agriculture, smart cities, and smart homes. Numerous studies have recently employed IoT technology to automate livestock farm operations. We looked at IoT-based livestock farm management systems in this study. To select the publications for this investigation, we conducted a systematic literature review (SLR) that complied with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria. The selected articles were divided into different categories according to their applications. Sensors, actuators, the main controller (gateway), communication protocols, storage, energy consumption, the use of renewable energy sources, scalability, security, and prediction techniques applied to the data collected for future prediction were all examined in this study as IoT technologies used to monitor animals. In this study, we found that only 22% of the articles addressed security concerns, 24% discussed scalability, 16% discussed renewable energy, 18% attempted energy consumption, and 33% employed prediction techniques based on the collected data. The challenges and future directions of intelligent livestock farming are emphasized.

Keywords: animal monitoring; Internet of Things; cattle monitoring; smart livestock management

check for updates

Citation: Terence, S.; Immaculate, J.; Raj, A.; Nadarajan, J. Systematic Review on Internet of Things in Smart Livestock Management Systems. *Sustainability* **2024**, *16*, 4073. https://doi.org/10.3390/su16104073

Academic Editor: Juan Miguel Navarro

Received: 27 January 2024
Revised: 22 April 2024
Accepted: 10 May 2024
Published: 13 May 2024

1. Introduction

The world's population is increasing day by day, and it is predicted to exceed 9 billion in the next 30 years. The majority of this growth is predicted to occur in developing countries, and as the population expands, so will the demand for animal products [1]. Advances in livestock farming technology known as "Precision Livestock Farming" or "Smart Livestock Farming" are being developed to meet the demand for animal products. The term "Precision Livestock Farming" (PLF) was coined at the beginning of the twenty-first century [2]. PLF is the use of technology in everyday life to autonomously assess livestock, livestock behavior, livestock yields, and agricultural ecology in order to help farm activities. This could be accomplished by activating automatic control systems or providing farmers with the necessary information to make management decisions [3]. In livestock farming, research is carried out utilizing various technologies such as sensor technologies [4,5], image processing [6,7], video processing [8,9], audio processing [10], signal processing [11], and behavior analysis [12] All of these techniques, however, have disadvantages such as high costs, difficulties retrieving and storing data, the absence of a graphical user interface (GUI), and scalability [13].

In recent years, the Internet of Things (IoT) has been used in a variety of fields, including smart homes [14], industries [15], agriculture [16], healthcare [17], traffic management [18], manufacturing [19], energy management [20] and transport [21]. Researchers have also begun to apply IoT to livestock farming [22,23]. IoT technologies enable farmers to access farm information from remote locations, and IoT systems automate certain farm devices, which greatly benefits farmers [24]. The data obtained from IoT devices play a vital role in the world of predictive analysis in artificial intelligence [25]. These data are helpful in understanding the behavior of humans, animals, climates, and so on [26]. Many studies have employed IoT approaches in livestock farming and animal monitoring due to their compatibility, low cost, easy data storage and access, and easy accessibility.

In this research, we reviewed the usage of IoT technology in livestock monitoring. Before beginning the review, we read prior review papers; we compare the features of previous work in Table 1.

Table 1. Comparison of prior research studies.

Authors	Year	Animals	Animal Details Analyzed	Systematic Literature Review (SLR) Applied	Technical Details Studied	Critical Parameters Analyzed
Akhigbe et al. [23]	2021	Cow, Pig, Goat, Bee	No	Yes	Yes	Yes
El Moutaouakil et al. [27]	2023	Cow, Beef	No	No	No	No
Vigneswari et al. [28]	2021	Cow	No	Yes	Yes	No
Nigade et al. [29]	2023	Cow	No	No	Yes	Yes
Singh et al. [30]	2020	Hen	No	No	No	No
Goyal et al. [31]	2024	Hen	No	Yes	Yes	No
Ojo et al. [32]	2022	Hen	Yes	Yes	Yes	Yes
Collins et al. [1]	2022	Pig	No	No	Yes	No
Zhang et al. [33]	2022	Pig	Yes	No	Yes	Yes
Hadjur et al. [34]	2022	Bee	No	No	Yes	No
Rastegari et al. [35]	2023	Fish	No	No	Yes	Yes
Petkovski et al. [36]	20221	Fish	No	Yes	Yes	No

A brief summary of Table 1 is given as follows:

- Most of the existing works concentrated only on one animal type.
- A few previous works did not analyze animal details such as the number of animals involved, the position of the smart belt tag, etc.
- Most existing work does not use systematic literature review (SLR) for paper selection.
- There is a lack of work in specifying technical details such as sensor and controller details.
- Most of the research work has not studied energy consumption, utilization of renewable energy, stability, etc.

In order to overcome the above-mentioned shortcomings, we used the SLR method to choose papers. Also, we classified IoT-based livestock monitoring systems. We studied the technical details of the experiment, location details, and other important details. The summary of our work contribution is given as follows:

- Current works concentrating on the application of the IoT for different animals and IoT applications are classified in livestock monitoring as IoT-based cattle monitoring systems, IoT-based bee farm monitoring systems, IoT-based poultry farm monitoring systems, and IoT-based fish farm monitoring systems.
- Animal details such as number of animals monitored, how animals are monitored, and the location of research were studied.
- The SLR method was used to choose relevant papers. With the help of the SLR method, we identified 70 research papers for review.
- Experiments' technical specifications and location details were examined.
- Critical parameters such as energy consumption, renewable energy utilization, scalability, security, cost, and data analytics were examined.

The rest of the study is organized as follows: Section 2 discusses the review selection method, Section 3 discusses IoT-based smart livestock farming, Section 4 discusses IoT-based cattle monitoring systems, IoT-based bee farm monitoring systems are given in Section 5, IoT-based poultry monitoring systems are described in Section 6, Section 7 describes IoT-based fish monitoring systems, challenges and future directions are given in Section 8, and Section 9 comprises the conclusions.

2. Review Selection Method

We selected manuscripts for this evaluation using the SLR approach [37], which compiled with the PRISMA criteria [38]. The PRISMA Checklist has been listed as Supplementary Materials. Manuscripts were chosen using the following keywords:

- (Smart Livestock Farming OR Smart Cattle Monitoring OR Smart Animal Farming OR Cattle Monitoring OR Animal Farming OR Livestock Farming OR Animal Monitoring OR Smart Animal Monitoring OR Animal Care) AND (Internet of Things OR IoT).

The following scientific databases were used to find research documents: Scopus, Web of Science, and Google Scholar.

Regarding the objective of the research, the following scientific queries were taken into consideration:

Query 1: Are IoT techniques used to automate the livestock farming process?
Query 2: Are IoT techniques implemented in real time?
Query 3: How effectively are IoT components utilized in the livestock farming process?
Query 4: Are animal details obtained from remote places using IoT techniques?

We applied the following criteria to filter the articles:

- Articles utilizing IoT technologies in real time to solve problems regarding animals;
- Articles published between 2015 and 2022;
- Articles published in English.

The PRISMA flow diagram is shown in Figure 1. Initially, we identified 1378 (n = 1378) papers. After removing duplicates (n = 517), articles in a language other than English (n = 6), records marked as ineligible by automation tools (n = 0), and records removed for other reasons (n = 0), 855 records were considered for screening (n = 855). It was found that 338 articles were review articles (n = 338); after removing those review articles, 517 articles were retrieved. It was found that 218 articles (n = 218) contained insufficient details, 134 articles (n = 134) were not in the scope of this view, and 95 articles (n = 95) did not contain implementation details. After removing those articles, 70 papers were identified for review. The year-wise paper selection for this review is shown in Figure 2. It clearly shows that attention towards applying IoT technologies to livestock farm activities increased in 2019.

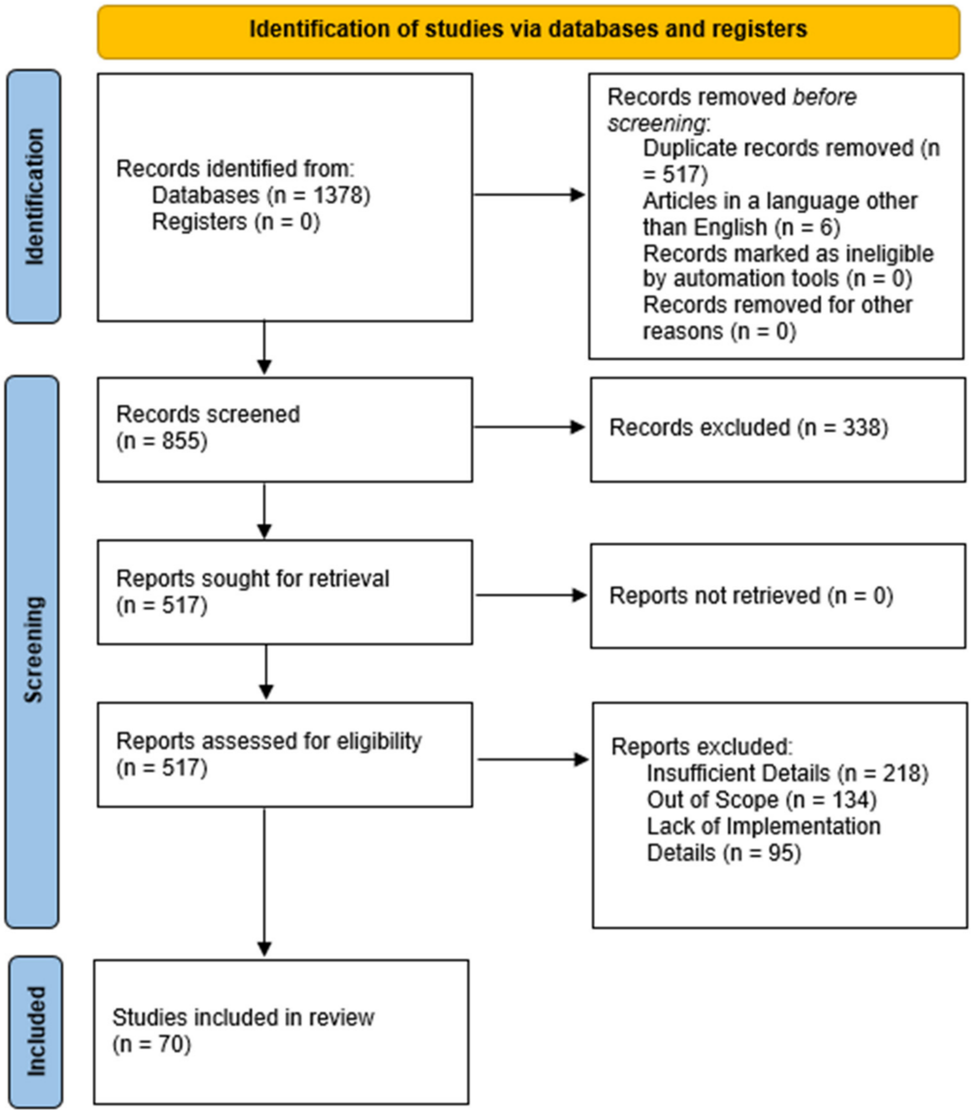

Figure 1. Review selection method.

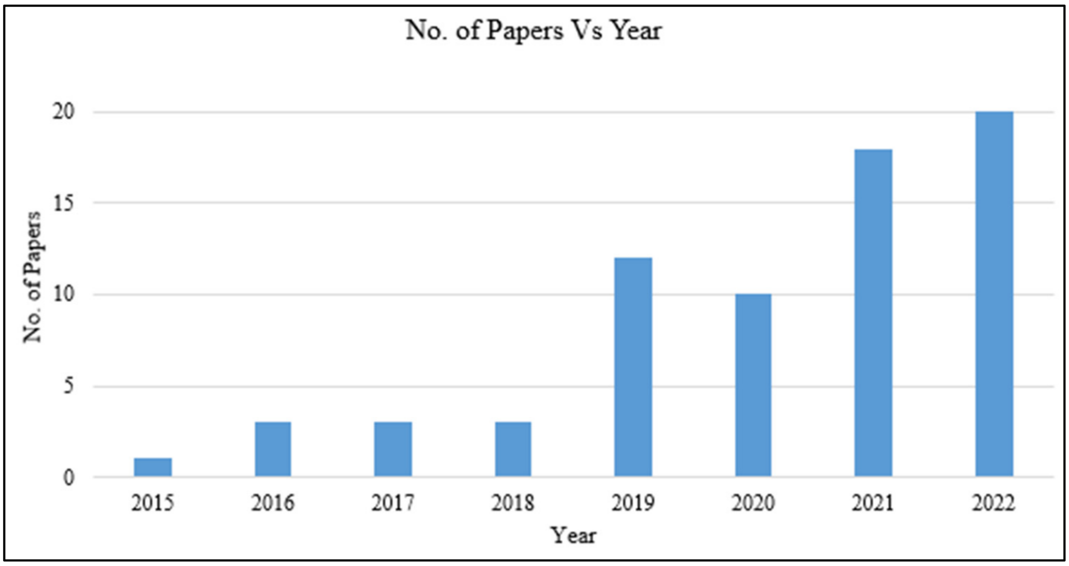

Figure 2. Year-wise paper selection.

3. IoT-Based Smart Livestock Farming

Livestock farming plays a vital role in feeding human society. It also assists farmers in increasing their financial wealth. The productivity of livestock farms is determined by the health of the animals. The health of the animals is affected by a variety of factors such as climate, food, water, and farm cleanliness [39]. Workforce, food, water, and electricity are the most expensive aspects of farming [40]. The primary role of IoT technologies in livestock is to reduce labor, monitor farm animals from remote locations, and provide a safe environment for farm animals [41]. Initially, various technologies such as Bluetooth and sensor networks were used to automate livestock farm work. The main disadvantages of these technologies are their high cost, data access and storage, and lack of a GUI [42].

To solve the aforementioned limitations, researchers have recently deployed low-cost sensors to observe farm settings and biosensors to track changes in farm animals. The data from the observed surroundings and animals are sent to controller devices. These controller devices are smart devices that can store data (on a memory card), process data, and communicate data to a server or cloud storage unit. The data can be accessed by users via online applications or mobile applications. Another significant benefit is that these IoT data are utilized to train AI and ML prediction models [43]. These model results assist farmers and end users in forecasting animal behavior, production rates, and so on. Another significant advantage is that the controller device may automate the functions of devices such as on/off motors depending on sensor data [44]. Farmers can also control these devices from afar, reducing labor requirements, travel costs, and so on. These are the primary reasons that IoT technologies are being used in cattle farm management. The intellectual view of the IoT in livestock farming is shown in Figure 3. The IoT technologies are mainly used for the following reasons in livestock farms.

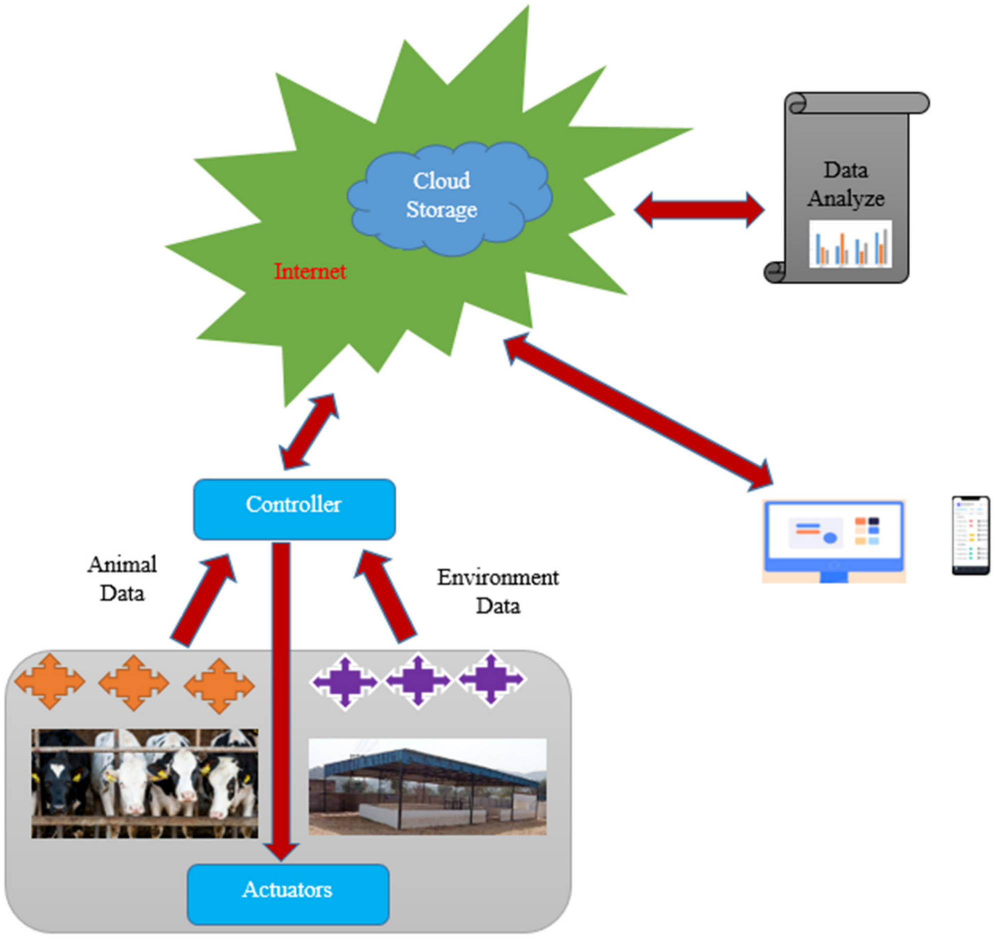

Figure 3. Intellectual view of IoT in livestock farms.

Accessing Animal Data: Animal details such as body temperature, pH, heartbeat, location, animal standing time, lying time, and location are measured with the help of respective sensors.

Accessing Environment Data: Environment details such as temperature, humidity, gases (CO_2, NH_3, H_2S, etc.), and light intensity are measured with the help of sensor devices. Sensors sense these data and send them to a controller. Generally, controllers are smart devices that act as minicomputers. The controller sends received data to the internet for cloud storage and data analysis. Users can access farm details and prediction details on their computers and/or mobile devices. Users can control devices like fans and lights from remote places with the help of IoT technologies. Dairy farms, poultry farms, fish farms, bee farms, and so on are the most common types of livestock farms. As shown in Figure 4, we have categorized IoT smart livestock farming approaches based on farm type into IoT-based cattle monitoring systems, IoT-based poultry farm monitoring systems, IoT-based bee farm monitoring systems, and IoT-based fish monitoring systems.

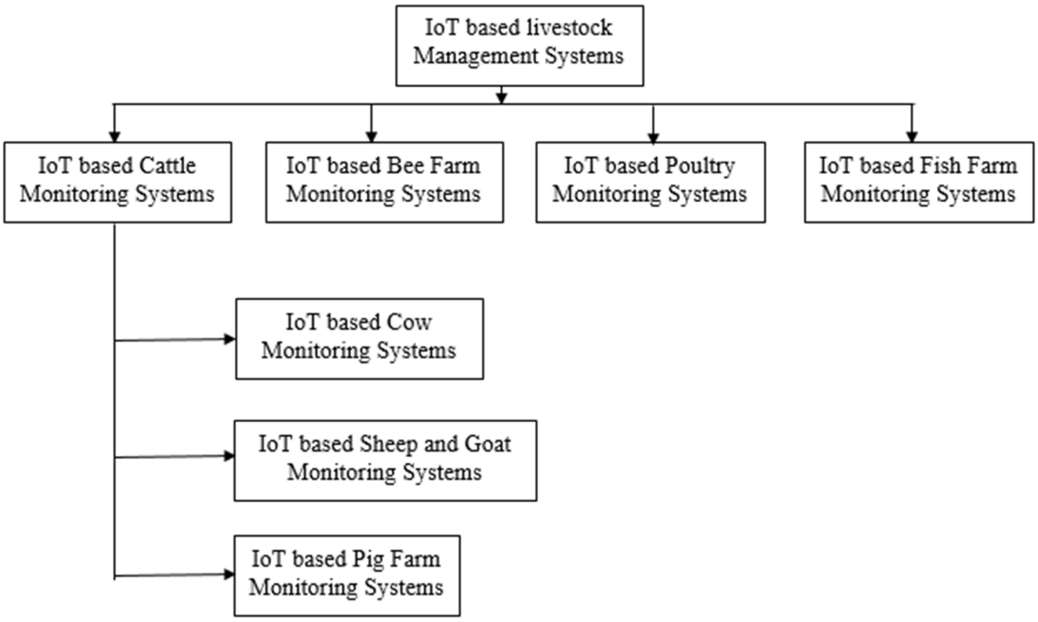

Figure 4. Classification of IoT-based livestock management systems.

4. IoT-Based Cattle Monitoring Systems

In this section, we study different IoT-based cattle monitoring systems. As shown in Figure 5, we classified IoT-based cattle monitoring systems into IoT-based cow farm monitoring systems, IoT-based goat farm monitoring systems, and IoT-based pig farm monitoring systems.

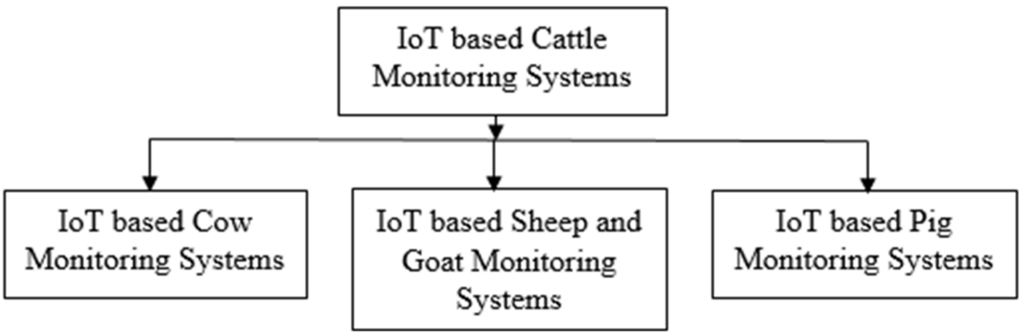

Figure 5. Classification of IoT-based cattle monitoring systems.

4.1. IoT-Based Cow Monitoring Systems

Many researchers used IoT technologies to identify and monitor cow activities. Also, IoT technologies helped automate different activities on cow farms. A detailed description of IoT-based cow farm monitoring systems is given here. Taneja et al. [45] used a long-range pedometer as a wearable device to analyze cow behaviors such as lying time, step count, and standing duration in Ireland. The observed data from the cows were sent to a transceiver through radio signals. The data were transferred to the MQTT fog node using a wired connection. The collected data were analyzed, and recommendations regarding the welfare of cows were given to farmers with the help of fog computing. The collected data were stored in the IBM cloud. The experiment was conducted on 150 cows in Waterford, Ireland. To reduce cost, radio signals were used instead of Wi-Fi signals, and the system helped farmers find anomalies among cows. The authors extended the work and detected lameness sickness 3 days in advance with 87% accuracy by using the K-NN classification algorithm [46]. Feng et al. [47] used an IoT system to identify the social behavior of cows in order to prevent mastitis infection. This system aids in the detection of cows that have had direct contact with mastitis-infected cows. To predict the cow's social behavior, two types of GPS devices were used. One GPS device type was installed in a cow shed, while another was attached to cow collars. A cow social activity graph model was used to identify cow social behavior. The system also predicted the rate of mastitis spread. The 14-day experiment was carried out at the University of Tennessee in the United States. The system aids in the prevention of mastitis among cows. Dineva et al. [48] used Amazon cloud services to store information about cow behavior such as stress level, growth, reproduction, and health. IoT sensors were used to collect data such as gyroscope, temperature, noise, humidity, and location data from cows, and the data were then transferred to a cloud platform via LoRa or the transmission control protocol (TCP). For video surveillance, a thermal camera and a video camera were used. Gateway devices (AWS IoT Greengrass) use Wi-Fi to send data to cloud storage. The observed data were used to train machine learning models to predict animal behavior. This paper lacks implementation details. Mirmanov et al. [49] used Internet of Things-based techniques to monitor the weight of cows on farms. Ultra-high-frequency radio-frequency identification (UHF RFID) tags were used to identify cows. Strain gauges were used to determine the weight of the cows. The measured cow weight was transmitted to an Arduino UNO controller and then to a Raspberry Pi gateway via LoRaWAN and Wi-Fi. A solar panel was used to power the equipment. The model was put to the test on a cow farm with 86 cows. The data were saved in JSON format in the REST API. The system's advantage is its low energy consumption with renewable energy.

Dutta et al. [50] used a GPS module to measure cow temperature and analyze motion processing. A temperature thermistor (NTCLE413E2103F102L) and a GPS module were attached to a cow using a cow collar in this system. The sensor data were routed to an ATMEL328P microprocessor gateway. The TinyGPS+ library, which is used in microcontrollers, is used to measure cow position and walking speed. A GSM or GPRS Quad-Band TTL UART modem is used to send the collected data to the server. The experiments were carried out in three locations in India: Mohanpur, Namkhana, and Durgapur. Thirteen cows were used in the experiment. Temperatures were measured at four different times, yielding a total of 605 datasets. The data were then classified and analyzed with XGBoost and RF. The system assists farmers in understanding the cows' standing and walking behavior. Arshad et al. [51] created a system for tracking cow temperature, heartbeat, and location. In this system, a cow wears a collar that contains a body temperature sensor (MLX90614), a stethoscope (CR-747SS), and a GPS. The temperature, heartbeat, and location of the cow were transmitted to a Node-MCU ESP8266x' gateway. Environment temperature, CO2, and air quality were measured by DHT11 and MQ135. The ultrasonic HC-SR04 sensor measured the water level in the tank. The PHP language was used to store all of the measured data on the server in the form of JSON. The system was designed to automatically activate a fan in a cow's barn. The system aids in the monitoring of a cow's health and position. Maroto-Molina et al. [52] tracked the location of individual cows using GPS and Bluetooth tags. Two types of devices were used in this system: cow collars and cow tags. A GPS module, Bluetooth reader, microcontroller, Sigfox modem, and battery were all included in the cow collar. The cow tag included a Bluetooth module, a microcontroller, and a battery. Cows were outfitted with cow tags that sent data to cows wearing cow collars. Using the MQTT protocol, the cow collar collects data from all cow tags and sends the current location to the server. Orion Context Broker manages data storage in the cloud. Farmers can track the location of their cows using mobile apps. The disadvantage of this method is that the batteries in the cow tag and cow collar frequently need to be replaced. Lovarelli et al. [53] designed custom devices to identify cow behaviors such as eating, lying, and chewing. Instead of using commercial sensors, the authors created their own using the EFR32BG13 Blue Gecko SiP. Sensors and other devices such as antennas, systems-on-board, and batteries are attached with plastic belts. The experiment was carried out on 32 cows in the Lombardy Region of Italy. Cows were fitted with plastic belts, and raw data were transmitted via Bluetooth to gateway and mobile applications. Using 4G signals, the gateway sent data to the cloud server. To identify the cows' behavior in the server, authors used decision tree algorithms such as K-nearest neighbors, random forest, and multi-layer perceptron. The system's limitation is that if a user is in a remote location, the user cannot access the cow details because cow details are accessed via Bluetooth technology.

Arcidiacono et al. [54] measured cow details such as temperature, humidity, pressure, and acceleration using Ruuvitag sensors, an IP video camera, and a Raspberry Pi. The Ruuvitag sensor was attached to the cow's leg and sent data to the Raspberry Pi. Data were saved in JSON format on an SD memory card. Using Raspbian's crontab, users were able to schedule, stop, restart, and pause data acquisition. In Italy, five cows were subjected to an experiment. When it comes to identifying cow behavior, the proposed system outperforms other designs. The system's limitation is that data are stored on SD cards rather than in the cloud, and users have no access to a user interface. Gündüz et al. [55] used IoT techniques to measure the pH and temperature of cows with rumen acidosis. Rumen-affected cows suffered from a lack of milk and pregnancy complications. The stomach size of these suffering cows would change, and their pH level would have a direct impact on their health. The pH level and temperature of the cow were measured using various sensors by the authors. A DS18B20 sensor was used to measure pH, and another DS18B20 sensor was used to measure temperature. As a gateway, a Wemos D1 microcontroller was used. These devices were cannulated into affected cows, and the sensors transmitted the pH level and temperature of the cow to the gateway. The gateway used Wi-Fi to send data to the server, and users (including farmers and veteran doctors) accessed data via the Internet. To conserve battery power, the system measured data every 15 min. Dineva et al. [56] defined an IoT architecture for monitoring cows on farms. Sensors in this system measure temperature, heart rate, and humidity and send the information to the gateway. The authors designed a custom gateway; it receives sensor details and sends data to the AWS cloud. The authors used AWS IoT Greengrass in the gateway for syncing and messing with processes. There are two types of communication protocols, such as LoRaWAN and Wi-Fi. The same IoT architecture was used by the authors in [57], where cows are tagged with devices that can measure heat and calving effort. In order to detect cow movement, cows were tagged with a belt with a motion sensor, which detects cow movement; also, in order to identify cows, QR tags were fixed in cow ears. The collected data are fed into Power BI Pro ML, which predicts the quantity of cow milk. The limitation of the system is its high cost. Hao et al. [58] used RFID signals to identify cows based on their weight in order to detect breeding. In this system, RFID tags were placed in cow ears. An RFID-based hand-held device was developed to identify cows, and an RFID reader was installed in a cow farm to read cow details, including weight. It was connected to the system using a wired network. The system also has a dashboard, which helps users check cow details. The system was deployed in Lincang, China. The system's limitation was that a computer was used as a gateway rather than a microcontroller such as a Raspberry Pi or a NodeMCU.

Righi et al. [59] combined IoT techniques and prediction models to predict milk production at a cow farm. In this system, milk production sensors measured milk quantity, and feed actuators controlled the amount of food given to the cow. These details were sent to the microcontroller, which acted as a gateway. Cows were identified by RFID tags and receivers. The gateway used the Internet to send data to the server. These data were analyzed and predicted using ARIMA, ANN, and RF models. The results showed that the ARIMA model provided better results than other algorithms. The limitation of the system was that it did not provide a GUI or a wired connection used to connect the gateway and server.

Zhang et al. [60] developed cattle monitoring systems that make use of a variety of sensors and control devices. Sensors such as temperature, gas (ammonia and carbon dioxide), humidity, and light intensity were used to monitor the various environmental parameters in cattle. For data communication, an RS-485 communication module was used. The main controller for data access and transmission was STC12LE5A60S2. In China, the system was tested on 11 cattle farms. The system's disadvantage is that the authors designed their own circuit using PCB rather than using a standard available gateway. Datta et al. [61] developed a communication channel model for cannula purposes. The authors experimented with the developed channel in a cannulated cow. An RF Explorer Signal Generator-based transmitter, an ANT700 antenna, and a power amplifier were used for this experiment. The authors inserted a transmitter into the cow's stomach and tested the received signals in an antenna that can be inserted into the cow's neck. Also, a Realsense D435i camera was used to record cow pictures and videos. The results showed that the system was able to reduce the communication loss in data transmission. Chung et al. [62] injected sensors into cows in order to measure the subcutaneous temperature. An RFID LifeChip Microchip was implanted near the left ear of cows to analyze the heat stress of the maximum milk-providing cow and the minimum milk-yielding cow. Data from the biosensor were read using an RFID scanner and sent to a LoRa hub. The temperature of the cow was then transmitted via Wi-Fi to a ThingSpeak cloud server. Long short-term memory (LSTM) was used to analyze the collected data. The experiment was carried out on three cows, two of which were high milk producers and one of which was a normal milk producer. These three cows were also monitored by a GoPro HERO6 Black video camera. The result showed that high-yielding cows' subcutaneous temperature is high compared with that of a normal-yielding cow. Popa et al. [63] used various sensors to monitor air pollutants in livestock farming. The primary goal of this work was to examine the air pollution emitted by cattle. CO, NH3, PM (PM2.5, PM1, PM10), relative humidity, and temperature were measured from the environment using various sensors. Dragino DLOS8 was used as a gateway. The system was used on a cow farm in Teleorman County, where two hundred cows were maintained for dairy purposes. The collected data were stored in a cloud platform. The advantage of the system is that cattle-related air pollution can be observed with the help of the system. The disadvantage of the system is that it would be used in an open environment. Saravanan et al. [64] applied IoT technologies to watch the health status of cows. The authors used sensors like LM35, MLX90614, a thermometer, and a three-axis accelerometer to measure cow body temperature, gesture recognition, rumination, and pulse. The sensors measure these details and send them to an ATmega 328 microcontroller, which acts as a gateway. The system can send data to smartphones using Bluetooth and Wi-Fi communication. The system stores collected data in the ThinkSpeak cloud platform. Each cow is identified by an RFID card. The system was implemented in Tirunelveli District, India. The users can access cow status data on a smartphone in remote places. Park et al. [65] used a GPS module to find the locations of grazing cows. The authors used GPS-enabled cow collars to identify the location of cows. Cows were divided into groups, and the cow leader was identified from the group. Users were able to determine cow locations with the help of the system. The MSP430F2274 MCU was used as a gateway, and 3G/4G GSM was used for data communication. Data were stored in the AWS cloud, and users could access the data through a web interface.

From this study, it is clear that most IoT-based cow monitoring systems are used to monitor cow behaviors, such as standing time, walking time, and eating behavior; cow temperature; and so on. IoT technologies are used to identify cows. This helps farmers analyze their health status. We have found that 62% of systems used different methodologies to identify cows, and 30% of systems used behavior analysis. There are a few systems that involve growth analysis, disease identification, and monitoring pollution caused by cattle. None of the systems involved cattle automation systems. This reveals that researchers need to contribute more to cow cattle automation and pollution monitoring using IoT technologies. In the next section, details about IoT-based sheep and goat monitoring systems are given.

4.2. IoT-Based Sheep and Goat Monitoring Systems

IoT-based sheep and goat monitoring systems are discussed in this section. Ojo et al. [66] proposed a smart collar for recording sheep locations. GPS and sensors were built into the smart collar. The sheep location was transmitted to the LoRaWAN gateway via the LoRa protocol. The data were saved in the Amazon AWS cloud. Grafana was used to display the data. The system was tested in Italy and helped track sheep movement between cattle land and farmland. Rao et al. [67] used a video camera and various sensors, including temperature, humidity, CO_2, NH_3, and H_2S sensors, to track the growth of goats. The data from these sensors were accessed by an RS485 hub. A Raspberry Pi was used as a gateway, and environmental variables were used to control devices such as fans and solenoids. The HTTP protocol was used to access all sensor and goat information, which was then stored in the MongoDB database. Users can view goat and environmental information via the web and mobile interfaces. For anomaly detection, the ML algorithms SVR and KNN are used. Jumi et al. [68] used a video camera and temperature sensor to monitor goats. In this system, a pan–tilt–zoom camera and MLX90614 temperature sensors are connected to a NodeMCU gateway. A temperature sensor is tagged on a goat's neck in order to measure the goat's body temperature. An experiment was performed with four goats. Users monitor goats' videos and view goats' temperatures in mobile and web applications. It would be good if the system provided an automatic warning message when a goat's body temperature exceeds the normal body temperature. Cui et al. [69] monitored the heart rate of sheep during transportation. In this system, the sheep pulse rate is measured using an APDS-9008 sensor, an MLX90615 infrared thermometer is used to measure sheep body temperature, and a DHT20 sensor is used to measure environment temperature and humidity. An ATmega328 microcontroller is used as a gateway. Bluetooth technology is used for wireless communications. The system is split into master and slave mode, in order to save energy consumption. Sheep are tagged with two types of bands. One band, on the neck, has a sheep body temperature sensor and pulse rate detection sensor; the other band, tagged on the body, has GPS, an environment temperature measurement sensor, and a gateway. The system was able to measure the heart rate of sheep during transportation.

Researchers applied IoT technologies to monitor goat weight and goat count and perform identification using video analysis, goat heart rate analysis, etc. Researchers may concentrate on automating goat farm activities using IoT technologies to help farmers reduce workforce costs. IoT-based pig monitoring systems are discussed in the next section.

4.3. IoT-Based Pig Monitoring Systems

The details of IoT-based pig farm monitoring systems are discussed in this section. Lee et al. [70] used Internet of Things (IoT) devices to monitor and count pigs in a pigsty. The pigs' ears were fitted with Bluetooth low-energy tags. Wireless broadband leaky coaxial cable antennas picked up the BLE tag signals and forwarded them to the main controller. The primary controller sent data to the server. An experiment was carried out with pigs from Seven Foods Co., Ltd., Kumamoto Prefecture, Japan, to analyze the system process, and 60 pigs were monitored. The system assisted in pig identification and also tracked pig movement. The system's limitation is that the user cannot access pig details via a mobile or web interface. In order to avoid piglet death due to pig crushing, Chen et al. [71] developed an IoT-based piglet screaming detection technique. Farrowing houses in this system are outfitted with a microphone, an IP camera, a temperature sensor, a floor vibration sensor, and a water drop. Using an Ethernet cable, the IP camera records video and sends it to the server. Before sending data to the server, the sensors collect and send environmental data, such as floor vibration. An Nvidia GeForce RTX system was used to implement AI algorithms for identifying piglet sounds caused by piglet crushing. If it was discovered that pig screaming was caused by pig crushing, floor vibration would be activated. A CNN model was used by the authors to classify the piglet sounds. The system was tested in Yi-Lan, Taiwan, and the results show that it detects piglet crushing early on and activates actuators. Lee et al. [72] identified undergrown pigs using image processing and deep learning methods. In this system, a video camera was installed in a pig house's ceiling. The camera data were sent to an embedded device (a multi-core CPU), which acted as a gateway. It processed data using image processing and deep learning techniques (TinyYOLO3) to identify pigs. The system successfully identified undergrown moving pigs. But it did not detect well-grown pigs. The advantage of this system was that it enabled real-time data processing and pig identification.

Bonde et al. [73] used geophone sensors to monitor pigs and analyze piglet growth. This sensor was able to detect pig position and movement changes. A video camera was also used with this sensor to monitor pig and piglet nursing behavior. The experiment was conducted at Betagro Farm in Lopburi, Thailand, from April to June 2019. The authors made use of SM-24 geophones, LTC6910 amplifiers, and a NodeMCU gateway. These devices were connected through Wi-Fi using the MQTT message model. The authors tested their pig growth analysis approach against the SVM model. The result showed that the proposed method's performance was better than the SVM model's performance. Chen et al. [74] used sensors and a camera to track the growth of pigs in Taiwan. The authors recorded pig behavior using a camera and utilized the Mask RCNN model to identify pig behavior. The algorithm was able to recognize a pig's head, body, tail, and behaviors such as feeding, drinking, and sleeping. The model was able to detect the level of pig growth. Sena et al. [75] used IoT technologies to automate pig farm activities. The authors employed a DHT11 temperature and humidity sensor, and they used an HC-SR04 ultrasonic sensor to detect the amount of food remaining in the food hopper. These sensors were linked to an ESP8266 microcontroller, which served as a gateway. The gateway was linked to a fan, a light, and a food hopper. These actuators were actuated based on measured values under particular parameters. The system was used in Thailand's Nakhon Si Thammarat province. The system's weakness was that, while it controlled the gadgets in the pig farm, it did not measure pig activity. Vaughan et al. [76] employed IoT technologies to measure pig weight and analyze pig motion on a pig farm. A plastic optical fiber (POF) sensor (PGR-FB1000 step-index POF), an ADC, and an ATM2560 Arduino Mega board comprised the system (gateway). The authors combined 22 POF sensors and created a mat for weighing pigs. The pig's weight was shown on an LCD screen, and the results revealed that the mat was more accurate than the present pig weight measurement system. Lee et al. [77] used RFID tags (IC tags) with antennas at Seven Foods Co. Ltd., Kikuchi City, Japan. In this system, IC tags were fixed to the ears of 40 pigs. IC tag details were recorded by four RFID antennas. Six hours per day, the activities of each pig were recorded. The limitation of the system was that the authors did not use pig information for any further analysis. Popa et al. [78] monitored the air pollution of cattle in Romania using IoT technologies. Temperature sensors, pressure sensors, humidity sensors, and air sensors were used to measure environment temperature, humidity, PM_1, $PM_{2.5}$, PM_{10}, CO_2, NO_2, and O_2. Measured values were sent to a gateway using LoRa. Sensor data were forwarded to the cloud using the MQTT protocol. The system was implemented in a cow farm that had 200 cows. The system finds a relationship between air pollution and climate parameters.

IoT-based cattle monitoring systems are classified based on activity, and details are given in Table 2. According to Table 2, the majority of cattle monitoring systems involve animal identification and behavior analysis. A significant number of applications also involve animal temperature monitoring. Few studies attempted to analyze growth and detect disease. There have been very few studies that include pollution monitoring and farm automation. Various aspects of cattle monitoring systems are listed in Table 3. Most of the IoT-based cattle monitoring systems involved animal identification, animal temperature surveillance, behavior analysis, and disease identification. From this analysis, it is clear that only a few systems automate cattle operations. From these studies, it is clear that most IoT-based cattle monitoring systems involve animal identification, behavior analysis, and temperature detection. It has also been found that researchers designed smart belts with different sensors for animals. These smart belts were tagged on animal necks or cow legs. These belts were used to identify animal location, body temperature, etc. Few studies have measured the pollution caused by cattle. This provides a new direction for researchers to find solutions for pollution caused by cattle. The applications of IoT-based bee farm monitoring systems are given in the next section.

Table 2. Classification of IoT-based cattle monitoring systems.

Application	Reference
Animal Identification	[47–52,56–59,62,64,65,70,70,77]
Behavior Analysis	[45,46,50,53,64,67,70–74,76]
Animal Temperature Surveillance	[50,51,54,56,57,62,64,67–69]
Growth/Weight Analysis	[49,58,67,74,76]
Disease Detection and Analysis	[47,48,57,61,64]
Pollution Monitoring	[63,67]
Farm Automation	[75]

Table 3. Various aspects of cattle monitoring systems.

Ref. No.	Year and Country	Animal Monitoring	Sensor Position	Environment Monitoring	Automation of Devices	Energy Consumption	Usage of Renewable Energy	Scalability	Security	Cloud Storage	Data Analysis and Prediction	Web or Mobile Access
[45,46]	2019, Ireland	✓	Leg	✗	✗	✗	✓	✗	✗	✓	✓	✓
[47]	2022, USA	✓	Neck	✗	✗	✗	✗	✗	✗	✓	✓	✗
[48]	2021, Bulgaria	✓	Neck	✓	✗	✗	✗	✓	✓	✓	✓	✓
[49]	2021, Kazakhstan	✓	Ear	✗	✗	✗	✗	✗	✗	✓	✗	✗
[50]	2021, India	✓	Neck	✗	✗	✗	✗	✗	✗	✓	✓	✓
[51]	2022, Pakistan	✓	Neck and body	✓	✓	✗	✗	✗	✗	✓	✗	✓
[52]	2019, Spain	✓	Neck and ear	✗	✗	✓	✗	✗	✗	✓	✗	✓
[53]	2022, Italy	✓	Neck	✗	✗	✗	✗	✗	✗	✓	✓	✓
[54]	2021, Italy	✓	Leg	✗	✗	✗	✗	✗	✗	✗	✓	✗
[55]	2022, Turkey	✓	Body	✗	✗	✗	✗	✗	✗	✓	✗	✓
[57]	2021, Bulgaria	✓	Neck and ear	✓	✗	✗	✗	✓	✓	✓	✓	✓
[58]	2017, China	✓	-	✗	✗	✗	✗	✗	✗	✗	✗	✓
[59]	2020, Brazil	✗	-	✓	✗	✗	✗	✗	✗	✓	✓	✗
[60]	2016, China	✗	-	✓	✗	✗	✓	✗	✗	✗	✗	✗
[61]	2022, US	✓	Stomach	✓	✗	✗	✗	✗	✗	✓	✗	✗
[62]	2020, US	✓	Ears	✗	✗	✗	✗	✗	✗	✓	✓	✗
[63]	2021, Romania	✗	-	✓	✗	✓	✗	✗	✗	✓	✓	✓
[64]	2017, India	✓	Ears, leg, nose, tail	✗	✗	✗	✗	✓	✗	✓	✓	✓
[65]	2021, Korea	✗	-	✓	✗	✓	✗	✓	✗	✓	✗	✓
[66]	2021, Italy	✓	Neck	✗	✗	✓	✗	✗	✓	✓	✗	✓
[67]	2020, China	✗	-	✓	✗	✗	✗	✗	✗	✗	✓	✓
[68]	2022, Indonesia	✓	Neck	✓	✗	✗	✗	✗	✗	✓	✗	✓
[69]	2019, China	✓	Neck, body	✓	✗	✓	✗	✗	✗	✗	✗	✗
[70]	2022, Japan	✓	Ear	✓	✗	✗	✗	✗	✗	✓	✗	✓
[71]	2021, Taiwan	✗	-	✓	✓	✗	✗	✗	✓	✓	✓	✓
[72]	2019, South Korea	✗	-	✓	✗	✗	✗	✓	✗	✗	✗	✗

Table 3. *Cont.*

Ref. No.	Year and Country	Animal Monitoring	Sensor Position	Environment Monitoring	Automation of Devices	Energy Consumption	Usage of Renewable Energy	Scalability	Security	Cloud Storage	Data Analysis and Prediction	Web or Mobile Access
[73]	2021, USA	✓	Leg	✓	✗	✗	✗	✓	✗	✗	✓	✗
[74]	2020, Taiwan	✗	-	✓	✗	✗	✗	✓	✗	✗	✗	✗
[75]	2022, Thailand	✗	-	✓	✓	✗	✗	✗	✗	✗	✗	✓
[76]	2017, UK	✗	-	✓	✗	✗	✗	✓	✗	✗	✗	✗
[77]	2019, Japan	✓	Ears	✗	✗	✗	✗	✗	✗	✗	✗	✗

5. IoT-Based Bee Farm Monitoring Systems

Research has been carried out to monitor bee activities with the help of IoT technology. Most of these systems are used to monitor beehive weight, the relationship between temperature and bee activities, etc. The details of IoT-based bee farm monitoring systems are given below.

Cejrowski et al. [79] used IoT technologies to record bee sounds in a bee colony in order to determine the relationship between bee sounds and temperature. Bee sounds were recorded using a digital microphone with a sampling frequency of 44,100 Hz. The system consists of an analog-to-digital converter (ADS1115), resistors, a MOSFET-N transistor, and a Raspberry Pi serving as a gateway. A bee sound lasting two seconds was recorded. The temperature was compared to the audio signals collected. For five months, the experiment was carried out. Three times per hour, the audio signals were recorded. In total, 35,830 bee audio signals were recorded and analyzed alongside temperature. The system's advantage is that it can be expanded with additional sensor devices. Gil-Lebrero et al. [80] used various sensors and a weighing machine to monitor beehives. A weighing machine and SHT15 humidity sensors were used to measure real-time beehive weight, and an MCP9700A temperature sensor was used in various locations throughout the hive. The measured values were sent to the server by a Waspmote module, which was based on an ATmega 1281 microcontroller. The Waspmote IDE and C programming libraries were used to access data. Wireless nodes were in sleep mode during data acquisition to save power. The study was carried out on 20 beehives in Spain. The system enabled beekeepers to remotely monitor beehives; it would be preferable if the system used renewable energy instead of battery power. To monitor bee colonies, Hong et al. [81] used a temperature and humidity sensor (DTH12), an acoustic sensor, an entrance sensor, and a weight sensor. Sensor readings were sent to an STM32 microprocessor. The information gathered was uploaded to a cloud server. SMS (short message service) was used to detect abnormal behavior in bee colonies. The experiment lasted 120 days in E110.81N24.85. The system aids in the analysis of the relationship between climate, bee entrance counts, and colony weight. Mrozek et al. [82] used IoT and ML techniques to analyze real-time videos of bees. The system's goal was to use a convolutional neural network (CNN) model to identify bees and the Varroa destructor insect in beehives. The Varroa destructor insect causes varroosis, a bee disease. The authors used a 5-megapixel camera to record bee videos in order to identify the varroosis bee disease among bees. Videos were captured and sent to a Raspberry Pi (gateway). The data were transferred to the AWS cloud by the gateway. Google Coral was linked to the Raspberry Pi, which served as an edge device, via USB. It used the CNN model to analyze the video recording and identified the varroosis bee disease. The details of the infected bee were communicated to users via the MQTT protocol.

Tashakkori et al. [83] monitored beehives with a humidity and temperature sensor, a microphone, and a Raspberry Pi camera. Data collected from beehives were sent to the Raspberry Pi. The Raspberry Pi sent data to a ThingSpeak server so that users could access them. The system could detect bees in beehives, and it counted bees using video processing. The main limitation of the system was that the collected data were not analyzed or used in any other way. Gabitov et al. [84] studied the relationship between outer and inner temperature in wild bee colonies using temperature and humidity sensors. To receive and transfer the data, two types of gateways (RAK7204 monoblock devices) were used. For data transmission, LoRaWAN technology was used. Grafana's cloud platform stored information. The system ran on batteries and was recharged by a photovoltaic panel. According to the findings, bees' behavior changes to match the external climate of the bee colony. Andrijević et al. [85] used a variety of sensors to track bee activity in beehives. This system counts bees and records beehive temperature, humidity, air quality, and outside air pressure, as well as humidity, temperature, UV index, UV IR light, light intensity, and so on. The main purpose of this system was to study bee activity in relation to environmental changes. Data were collected and saved in the cloud, while mathematical and recurrent neural network models such as ARIMA, LSTM, GRU, and RNN models were utilized to forecast bee behavior. A web interface allowed users to access data. The experiment was conducted for 15 days in October 2021, with 5 min intervals. For additional investigation, the authors could have used weight sensors, carbon dioxide sensors, and oxygen sensors. The temperature, humidity, and weight of beehives were measured by Zabasta et al. [86,87], and bee behavior was observed using an IP camera. Temperature, humidity, and weight sensors sent data to Node-RED, which acted as a gateway server via an MQTT broker. GSM was employed for communication between sensors and MQTT gateways in the system. The experiment was carried out at the Riga Botanic Garden in Latvia. The system's main disadvantage is that it lacks coordinator nodes (gateways), making it difficult to manage sensors and devices. Zgank et al. [88] monitored bee activities based on bee sounds. To analyze bee activity, bee sounds were recorded and transferred to a server using the GSM network. Then, reordered sounds were classified using mel-frequency cepstral coefficients (MFCCs), and then data were classified using hidden Markov models (HMMs) and deep neural network (DNN) models. The result showed that a DNN model yields higher accuracy than HMM. Table 4 shows that the majority of IoT-based bee farm monitoring systems are engaged in beehive weight and temperature surveillance activities. Table 5 includes a list of several features of bee farm monitoring systems.

Table 4. Classification of IoT-based bee farm monitoring systems.

Application	Reference
Bee Count	[85]
Behavior Analysis	[82,83]
Animal Temperature Surveillance	[80,81,83–87]
Growth/Weight Analysis	[80,81,86,87]

From this study, it is clear that researchers used IoT technologies to monitor the humidity and temperature of bee colonies. Also, different devices were used to measure beehive weights. Few studies attempted to understand bee behavior. Poultry farm activities are automated by IoT technologies. We provide details of IoT-based poultry farm activities in the next section.

Table 5. Various aspects of IoT-based bee farm monitoring systems.

Ref. No.	Year and Country	Animal Monitoring	Sensor Position	Environment Monitoring	Automation of Devices	Energy Consumption	Usage of Renewable Energy	Scalability	Security	Cloud Storage	Data Analysis and Prediction	Web or Mobile Access
[79]	2021, Poland	✗	-	✓	✗	✗	✗	✗	✗	✗	✗	✗
[80]	2021, Poland	✗	-	✓	✗	✓	✓	✗	✓	✓	✗	✗
[81]	2020, China	✗	-	✓	✗	✗	✓	✗	✗	✓	✗	✗
[82]	2021, Poland	✗	-	✓	✗	✓	✗	✗	✓	✓	✓	✓
[83]	2021, US	✓	Inside Beehives	✓	✗	✗	✗	✗	✗	✓	✗	✓
[84]	2022, Russia	✓	Inside Beehives	✓	✗	✗	✗	✗	✗	✓	✗	✗
[85]	2022, Serbia	✓	Inside Beehives	✓	✗	✓	✗	✗	✗	✓	✓	✓
[86,87]	2019, Latvia	✓	-	✗	✗	✗	✓	✗	✗	✓	✗	✗
[88]	2021, Slovenia	✓	-	✗	✗	✗	✗	✗	✗	✓	✓	✓

6. IoT-Based Poultry Monitoring Systems

Temperature, humidity, and light are vital parameters for hen growth and healthy life. With the help of IoT technologies, researchers applied sensors to measure poultry environments and automated devices to maintain constant temperature, humidity, and light in poultry farms. The details regarding IoT-based poultry farms are given below.

Chien et al. [89] designed a smart system to monitor and analyze the egg-laying behavior of hens. RFID tags were attached to hens' legs in this system, and an RFID receiver installed in the hen nest box identified hen movements. In order to identify an egg, a strain gauge pressure sensor was used. The collected data were sent to an Arduino board (MEGA-2560), and the data were then sent to cloud storage, an NTP server, and an SD memory card via a gateway. An experiment was conducted on four hens at the National Ilan University, Taiwan, for 45 days. Infrared cameras were used to monitor the hens to verify the RFID signals. The system helped farmers monitor the laying nature of hens. Gobinath et al. [90] automated poultry farm activities and presented a system that helps to provide constant temperature and light. In this system, existing poultry farm activities are replaced with different sensors and different devices. Temperature sensor details help to automate foggers and water pumps with the help of a relay. An ultrasonic sensor helps to measure a food tray with the help of a gear motor. To feed hens, hen food is supplied to hens with the help of a gear motor. The gear motor supplies food to hens and also moves the food trolley two times per day. An Arduino Uno ATmega328 is used as a gateway that receives sensor details and automates devices with the help of a relay. The main drawback of the system is that its data are not stored or processed for future analysis. Pereira et al. [91] designed a low-cost hen farm monitoring system. In this system, to measure temperature and humidity, a DHT22 sensor was used, an MQ-137 electrochemical sensor was used to measure ammonia levels in the air, and a light-dependent resistor sensor was used to measure luminosity. These devices sent data to the gateway (Wemos Mini D1), and the gateway sent data to the server using Wi-Fi. Users were able to access farm details via a mobile application. An experiment was conducted at the Federal Institute of Education in Brazil for five days. The proposed low-cost system outperformed other commercially available devices. Niranjan et al. [92] used various sensors to monitor a hen egg incubator. In this system, two temperature sensors, namely DHT11 and DS18B20, were used to monitor temperature; a humidity sensor (HSM-20G) was used to read humidity; a reed switch was used to monitor the tilt of eggs in the incubator; and to monitor the water level, stainless steel rods were used in the egg incubator. NodeMCU (ESP8266) was controlled by ESP8266 and PIC16F887 controllers. To control air circulation, DC fans were used. The result showed that the best temperature for an incubator is 36.5 °C to 38 °C. Users were able to monitor environment parameters on their mobile devices using the Blynk application. The system's limitation was that data were not stored on a server or in the cloud.

Zhang et al. [93] used IoT and ML techniques to identify geese breeding eggs indoors. A cage was designed so that only one goose could enter the nest and lay an egg. Geese in this system are tagged with RFID tags that are installed in the cage. When geese enter the nest, their identification details are sent to the gateway (Celeron J1800 CPU, Intel, Santa Clara, CA, USA), and the gateway then sends the data to a cloud server for storage. Hikvision DS-IPC-T12H2-I/POE cameras (Hikvision, Hangzhou, China) are used to record video of the object in order to identify it. The video is split into images, which are then processed by Pytoch's deep learning frame using a modified single-shot multi-box detector (SSD). The object information is printed on the quick response codes of eggs (QR codes). The experiment was carried out at Yangzhou University in China.

Peprah et al. [94] created a solar-powered smart egg incubator to address Africa's power shortage. The authors used Arduino as a gateway in this system. In the incubator, temperature and humidity were measured using temperature and humidity sensors. The sensed values were sent to the gateway; if the incubator temperature fell below 37.5 degrees Celsius, the gateway sent an SMS message to the user and the heater. Similarly, if the humidity value was less than the threshold value, the heater was turned on. Based on the threshold value, the gateway turned the heater and motor on and off. It aided in avoiding unnecessary power consumption in the incubator. Furthermore, because the solar incubator was powered by solar energy, the power issue was avoided. Feiyang et al. [95] used RFID tags to track hens in poultry farms. In this system, hens were fitted with RFID tags, and RFID receivers were installed on various posts throughout hen farms. This system was able to identify hens and their movement, resting time, and ability to find (snatch) food, and a weighing device was used to measure the hens' weight. The k-means clustering algorithm was used to analyze these details, and the hens were classified as normal, active, or sick. An experiment on 24 hens was carried out in Jianggao, China. It would have been preferable if the system had used more sensors to improve classification accuracy. Furthermore, no gateway or graphical user interface (GUI) was used by the system. Various IoT components used in poultry monitoring systems are shown in Table 6, and various aspects of poultry monitoring systems are displayed in Table 7. Mitkari et al. [96] developed an automated food supply and temperature control system for a poultry farm. This system has a moving food-providing system. Using Bluetooth signals, users can turn on and off the food valve of the food container. A DHT22 sensor is used to measure the temperature of the chicken farm and to activate the sprinkler via a relay. An Arduino ATMEGA328P gateway is used to control the devices. The system does not keep details about poultry farms for later examination. Few researchers applied IoT technologies to monitor fish and automate fish farm activities. These IoT-based fish farm monitoring systems are discussed in the next section.

Table 6. Classification of IoT-based poultry monitoring systems.

Application	Reference
Animal Identification	[95]
Behavior Analysis	[89,95]
Animal Temperature Monitoring	-
Growth/Weight Analysis	[95]
Disease Detection and Analysis	-
Pollution Monitoring	[91,97–99]
Farm Automation	[90,92–94,96,100–102]

Table 7. Various aspects of IoT-based poultry farm monitoring systems.

Ref. No.	Year and Country	Animal Monitoring	Sensor Position	Environment Monitoring	Automation of Devices	Energy Consumption	Usage of Renewable Energy	Scalability	Security	Cloud Storage	Data Analysis and Prediction	Web or Mobile Access
[89]	2018, Taiwan	✓	Legs	✓	✗	✗	✗	✗	✗	✓	✗	✗
[91]	2020, Brazil	✗	-	✓	✗	✗	✗	✗	✗	✗	✗	✓
[92]	2021, India	✗	-	✓	✗	✗	✓	✓	✗	✗	✗	✓
[93]	2022, China	✗	-	✓	✓	✗	✗	✗	✓	✗	✗	✗
[94]	2022, Ghana	✗	-	✓	✓	✗	✓	✗	✗	✗	✗	✗
[95]	2016, China	✓	Legs	✗	✗	✗	✗	✗	✗	✓	✓	✗
[90]	2021, India	✗	-	✓	✓	✗	✗	✗	✗	✗	✗	✗
[96]	2019, India	✗	-	✓	✓	✗	✗	✗	✗	✗	✗	✗
[100]	2019, China	✗	-	✓	✓	✗	✓	✓	✗	✗	✗	✗
[97]	2018, Pakistan	✗	-	✓	✓	✗	✗	✗	✗	✗	✗	✗
[98]	2015, China	✗	-	✓	✓	✗	✗	✗	✗	✗	✗	✗
[101]	2020, Viet Nam	✗	-	✓	✓	✗	✗	✗	✗	✗	✗	✓
[99]	2022, Latvia	✗	-	✓	✓	✗	✗	✗	✗	✓	✗	✓
[102]	2022, Zimbabwe	✗	-	✓	✓	✓	✗	✗	✗	✗	✗	✗

7. IoT-Based Fish Farm Monitoring Systems

Water quality is an important parameter for fish growth [103]. Underwater sensors are used to measure water quality [104]. Researchers measure the turbidity level, oxygen content, pH, turbidity level, and temperature in water with the help of sensors, and these data help to understand water quality and fish behavior with respect to water quality. IoT-based fish farm monitoring systems are given below.

Yang et al. [2] proposed an acoustic telemetry system for detecting changes in the environment and studying fish characteristics. Microcontrollers, Arduino boards, Wi-Fi modems, wind speed sensors, weather stations, satellite modems, acoustic telemetry modems, Ethernet modems, and other devices were used in the systems. On 26 August 2020 and 23 September 2022, the system was tested near Ice Harbor Dam in the United States. The system was capable of detecting fish migration, water flow patterns, and aquatic environmental changes. The system has the advantage of being able to monitor changes in the relationship between offshore and onshore measurements. Putra et al. [105] created a portable IoT-based water quality measurement device to monitor water quality in fish farms. In this system, a turbidity sensor was used to measure the turbidity level in water, and an RGB sensor, along with a potentiometer, was used to ensure that the intensity of the water was uniform. These sensors sent environment details to NodeMCU (the gateway), and a GPS device was used to determine the location. The hardware device transmitted data to the mobile device via Bluetooth. These files were saved in the cloud. The system was set up in Bedadung River, Indonesia. A commercial turbidity meter was used to validate the system's output. The results demonstrated that the system could detect turbidity levels ranging from 0 to 500 NTU with an RMSE of 20 to 30. The system's advantage was its low cost in comparison to commercial products, but it suffers from its high RMSE.

Chiu et al. [106] used multiple sensors to collect data from a fishpond and control different actions based on the measured values. The authors used a dissolved oxygen sensor, a pH sensor, a turbidity sensor, and a temperature sensor in this system to measure oxygen content, pH, turbidity level, and temperature in water. Wi-Fi was used to send the collected data to a gateway (Arduino Mega2560). Based on the received values, the gateway controlled the actions of devices such as a water pump, heater, agitator, smart feeding device, and limit switch. In addition, gateways sent data to cloud storage. Further data were analyzed using deep learning models, which predicted fish growth. Users could also use IPCAM to monitor fish. Similarly, users could view fish and environmental variables and control the devices via a mobile application. The authors evaluated the designed system in the monitoring of the growth of California bass fish. The system's limitation was that, while it was ideal for small fishponds, it was difficult to scale up to larger aquaculture operations due to the high cost. Tamim et al. [107] collected aquatic environmental data using various sensors. In this system, the authors measured water temperature, ammonia level, oxygen level, and pH level using a temperature sensor, an ammonia kit, an oxygen kit, and a pH sensor. NodeMCU received the measured values. Using the Massachusetts Institute of Technology application, users were able to obtain information in a mobile app. Data in Google Firebase were stored in JSON format. The authors used a small lab setup to test the system. The system's limitation is its lack of compatibility. Dupont et al. [108] measured water temperature, water pH, and water dissolved oxygen levels using different sensors. The authors used an Arduino Pro Mini as a gateway. Data were stored in a MongoDB database, and users could access the data using a smartphone with the help of Kibana. The model was deployed in Kumah Farms, Ghana, in January 2017, and it weighed over 18 pounds. The limitations of the system are that it does not monitor fish and that the battery should be replaced at regular intervals. Reduan et al. [109] used DFRobot Turbidity, DS18B2, and DFRobot PH meters to measure the dissolved oxygen, temperature, and pH levels of water. All these devices were connected to an Arduino board. With the use of a GSM module, data were sent to an LCD screen for display in SMS format. Then, the data were stored in Excel format for future access. The experiment was conducted in June 2021. The limitation of the system was that it did not utilize energy optimization and had no

GUI or remote access. Rashid et al. [110] applied IoT technologies to automate a biofloc pond in Bangladesh. The authors used temperature sensors, total dissolved solid sensors, and pH sensors with an Arduino UNO. The system helped workers at the biofloc pond measure water properties without any manual work. The collected data were applied to a machine learning algorithm for prediction purposes, and the result showed it obtained 77% accuracy. Susanti et al. [111] used total dissolved solid (TDS) sensors, temperature sensors, and pH sensors to measure the water quality of aquaculture systems. Sensors such as DS18B20, SEN0161, and SEN0244 were connected with a NodeMCU ESP8266 gateway. The system has an LCD screen that displays the sensor values. The users can access the sensor data using an Android mobile application. The advantage of the system is its low cost. Gao et al. [112] used IoT techniques to trace the quality of the water in a freshwater fish tank. Fish were tagged with QR codes so that each individual fish could be traced, and each fish's behavior and growth details were stored in a database. Based on the measured values, water filtration actuators could be controlled. The main benefit of the system was the web interface, which allowed customers to log in and track the water quality and fish growth details before purchasing fish. Hassan et al. [113] used a LoRA module to monitor fish and water properties in marine farms. To collect data underwater, acoustic test tags (Thelma Biotel AS) and TBR-700-RT acoustic receivers were used. These data were then transferred to the surface and accessed by a LoRa Add-on Module before being forwarded to a MultiConnect Conduit (MTCDT-H5-210L) that served as a gateway. Using the MQTT protocol, the gateway sent data to the Internet. An experiment was carried out in Norway to investigate real-time data access from a marine farm. The system's advantage was its ability to transfer marine farm information over up to 450 m underwater using the LoRa technique. The system's limitation was that it did not monitor fish details such as location and behavior. Table 8 indicates that the majority of IoT-based fish monitoring systems monitor water quality parameters such as temperature, oxygen level, and pH level. Table 9 presents a list of fish monitoring systems features.

Table 8. Classification of IoT-based fish farm monitoring systems.

Application	Reference
Water Flow and Fish Migration Detection	[2]
Pollution (Water Characteristics) Monitoring	[105–109,111]
Farm Automation	[110]

Table 9. Various aspects of IoT-based fish farm monitoring systems.

Ref. No.	Year and Country	Animal Monitoring	Sensor Position	Environment Monitoring	Automation of Devices	Energy Consumption	Usage of Renewable Energy	Scalability	Security	Cloud Storage	Data Analysis and Prediction	Web or Mobile Access
[2]	2022, China	✗	-	✓	✗	✓	✗	✓	✗	✓	✗	✗
[105]	2022, Indonesia	✗	-	✓	✗	✗	✗	✗	✓	✓	✓	✓
[106]	2022	✗	-	✓	✓	✗	✗	✗	✓	✓	✓	✓
[107]	2021, Bangladesh	✗	-	✓	✗	✗	✗	✗	✗	✓	✗	✗
[108]	2018, France	✗	-	✓	✗	✗	✗	✓	✗	✗	✗	✓
[109]	2021, Malaysia	✗	-	✓	✗	✗	✗	✗	✗	✗	✗	✗
[110]	2021, Bangladesh	✗	-	✓	✗	✗	✗	✗	✗	✗	✓	✗
[111]	2021, Indonesia	✗	-	✓	✗	✗	✗	✗	✗	✗	✗	✓
[112]	2019, China	✓	Fin	✓	✓	✗	✗	✗	✗	✓	✓	✓
[113]	2019, Norway	✗	-	✓	✗	✓	✗	✗	✗	✓	✗	✗

8. Discussion and Future Directions

The application of the Internet of Things (IoT) to livestock farming gives a lot of advantages to farmers, but we have observed a few limitations in existing IoT-based livestock farming techniques. The following limitations should be overcome in the future to improve the effectiveness and efficiency of farmers working with their livestock.

Animal and Environment Monitoring:

Animals are vital to livestock management. Animal welfare is critical in livestock monitoring. As a result, it is critical to monitor livestock animals. According to Figure 6, 65% of cattle monitoring systems can monitor cattle using necessary sensors and video cameras. This aids in the understanding of animal behavior as well as the prediction of farm outcomes such as milk yield and animal weight gains and losses. Approximately 15% of bee farm monitoring systems track bee behavior parameters such as hive weight and bee sounds. However, only 6% of poultry farm management systems monitor hens. It is difficult to equip each hen with sensors in a poultry farm because of the abundance of hens. Video analysis and sound analysis could be used to monitor large number of hens. Figure 7 shows the environment monitoring of different livestock systems.

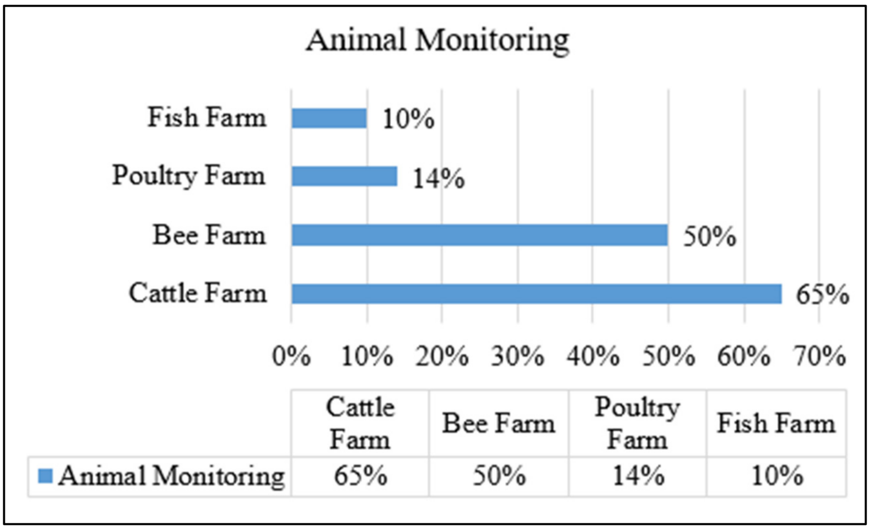

Figure 6. Animal monitoring in IoT-based livestock farms.

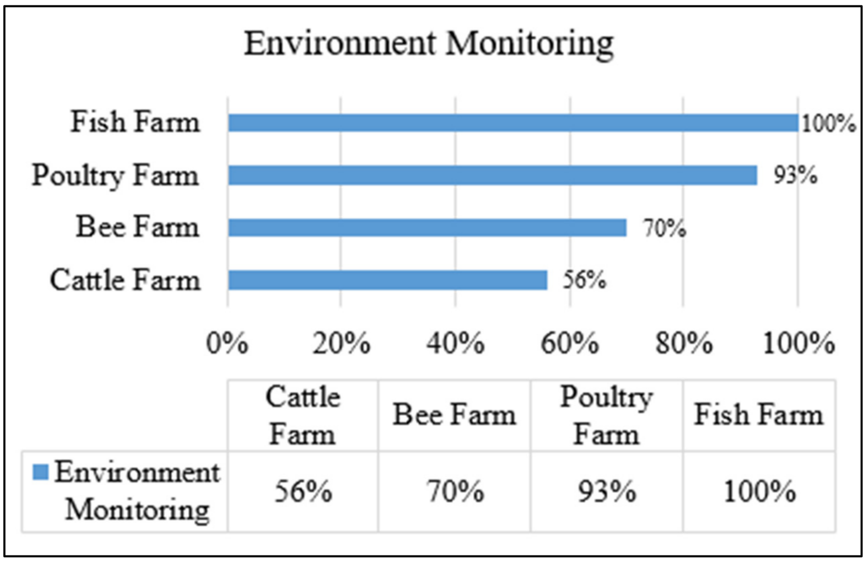

Figure 7. Environment monitoring in IoT-based livestock farms.

Device Automation:

The Internet of Things enables us to automate devices when certain conditions are met. It would be extremely beneficial for farmers and livestock workers. However, as shown in Figure 8, 12%, 20%, and 71% of cattle monitoring systems, poultry monitoring systems, and fish monitoring systems use IoT technology to automate farm activities. Most IoT-based poultry monitoring systems measure environmental parameters such as temperature and humidity and automate devices like sprinklers, fans, lights, and incubators. Very few devices are automated in cattle farms, fish farms, and bee farms. Since the workforce is one of the major costs of livestock farming, researchers should design a system to automate various necessary devices such as water motors, feeding systems, lights, fans, and heaters in cattle, fish, and bee farms.

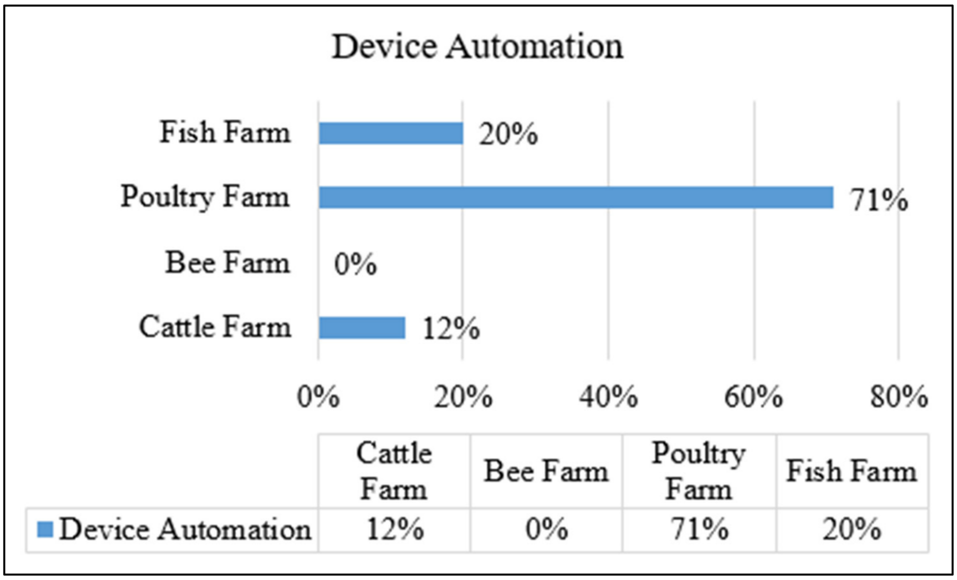

Figure 8. Device automation in IoT-based livestock farms.

Energy Consumption:

Since all smart devices require power, a system should be designed to utilize as little energy as possible. As shown in Figure 9, only 18% of cattle monitoring systems, 30% of bee monitoring systems, 7% of poultry farm monitoring systems, and 20% of fish farm monitoring systems used energy consumption reduction concepts such as the sleep/awake concept. The sleep/awake method involves sensors, actuators, and other devices sleeping most of the time and only activating when necessary. These devices will only receive power when devices are active; when devices are sleeping, the power will be turned off. This cuts down on the use of unnecessary energy. Incorporating awake and sleeping techniques into smart livestock husbandry techniques would be beneficial for future research [114,115]. Researchers could apply techniques like sensor- and actuator-based energy utilization methodologies [116,117], cloud-based energy optimization [118,119], and network-level energy optimization [120–122] for energy consumption.

Usage of Renewable Energy:

Several of the current research investigations in intelligent cattle husbandry employ batteries. According to Figure 10, just 6% of livestock agricultural monitoring systems for cattle, 30% of monitoring systems for beehives, and 21% of monitoring systems for poultry farms use renewable energy. When deployed on a large livestock farm, a system may necessitate a significant quantity of electric/battery power. Solar energy, thermoelectric energy, radio frequency energy, and electromagnetic energy should all be investigated as alternatives to battery or electrical energy. This will help to minimize electricity costs while also benefiting the environment [123,124]. Also, future IoT-based animal monitoring systems could concentrate more on micro-energy harvesting techniques [125], multi-model energy harvesting schemes [126], and microgrid structures [127] for renewable energy generation and distribution.

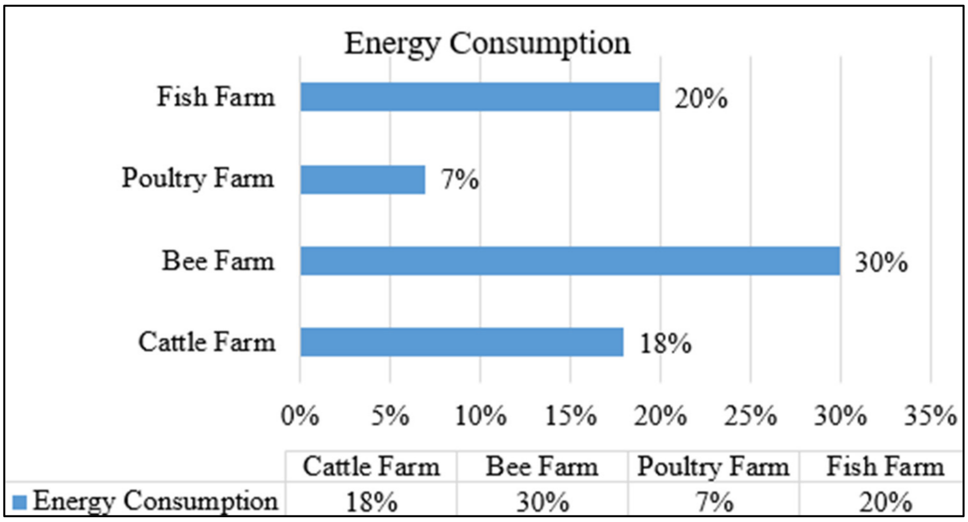

Figure 9. Energy consumption in IoT-based livestock farms.

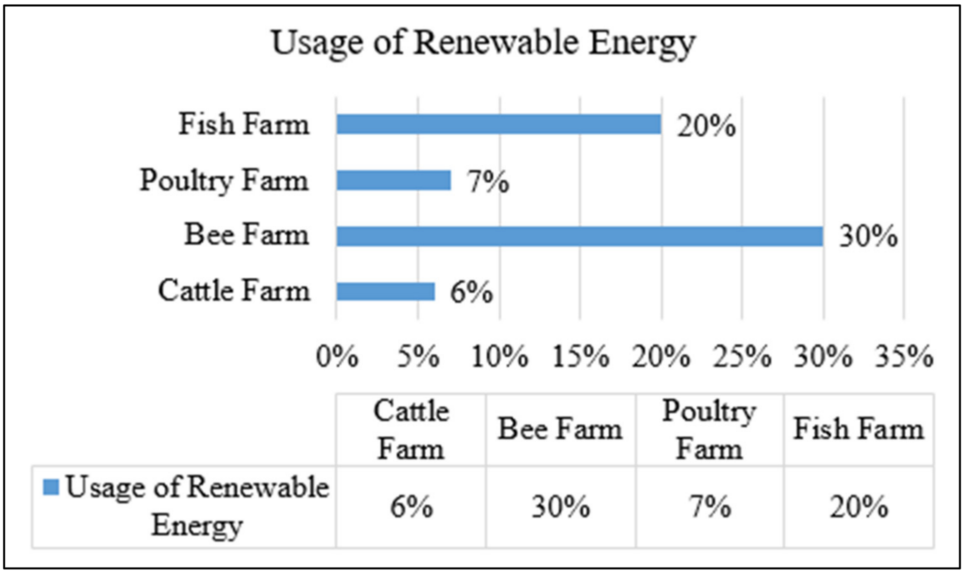

Figure 10. Usage of renewable energy in IoT-based livestock farms.

Scalability:

Researchers should build smart systems so that farmers can add or remove sensors, actuators, and gateways as needed. Most existing smart farming techniques utilize IoT technologies only for certain farm animals rather than all farm animals. A system should provide an easy mechanism for adding/removing devices, such as a plug-and-play method, so that farmers may simply add/remove devices in smart livestock farming [128,129]. Nevertheless, as illustrated in Figure 11, just 26% of fish farm monitoring systems, 20% of bee farm monitoring systems, 21% of poultry farm monitoring systems, and 20% of cattle farm monitoring systems offered the capability to quickly add and remove devices in IoT-based animal farming approaches.

Data Security:

Most communication methodologies, such as ZigBee and Wi-Fi, are vulnerable to numerous security assaults [130]. For example, ZigBee is susceptible to packet decoding, data manipulation, and traffic sniffing concerns, while IEEE 802.11 is susceptible to jamming, scrambling, and passive assaults. The necessary critical work should be completed to safeguard data transmission and trust management strategies in the IoT [131]. Researchers could use AWS IoT device defender [127], Azure IoT Hubs [132], and AWS IoT [133] services for secure data storage and transfer. This will help to prevent different security attacks and provide secure data transmission, storage, and accessibility. The essential measures for increasing security in IoT-based animal livestock farming, however, as per Figure 12, have only been implemented by 18% of cow monitoring systems, 20% of bee monitoring systems, 7% of poultry monitoring systems, and 30% of fish monitoring systems.

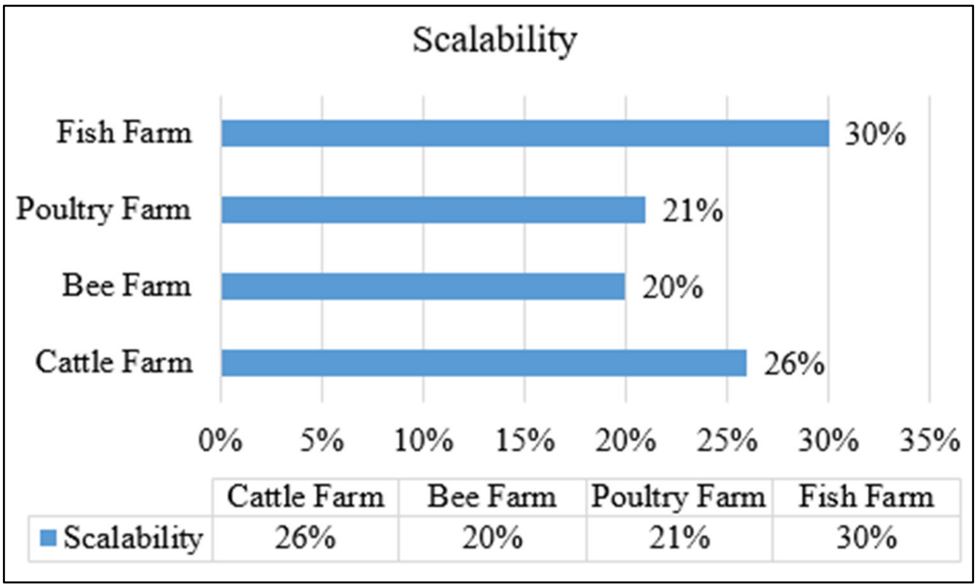

Figure 11. Scalability in IoT-based livestock farms.

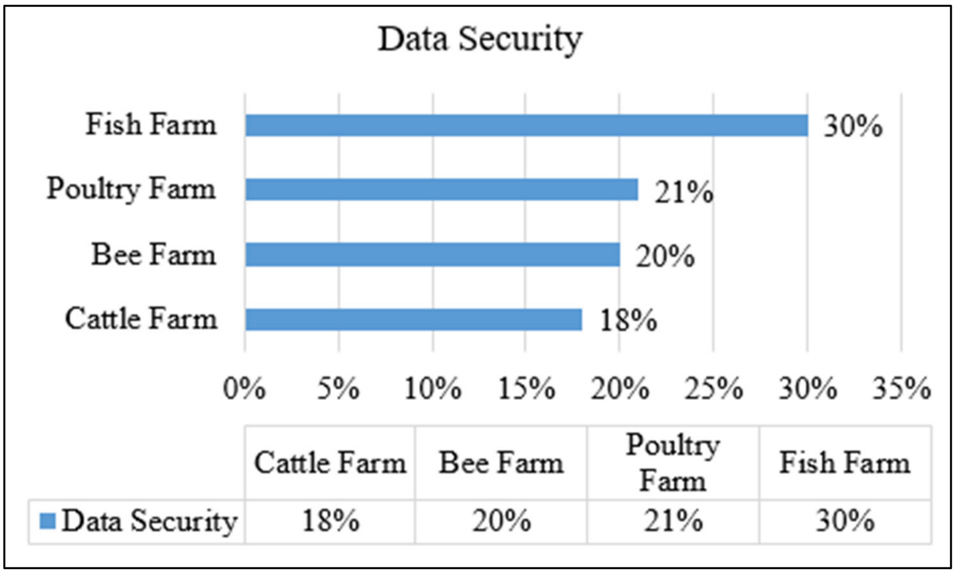

Figure 12. Data security in IoT-based livestock farms.

Cloud Storage and Web/Mobile Interface:

Data persistence, availability, and accessibility are critical parameters. Instead of storing data on SD cards or in local memory, it would good option to store data in the cloud. Many open-source cloud platforms are available for storing IoT details. Cloud storage helps to ensure data persistence, availability, and accessibility. But still, many systems are using local storage instead of cloud storage. Also, users should have a proper platform for accessing farm data from anywhere at any time. But many systems use LCD/LED display devices. Also, many systems do not provide a proper interface for data accessibility. Instead of using traditional display devices, researchers should use web interfaces and mobile interfaces for data accessibility. Figures 13 and 14 show cloud storage utilization and web and mobile interface details for livestock farms.

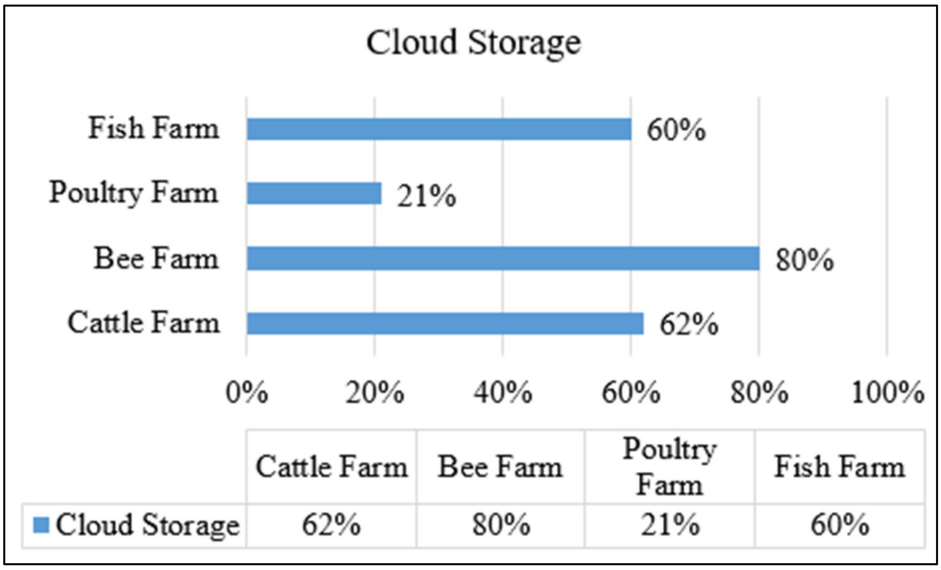

Figure 13. Cloud storage in IoT-based livestock farms.

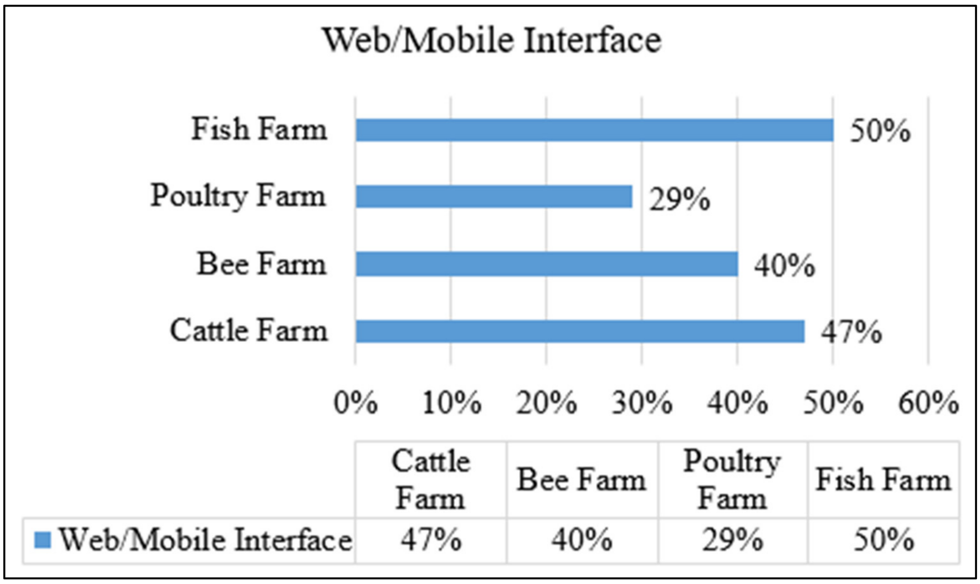

Figure 14. Web/mobile interface in IoT-based livestock farms.

Data Analysis and Prediction:

Smart farming systems help to record animal and environmental details using IoT technology and store them on servers without further processing. Instead of storing idle data, a suitable ML, AI, and mathematical model should be employed for prediction, assisting farmers in planning for their future processes [134,135]. From Figure 15, it was discovered that approximately 40% of cattle, bee farm, and fish monitoring systems used a machine learning, artificial intelligence, or mathematical prediction model to predict animal behavior based on farm data. This analysis helps predict animal behavior, disease, growth, etc.

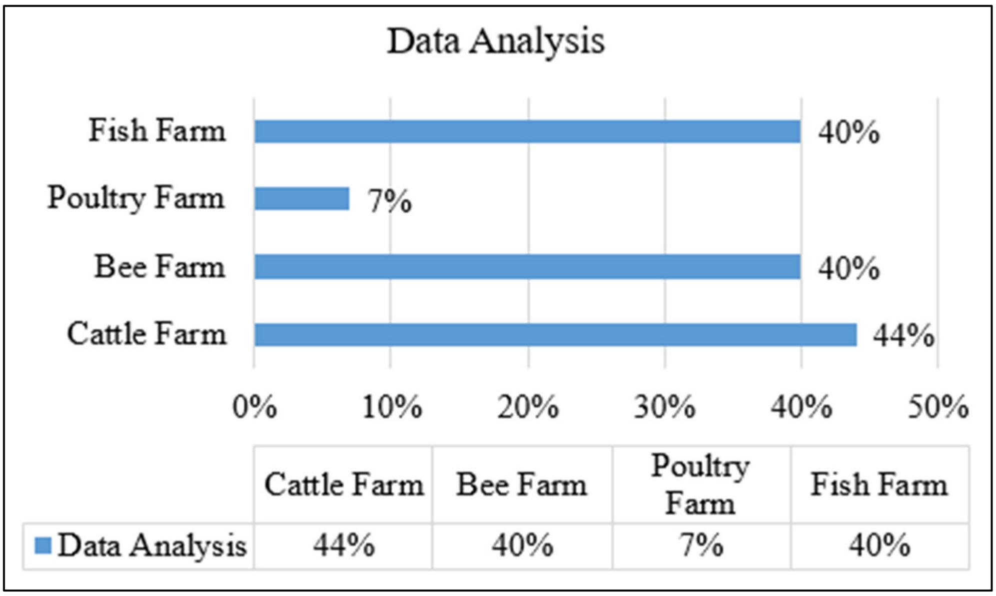

Figure 15. Data analysis in IoT-based livestock farms.

In general, animal monitoring and livestock husbandry need a significant amount of workforce, effort, time, and money. To lessen these, IoT technologies are used in animal monitoring.

Table 10 shows different IoT technologies, such as devices, controllers, communication protocols, storage, security, and GUI details, of IoT-based smart livestock farming systems.

Table 10. IoT technologies used in smart livestock farming.

Author	IoT Devices	Controller	Communication Protocol	Storage	Security	GUI
Yang et al. [2]	Microcontroller unit, water leak sensor, acoustic telemetry modem, acoustic receiver, cellular and satellite modem, weather station	Arduino Zero	Ethernet and Wi-Fi modem	-	-	-
Popa et al. [63]	CH4S sensor, Cox sensor, Nox sensor, ammonia sensor, water level sensor, weight sensor, humidity and temperature sensor	Dragino DLOS8	LoRa	Cloud	-	Web app
Zhang et al. [60]	Temperature sensor, wind speed, gas sensor (to read ammonia and carbon dioxide), humidity and light intensity sensors, RS-485 communication module	Main controller STC12LE5A60S2	TCP/IP	-	-	-
Taneja et al. [45]	Radio-based long-range pedometer (LRP)	Computer	Radio communication, MQTT protocol	Cloud	-	Mobile app
Feng et al. [47]	GPS	Computer	Offline analysis	-	-	-
Dineva et al. [48]	IoT sensors, video camera, thermal camera, GPS	AWS IoT Greengrass	Wi-Fi and MQTT	Cloud	Inbuilt security pillar	-
Mirmanov et al. [49]	UHF RFID tags, strain gauges	Raspberry Pi	LoRaWAN and Wi-Fi	-	Cryptography attack detection module	-

Table 10. *Cont.*

Author	IoT Devices	Controller	Communication Protocol	Storage	Security	GUI
Dutta et al. [50]	Temperature thermistor (NTCLE413E2103F102L) and GPS module	ATMEL328P microprocessor	GSM/GPRS Quad Band TTL UART modem	Cloud	-	Mobile app
Arshad et al. [51]	Body temperature sensor, stethoscope sensor, GPS	Node-MCU	Offline data collection	-	-	-
Maroto-Molina et al. [52]	GPS module, Bluetooth module	Microcontroller	Bluetooth, MQTT Protocol	Cloud	-	Mobile app
Lovarelli et al. [53]	EFR32BG13 Blue Gecko SiP	-	4G GSM	Cloud	-	Mobile app
Datta et al. [61]	RF Explorer, ANT700 antenna	-	-	Cloud storage	-	-
Chung et al. [62]	RFID LifeChip Microchip	-	Wi-Fi, LoRa	Cloud	-	-
Righi et al. [59]	RFID tags, milk production sensors	MooField controller	-	Cloud	-	No GUI
Ojo et al. [66]	Inertial sensors, Global Positioning System (GPS) receiver	STM32L0 MCU	LoRaWAN	Cloud	AWS lambda	Mobile and Web app
Rao et al. [67]	NH_3, CO_2, and temperature and humidity sensors; H2S sensors; RS485 HUB; camera	Raspberry Pi	-	NoSQL DB	-	Web app
Jumi et al. [68]	Pan–tilt–zoom camera, MLX90614 temperature sensors	NodeMCU gateway	-	-	-	Web and Mobile app
Cui et al. [69]	APDS-9008 sensor, MLX90615 infrared thermometer, DHT20 sensor	ATmega328 microcontroller	Bluetooth technology	-	-	-
Lee et al. [70]	Bluetooth tags, wireless broadband leaky coaxial cable antennas	-	Bluetooth	-	-	-
Chen et al. [71]	Microphone, IP camera, temperature sensor, floor vibration sensor, and water drop	-	Ethernet cable	-	Data bank coupling with DB	Mobile app
Lee et al. [72]	Video camera	A multi-core CPU	-	-	-	-
Bonde et al. [73]	Geophone sensors, video camera	NodeMCU	Wi-Fi using the MQTT message model	-	-	-
Sena et al. [75]	DHT11 temperature and humidity sensor, HC-SR04 ultrasonic sensor	ESP8266 microcontroller	-	-	-	-
Vaughan et al. [76]	Plastic optical fiber (POF) sensor	ATM2560 Arduino Mega board	-	-	-	LCD Screen
Popa et al. [78]	Temperature sensor, pressure sensor, humidity sensors, and air sensors	-	MQTT protocol	Cloud	-	-
Cejrowski et al. [79]	Microphone, analog-to-digital converter (ADS1115), resistors, and MOSFET-N transistor	Raspberry Pi	-	-	-	-
Gil-Lebrero et al. [80]	SHT15 humidity sensors, MCP9700A temperature sensor	Waspmote module	-	Cloud	Extra Security Layer	-

Table 10. *Cont.*

Author	IoT Devices	Controller	Communication Protocol	Storage	Security	GUI
Hong et al. [81]	Temperature and humidity sensor (DTH12), acoustics sensor, entrance sensor, weight sensor	STM32 microprocessor	Wi-Fi	Cloud	-	Web app
Mrozek et al. [82]	5-megapixel camera	Raspberry Pi	MQTT protocol	Cloud	-	-
Tashakkori et al. [83]	Humidity and temperature sensor, microphone, Raspberry Pi camera	Raspberry Pi	MQTT protocol	Cloud storage	-	ThingsBoard
Gabitov et al. [84]	Temperature and humidity sensors	RAK7204 monoblock devices	LoRaWAN	Cloud storage	-	-
Andrijević et al. [85]	Temperature, humidity, and air quality sensors	Raspberry Pi	-	-	-	Web app
Zabasta et al. [86,87]	IP camera, temperature, humidity, and weight sensors	Waspmote module	GSM and MQTT gateways	-	-	-
Zgank et al. [88]	Voice recorder	-	GSM	Cloud	-	Mobile app
Cejrowski et al. [79]	Microphone, analog-to-digital converter (ADS1115), resistors, and MOSFET-N transistor	-	-	-	-	-
Chien et al. [89]	RFID tags, RFID receiver, strain gauge pressure sensor	Arduino	Wi-Fi	Cloud storage	-	-
Gobinath et al. [90]	Temperature sensor, ultrasonic sensor	Arduino Uno ATmega328	-	-	-	-
Pereira et al. [91]	Temperature and humidity sensor (DHT22), electrochemical sensor (MQ-137), light-dependent resistor sensor	Wemos Mini D1	Wi-Fi	-	-	-
Niranjan et al. [92]	Temperature sensor (DHT11 and DS18B20), humidity sensor (HSM-20G), Reed switch, water level sensor	NodeMCU (ESP8266)	-	Blynk application	-	-
Dineva et al. [56]	Custom IoT devices, QR tag	Custom gateway	LoRaWAN and Wi-Fi	Cloud storage	-	-
Dineva et al. [57]	Custom IoT Devices, QR tags	Custom gateway	LoRaWAN and Wi-Fi	Cloud storage	Azure IoT Hubs	Power BI
Putra et al. [105]	Turbidity sensor, RGB sensor, potentiometer	NodeMCU	Bluetooth	Cloud storage	Third-party data storage and processing system	Mobile app
Chiu et al. [106]	Oxygen sensor, pH sensor, turbidity sensor, temperature sensor	Arduino Mega2560	Wi-Fi	Cloud storage and AI	-	-
Tamim et al. [107]	Temperature sensor, ammonia kit, oxygen kit, pH sensor	NodeMCU	Wi-Fi	Cloud storage	-	-
Gao et al. [112]	Turbidity sensor, temperature sensor, pH sensor, dissolved oxygen sensor	Arduino Mega2560	Wi-Fi	Cloud	-	Mobile app

Table 10. *Cont.*

Author	IoT Devices	Controller	Communication Protocol	Storage	Security	GUI
Dupont et al. [108]	Water temperature, water pH sensor	Arduino Pro Mini	-	-	-	-
Reduan et al. [109]	DFRobot Turbidity, DS18B2, and DFRobot pH meters	Arduino board	GSM module	Cloud storage	-	No GUI
Rashid et al. [110]	Temperature sensors, total dissolved solid sensors, pH sensors	Arduino UNO	-	-	-	-
Susanti et al. [111]	Total dissolved solid (TDS) sensors, temperature sensors, and pH sensors	NodeMCU ESP8266	-	-	-	Mobile app
Hao et al. [58]	RFID tag, weight machine	-	Wired network	Database	-	Web app
Park et al. [65]	GPS tag	-	Bluetooth	Database	-	-
Chen et al. [74]	Video camera	Computer	Wired network	-	-	-
Lee et al. [77]	IC tags, antenna	Computer	Wired network	-	-	-
Zhang et al. [93]	RFID tag, photoelectric sensor, conveyer belt drive motor, stepper motor	Computer	-	Database	-	-
Hassan et al. [113]	Acoustic test tags (Thelma Biotel AS) and TBR-700-RT acoustic receivers	MultiConnect Conduit (MTCDT-H5-210L)	LoRA module, MQTT protocol	-	-	-

9. Conclusions

In general, animal monitoring and livestock husbandry need a significant amount of workforce, effort, time, and money. To lessen these, IoT technologies are used in animal monitoring and livestock farming. IoT technologies are used to monitor animal behavior and animal health, automate farm daily activities, improve farm protection, monitor environmental changes, and anticipate future events based on collected data. According to the findings of this study, current smart animal monitoring systems should focus more on energy utilization, scalability, security, and the use of renewable energy. Researchers should also concentrate on animal disease finding, the isolation of infected animals, water conservation, farm management, animal growth monitoring, and automatic food feeding systems. The data collected from IoT devices should be used with the necessary machine learning and deep learning techniques for animal activity, disease, and growth prediction. This will help farmers to take the essential steps based on predictions. Future work should concentrate more on the impact of AI in livestock monitoring and the role of the IoT in establishing connections between farm owners and customers.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/su16104073/s1: PRISMA 2020 checklist.

Author Contributions: Conceptualization, Methodology, Review Writing—S.T.; Review Writing, Visualization—J.I.; Data Curation, Resources—A.R.; Visualization, Validation—J.N. 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: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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

References

1. Collins, L.M.; Smith, L.M. Review: Smart agri-systems for the pig industry. *Animal* **2022**, *16*, 100518. [CrossRef]
2. Yang, Y.; Elsinghorst, R.; Martinez, J.J.; Hou, H.; Lu, J.; Deng, Z.D. A real-time underwater acoustic telemetry receiver with edge computing for studying fish behavior and environmental sensing. *IEEE Internet Things J.* **2022**, *9*, 17821–17831. [CrossRef]
3. Rowe, E.; Dawkins, M.S.; Gebhardt-Henrich, S.G. A systematic review of precision livestock farming in the poultry sector: Is technology focussed on improving bird welfare? *Animals* **2019**, *9*, 614. [CrossRef] [PubMed]
4. Corkery, G.; Ward, S.; Kenny, C.; Hemmingway, P. Incorporating smart sensing technologies into the poultry industry. *J. World's Poult. Res.* **2013**, *3*, 106–128.
5. Tedeschi, L.O.; Greenwood, P.L.; Halachmi, I. Advancements in sensor technology and decision support intelligent tools to assist smart livestock farming. *J. Anim. Sci.* **2021**, *99*, skab038. [CrossRef] [PubMed]
6. Romanini, C.E.B.; Viazzi, S.; Borgonovo, F.; Costa, A.; Guarino, M.; Leroy, T.; Berckmans, D. Farm animals monitoring tool based on image processing technique. In Proceedings of the 1st International Workshop on Veterinary Biosignals and Biodevices, VBB 2012, in Conjunction with BIOSTEC 2012, Rome, Italy, 24–26 February 2022; pp. 60–68.
7. Pradana, Z.H.; Hidayat, B.; Darana, S. Beef cattle weight determine by using digital image processing. In Proceedings of the 2016 International Conference on Control, Electronics, Renewable Energy and Communications (ICCEREC), Bandung, Indonesia, 13–15 September 2016; pp. 179–184.
8. Pluk, A.; Bahr, C.; Poursaberi, A.; Maertens, W.; Van Nuffel, A.; Berckmans, D. Automatic measurement of touch and release angles of the fetlock joint for lameness detection in dairy cattle using vision techniques. *J. Dairy Sci.* **2012**, *95*, 1738–1748. [CrossRef]
9. Poursaberi, A.; Bahr, C.; Pluk, A.; Van Nuffel, A.; Berckmans, D. Real-time automatic lameness detection based on back posture extraction in dairy cattle: Shape analysis of cow with image processing techniques. *Comput. Electron. Agric.* **2010**, *74*, 110–119. [CrossRef]
10. Šimić, R.; Matković, K.; Ostović, M.; Pavičić, Ž.; Mihaljević, Ž. Influence of an enriched environment on aggressive behaviour in beef cattle. *Vet. Stanica* **2018**, *49*, 239–245.
11. Usher, C.T.; Daley, W.; Webster, B.; Ritz, C. Signal processing for animal behavior detection. In Proceedings of the 2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Atlanta, GA, USA, 3–5 December 2014; pp. 1145–1149.
12. Girard, M.T.E.; Zuidhof, M.J.; Bench, C.J. Feeding, foraging, and feather pecking behaviours in precision-fed and skip-a-day-fed broiler breeder pullets. *Appl. Anim. Behav. Sci.* **2017**, *188*, 42–49. [CrossRef]
13. Qiao, Y.; Kong, H.; Clark, C.; Lomax, S.; Su, D.; Eiffert, S.; Sukkarieh, S. Intelligent perception-based cattle lameness detection and behaviour recognition: A review. *Animals* **2021**, *11*, 3033. [CrossRef] [PubMed]
14. Williams, V.; Immaculate, J. Survey on Internet of Things based smart home. In Proceedings of the 2019 International Conference on Intelligent Sustainable Systems (ICISS), Palladam, India, 21–22 February 2019; pp. 460–464.
15. Aleksic, S. A survey on optical technologies for IoT, smart industry, and smart infrastructures. *J. Sens. Actuator Netw.* **2019**, *8*, 47. [CrossRef]
16. Terence, J.S.; Purushothaman, G. Low-Cost Real-Time Implementation of Malicious Packet Dropping Detection in Agricultural IoT Platform. In *Advances in Distributed Computing and Machine Learning*; Springer: Singapore, 2021; pp. 87–97.
17. Kashani, M.H.; Madanipour, M.; Nikravan, M.; Asghari, P.; Mahdipour, E. A systematic review of IoT in healthcare: Applications, techniques, and trends. *J. Netw. Comput. Appl.* **2021**, *192*, 103164. [CrossRef]
18. Damadam, S.; Zourbakhsh, M.; Javidan, R.; Faroughi, A. An Intelligent IoT Based Traffic Light Management System: Deep Reinforcement Learning. *Smart Cities* **2022**, *5*, 1293–1311. [CrossRef]
19. Brandín, R.; Abrishami, S. IoT-BIM and blockchain integration for enhanced data traceability in offsite manufacturing. *Autom. Constr.* **2024**, *159*, 105266.
20. Wang, W.C.; Dwijendra, N.K.; Sayed, B.T.; Alvarez, J.R.; Al-Bahrani, M.; Alviz-Meza, A.; Cárdenas-Escrocia, Y. Internet of things energy consumption optimization in buildings: A step toward sustainability. *Sustainability* **2023**, *15*, 6475. [CrossRef]
21. Sfar, A.R.; Challal, Y.; Moyal, P.; Natalizio, E. A game theoretic approach for privacy preserving model in IoT based transportation. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 4405–4414. [CrossRef]
22. Markov, N.; Stoycheva, S.; Hristov, M.; Mondeshka, L. Digital management of technological processes in cattle farms: A review. *J. Cent. Eur. Agric.* **2022**, *23*, 486–495. [CrossRef]
23. Akhigbe, B.I.; Munir, K.; Akinade, O.; Akanbi, L.; Oyedele, L.O. IoT technologies for livestock management: A review of present status, opportunities, and future trends. *Big Data Cogn. Comput.* **2021**, *5*, 10. [CrossRef]
24. Bhakta, I.; Phadikar, S.; Majumder, K. State-of-the-art technologies in precision agriculture: A systematic review. *J. Sci. Food Agric.* **2019**, *99*, 4878–4888. [CrossRef] [PubMed]
25. Ilyas, M.U.; Ahmad, M.; Saleem, S. Internet-of-Things-Infrastructure-as-a-Service: The democratization of access to public Internet-of-Things Infrastructure. *Int. J. Commun. Syst.* **2020**, *33*, e4562. [CrossRef]
26. Hamid, O.H. Data-Centric and Model-Centric AI: Twin Drivers of Compact and Robust Industry 4.0 Solutions. *Appl. Sci.* **2023**, *13*, 2753. [CrossRef]
27. El Moutaouakil, K.; Jdi, H.; Jabir, B.; Falih, N. Digital Farming: A Survey on IoT-based Cattle Monitoring Systems and Dashboards. *AGRIS Line Pap. Econ. Inform.* **2023**, *15*, 31–39. [CrossRef]

28. Vigneswari, T. Smart IoT cloud based livestock monitoring system: A survey. *Turk. J. Comput. Math. Educ. TURCOMAT* **2021**, *12*, 3308–3315.
29. Nigade, A.S.; Shelke, M.; Gavhane, S.; Mashale, S.; Ratnaparkhi, B. Review Paper on IOT based Cattle Health Monitoring System. In Proceedings of the 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), Lonavla, India, 7–9 April 2023; pp. 1–4.
30. Singh, M.; Kumar, R.; Tandon, D.; Sood, P.; Sharma, M. Artificial intelligence and iot based monitoring of poultry health: A review. In Proceedings of the 2020 IEEE International Conference on Communication, Networks and Satellite (Comnetsat), Lombok, Indonesia, 17–18 December 2020; pp. 50–54.
31. Goyal, V.; Yadav, A.; Mukherjee, R. A Literature Review on the Role of Internet of Things, Computer Vision, and Sound Analysis in a Smart Poultry Farm. *ACS Agric. Sci. Technol.* **2024**, *4*, 368–388. [CrossRef]
32. Ojo, R.O.; Ajayi, A.O.; Owolabi, H.A.; Oyedele, L.O.; Akanbi, L.A. Internet of Things and Machine Learning techniques in poultry health and welfare management: A systematic literature review. *Comput. Electron. Agric.* **2022**, *200*, 107266. [CrossRef]
33. Zhang, Z.; Zhang, H.; He, Y.; Liu, T. A Review in the automatic detection of pigs behavior with sensors. *J. Sens.* **2022**, *2022*, 4519539. [CrossRef]
34. Hadjur, H.; Ammar, D.; Lefèvre, L. Toward an intelligent and efficient beehive: A survey of precision beekeeping systems and services. *Comput. Electron. Agric.* **2022**, *192*, 106604. [CrossRef]
35. Rastegari, H.; Nadi, F.; Lam, S.S.; Ikhwanuddin, M.; Kasan, N.A.; Rahmat, R.F.; Mahari, W.A.W. Internet of Things in aquaculture: A review of the challenges and potential solutions based on current and future trends. *Smart Agric. Technol.* **2023**, *4*, 100187. [CrossRef]
36. Petkovski, A.; Ajdari, J.; Zenuni, X. IoT-based Solutions in Aquaculture: A Systematic Literature Review. In Proceedings of the 2021 44th International Convention on Information, Communication and Electronic Technology (MIPRO), Opatija, Croatia, 27 September–1 October 2021; pp. 1358–1363.
37. Mengist, W.; Soromessa, T.; Legese, G. Method for conducting systematic literature review and meta-analysis for environmental science research. *MethodsX* **2020**, *7*, 100777. [CrossRef] [PubMed]
38. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]
39. Burkhardt, F.K.; Hayer, J.J.; Heinemann, C.; Steinhoff-Wagner, J. Drinking behavior of dairy cows under commercial farm conditions differs depending on water trough design and cleanliness. *Appl. Anim. Behav. Sci.* **2022**, *256*, 105752. [CrossRef]
40. Grandin, T. Crossing the divide between academic research and practical application of ethology and animal behavior information on commercial livestock and poultry farms. *Appl. Anim. Behav. Sci.* **2019**, *218*, 104828. [CrossRef]
41. Grodkowski, G.; Sakowski, T.; Puppel, K.; Baars, T. Comparison of different applications of automatic herd control systems on dairy farms—A review. *J. Sci. Food Agric.* **2018**, *98*, 5181–5188. [CrossRef]
42. Jo, S.K.; Park, D.H.; Park, H.; Kim, S.H. Smart livestock farms using digital twin: Feasibility study. In Proceedings of the 2018 International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Republic of Korea, 11–13 October 2023; pp. 1461–1463.
43. Majumdar, P.; Mitra, S. IoT and Machine Learning-Based Approaches for Real Time Environment Parameters Monitoring in Agriculture: An Empirical Review. In *Agricultural Informatics: Automation Using the IoT and Machine Learning*; Wiley: Hoboken, NJ, USA, 2021; pp. 89–115.
44. Li, D.; Nanseki, T.; Chomei, Y.; Kuang, J. A review of smart agriculture and production practices in Japanese large-scale rice farming. *J. Sci. Food Agric.* **2023**, *103*, 1609–1620. [CrossRef] [PubMed]
45. Taneja, M.; Jalodia, N.; Byabazaire, J.; Davy, A.; Olariu, C. SmartHerd management: A microservices-based fog computing–assisted IoT platform towards data-driven smart dairy farming. *Softw. Pract. Exp.* **2019**, *49*, 1055–1078. [CrossRef]
46. Taneja, M.; Byabazaire, J.; Jalodia, N.; Davy, A.; Olariu, C.; Malone, P. Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle. *Comput. Electron. Agric.* **2020**, *171*, 105286. [CrossRef]
47. Feng, Y.; Niu, H.; Wang, F.; Ivey, S.J.; Wu, J.J.; Qi, H.; Almeida, R.A.; Eda, S.; Cao, Q. SocialCattle: IoT based mastitis detection and control through social cattle behavior sensing in smart farms. *IEEE Internet Things J.* **2021**, *9*, 10130–10138. [CrossRef]
48. Dineva, K.; Atanasova, T. Design of scalable IoT architecture based on AWS for smart livestock. *Animals* **2021**, *11*, 2697. [CrossRef] [PubMed]
49. Mirmanov, A.; Alimbayev, A.; Baiguanysh, S.; Nabiev, N.; Sharipov, A.; Kokcholokov, A.; Caratelli, D. Development of an IoT platform for stress-free monitoring of cattle productivity in precision animal husbandry. *Adv. Sci. Technol. Eng. Syst. J.* **2021**, *6*, 501–508. [CrossRef]
50. Dutta, D.; Natta, D.; Mandal, S.; Ghosh, N. MOOnitor: An IoT based multi-sensory intelligent device for cattle activity monitoring. *Sens. Actuators A Phys.* **2022**, *333*, 113271. [CrossRef]
51. Arshad, J.; Rehman, A.U.; Othman, M.T.B.; Ahmad, M.; Tariq, H.B.; Khalid, M.A.; Moosa, M.A.R.; Shafiq, M.; Hamam, H. Deployment of Wireless Sensor Network and IoT Platform to Implement an Intelligent Animal Monitoring System. *Sustainability* **2022**, *14*, 6249. [CrossRef]
52. Maroto-Molina, F.; Navarro-García, J.; Príncipe-Aguirre, K.; Gómez-Maqueda, I.; Guerrero-Ginel, J.E.; Garrido-Varo, A.; Pérez-Marín, D.C. A low-cost IoT based system to monitor the location of a whole herd. *Sensors* **2019**, *19*, 2298. [CrossRef]

53. Lovarelli, D.; Brandolese, C.; Leliveld, L.; Finzi, A.; Riva, E.; Grotto, M.; Provolo, G. Development of a New Wearable 3D Sensor Node and Innovative Open Classification System for Dairy Cows' Behavior. *Animals* **2022**, *12*, 1447. [CrossRef] [PubMed]
54. Arcidiacono, C.; Mancino, M.; Porto, S.M.C.; Bloch, V.; Pastell, M. IoT device-based data acquisition system with on-board computation of variables for cow behaviour recognition. *Comput. Electron. Agric.* **2021**, *191*, 106500. [CrossRef]
55. Gündüz, K.A.; Başçiftçi, F. IoT based pH monitoring for detection of rumen acidosis. *Arq. Bras. Med. Veterinária Zootec.* **2022**, *74*, 457–472. [CrossRef]
56. Dineva, K.; Atanasova, T. Expandable IoT Architecture for Livestock in Agriculture 5.0. *Int. Multidiscip. Sci. GeoConference SGEM* **2021**, *21*, 93–100.
57. Dineva, K.; Atanasova, T. Cloud Data-Driven Intelligent Monitoring System for Interactive Smart Farming. *Sensors* **2022**, *22*, 6566. [CrossRef] [PubMed]
58. Hao, S.B.; Cai, S.H.; Sun, R.Z.; Li, J.Y.; Cheng, C.M. Design and implement of IoT based beef cattle breeding system. *Int. Agric. Eng. J.* **2017**, *26*, 1–8.
59. Righi, R.; Goldschmidt, G.; Kunst, R.; Deon, C.; da Costa, C.A. Towards combining data prediction and internet of things to manage milk production on dairy cows. *Comput. Electron. Agric.* **2020**, *169*, 105156. [CrossRef]
60. Zhang, J.; Kong, F.; Zhai, Z.; Han, S.; Wu, J.; Zhu, M. Design and development of IoT monitoring equipment for open livestock environment. *Int. J. Simul. Syst. Sci. Technol.* **2016**, *17*, 2–7.
61. Datta, A.; Kaur, U.; Malacco, V.; Nath, M.; Chatterjee, B.; Donkin, S.S.; Voyles, R.M.; Sen, S. Sub-GHz In-Body to Out-of-Body Communication Channel Modeling for Ruminant Animals for Smart Animal Agriculture. *IEEE Trans. Biomed. Eng.* **2022**, *70*, 1219–1230. [CrossRef] [PubMed]
62. Chung, H.; Li, J.; Kim, Y.; Van Os, J.M.; Brounts, S.H.; Choi, C.Y. Using implantable biosensors and wearable scanners to monitor dairy cattle's core body temperature in real-time. *Comput. Electron. Agric.* **2020**, *174*, 105453. [CrossRef]
63. Popa, R.A.; Popa, D.C.; Mărginean, G.E.; Suciu, G.; Bălănescu, M.; Paștea, D.; Vulpe, A.; Vochin, M.; Drăgulinescu, A.M. Hybrid Platform for Assessing Air Pollutants Released from Animal Husbandry Activities for Sustainable Livestock Agriculture. *Sustainability* **2021**, *13*, 9633. [CrossRef]
64. Saravanan, K.; Saraniya, S. Cloud IOT based novel livestock monitoring and identification system using UID. *Sens. Rev.* **2017**, *38*, 21–33.
65. Park, J.K.; Park, E.Y. Monitoring method of movement of grazing cows using cloud-based system. *ECTI Trans. Comput. Inf. Technol.* **2021**, *15*, 24–33.
66. Ojo, M.O.; Viola, I.; Baratta, M.; Giordano, S. Practical experiences of a smart livestock location monitoring system leveraging gnss, lorawan and cloud services. *Sensors* **2021**, *22*, 273. [CrossRef] [PubMed]
67. Rao, Y.; Jiang, M.; Wang, W.; Zhang, W.; Wang, R. On-farm welfare monitoring system for goats based on Internet of Things and machine learning. *Int. J. Distrib. Sens. Netw.* **2020**, *16*, 1550147720944030. [CrossRef]
68. Achmad, J.; Tedjo Mulyono, Z.; Hayati, N. Design of Health Monitoring System based on Internet of Things Online-Live-Realtime (OLR). *Int. J. Eng. Res. Technol.* **2022**, *11*. [CrossRef]
69. Cui, Y.; Zhang, M.; Li, J.; Luo, H.; Zhang, X.; Fu, Z. WSMS: Wearable stress monitoring system based on IoT multi-sensor platform for living sheep transportation. *Electronics* **2019**, *8*, 441. [CrossRef]
70. Lee, G.; Ogata, K.; Kawasue, K.; Sakamoto, S.; Ieiri, S. Identifying-and-counting based monitoring scheme for pigs by integrating BLE tags and WBLCX antennas. *Comput. Electron. Agric.* **2022**, *198*, 107070. [CrossRef]
71. Chen, W.E.; Lin, Y.B.; Chen, L.X. PigTalk: An AI-based IoT platform for piglet crushing mitigation. *IEEE Trans. Ind. Inform.* **2020**, *17*, 4345–4355. [CrossRef]
72. Lee, S.; Ahn, H.; Seo, J.; Chung, Y.; Park, D.; Pan, S. Practical monitoring of undergrown pigs for IoT based large-scale smart farm. *IEEE Access* **2019**, *7*, 173796–173810. [CrossRef]
73. Bonde, A.; Codling, J.R.; Naruethep, K.; Dong, Y.; Siripaktanakon, W.; Ariyadech, S.; Sangpetch, A.; Sangpetch, O.; Pan, S.; Noh, H.Y.; et al. Pignet: Failure-tolerant pig activity monitoring system using structural vibration. In Proceedings of the 20th International Conference on Information Processing in Sensor Networks (Co-Located with CPS-IoT Week 2021), Nashville, TN, USA, 18–21 May 2021; pp. 328–340.
74. Chen, Y.R.; Ni, C.T.; Ng, K.S.; Hsu, C.L.; Chang, S.C.; Hsu, C.B.; Chen, P.Y. An AI-based System for Monitoring Behavior and Growth of Pigs. In Proceedings of the 2020 International Computer Symposium (ICS), Tainan, Taiwan, 17–19 December 2020; pp. 91–95.
75. Sena, P.; Kaiwman, B. The Use of Internet of Things technology to develop a smart farm prototype for pig farming. *Creat. Sci.* **2022**, *14*, 245673. [CrossRef]
76. Vaughan, J.; Green, P.M.; Salter, M.; Grieve, B.; Ozanyan, K.B. Floor sensors of animal weight and gait for precision livestock farming. In Proceedings of the 2017 IEEE Sensors, Glasgow, UK, 29 October–1 November 2017; pp. 1–3.
77. Lee, G.; Kim, M.; Koroki, K.; Ishimoto, A.; Sakamoto, S.H.; Ieiri, S. Wireless IC tag based monitoring system for individual pigs in pig farm. In Proceedings of the 2019 IEEE 1st Global Conference on Life Sciences and Technologies (LifeTech), Osaka, Japan, 12–14 March 2019; pp. 168–170.
78. Popa, R.A.; Popa, D.C.; Pogurschi, E.N.; Vidu, L.; Marin, M.P.; Tudorache, M.; Suciu, G.; Bălănescu, M.; Burlacu, S.; Budulacu, R.; et al. Comparative Evaluation of the Dynamics of Animal Husbandry Air Pollutant Emissions Using an IoT Platform for Farms. *Agriculture* **2023**, *13*, 25. [CrossRef]

79. Cejrowski, T.; Szymański, J. Buzz-based honeybee colony fingerprint. *Comput. Electron. Agric.* **2021**, *191*, 106489. [CrossRef]
80. Gil-Lebrero, S.; Quiles-Latorre, F.J.; Ortiz-López, M.; Sánchez-Ruiz, V.; Gámiz-López, V.; Luna-Rodríguez, J.J. Honey bee colonies remote monitoring system. *Sensors* **2016**, *17*, 55. [CrossRef] [PubMed]
81. Hong, W.; Xu, B.; Chi, X.; Cui, X.; Yan, Y.; Li, T. Long-term and extensive monitoring for bee colonies based on internet of things. *IEEE Internet Things J.* **2020**, *7*, 7148–7155. [CrossRef]
82. Mrozek, D.; Gòrny, R.; Wachowicz, A.; Małysiak-Mrozek, B. Edge-Based Detection of Varroosis in Beehives with IoT Devices with Embedded and TPU-Accelerated Machine Learning. *Appl. Sci.* **2021**, *11*, 11078. [CrossRef]
83. Tashakkori, R.; Hamza, A.S.; Crawford, M.B. Beemon: An IoT based beehive monitoring system. *Comput. Electron. Agric.* **2021**, *190*, 106427. [CrossRef]
84. Gabitov, I.; Linenko, A.; Yumaguzhin, F.; Akchurin, S.; Valishin, D. The System of Remote Monitoring of Microclimate Parameters of Bee Colonies. *J. Ecol. Eng.* **2022**, *23*, 264–273. [CrossRef]
85. Andrijević, N.; Urošević, V.; Arsić, B.; Herceg, D.; Savić, B. IoT monitoring and prediction modeling of honeybee activity with alarm. *Electronics* **2022**, *11*, 783. [CrossRef]
86. Zabasta, A.; Zhiravetska, A.; Kunicina, N.; Kondratjevs, K. Technical implementation of IoT concept for bee colony monitoring. In Proceedings of the 2019 8th Mediterranean Conference on Embedded Computing (MECO), Budva, Montenegro, 10–14 June 2019; pp. 1–4.
87. Zabasta, A.; Kunicina, N.; Kondratjevs, K.; Ribickis, L. IoT approach application for development of autonomous beekeeping system. In Proceedings of the 2019 International Conference in Engineering Applications (ICEA), Sao Miguel, Portugal, 8–11 July 2019; pp. 1–6.
88. Zgank, A. IoT based bee swarm activity acoustic classification using deep neural networks. *Sensors* **2021**, *21*, 676. [CrossRef] [PubMed]
89. Chien, Y.R.; Chen, Y.X. An RFID-based smart nest box: An experimental study of laying performance and behavior of individual hens. *Sensors* **2018**, *18*, 859. [CrossRef] [PubMed]
90. Gobinath, T.; Raj, B.T.; Vintorian, T.; Paranthaman, M. IoT Based Poultry Farm Lighting Fogger and Smart Feeding Trolley. *Int. J. Mod. Agric.* **2021**, *10*, 3195–3201.
91. Pereira, W.F.; da Silva Fonseca, L.; Putti, F.F.; Góes, B.C.; de Paula Naves, L. Environmental monitoring in a poultry farm using an instrument developed with the internet of things concept. *Comput. Electron. Agric.* **2020**, *170*, 105257. [CrossRef]
92. Niranjan, L.; Venkatesan, C.; Suhas, A.R.; Satheeskumaran, S.; Nawaz, S.A. Design and implementation of chicken egg incubator for hatching using IoT. *Int. J. Comput. Sci. Eng.* **2021**, *24*, 363–372. [CrossRef]
93. Zhang, Y.; Ge, Y.; Yang, T.; Guo, Y.; Yang, J.; Han, J.; Gong, D.; Miao, H. An IoT based Breeding Egg Identification and Coding System for Selection of High-Quality Breeding Geese. *Animals* **2022**, *12*, 1545. [CrossRef] [PubMed]
94. Peprah, F.; Gyamfi, S.; Amo-Boateng, M.; Buadi, E.; Obeng, M. Design and construction of smart solar powered egg incubator based on GSM/IoT. *Sci. Afr.* **2022**, *17*, e01326. [CrossRef]
95. Feiyang, Z.; Yueming, H.; Liancheng, C.; Lihong, G.; Wenjie, D.; Lu, W. Monitoring behavior of poultry based on RFID radio frequency network. *Int. J. Agric. Biol. Eng.* **2016**, *9*, 139–147.
96. Mitkari, S.; Pingle, A.; Sonawane, Y.; Walunj, S.; Shirsath, A. IOT based smart poultry farm. *System* **2019**, *6*, 2380–2384.
97. Lashari, M.H.; Memon, A.A.; Shah, S.A.A.; Nenwani, K.; Shafqat, F. Iot based poultry environment monitoring system. In Proceedings of the 2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS), Bali, Indonesia, 1–3 November 2018; pp. 1–5.
98. Li, H.; Wang, H.; Yin, W.; Li, Y.; Qian, Y.; Hu, F. Development of a remote monitoring system for henhouse environment based on IoT technology. *Future Internet* **2015**, *7*, 329–341. [CrossRef]
99. Bumanis, N.; Arhipova, I.; Paura, L.; Vitols, G.; Jankovska, L. Data conceptual model for smart poultry farm management system. *Procedia Comput. Sci.* **2022**, *200*, 517–526. [CrossRef]
100. Zhai, Z.; Zhang, J.; Chai, X.; Kong, F.; Wu, J.; Zhang, J.; Han, S. A laying hen breeding environment monitoring system based on internet of things. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *371*, 32039. [CrossRef]
101. Son, T.N.; Hoan, L.T.; Cuong, N.C.; Van Minh, P.; Van Hoa, R. Remote Monitoring and Control of Poultry Farm based on IoT Technology. *Int. J. Electr. Electron. Eng.* **2020**, *7*, 12–15. [CrossRef]
102. Chigwada, J.; Mazunga, F.; Nyamhere, C.; Mazheke, V.; Taruvinga, N. Remote poultry management system for small to medium scale producers using IoT. *Sci. Afr.* **2022**, *18*, e01398. [CrossRef]
103. Lin, Y.-B.; Tseng, H.-C. FishTalk: An IoT based mini aquarium system. *IEEE Access* **2019**, *7*, 35457–35469. [CrossRef]
104. Lee, C.; Wang, Y.J. Development of a cloud-based IoT monitoring system for Fish metabolism and activity in aquaponics. *Aquac. Eng.* **2020**, *90*, 102067. [CrossRef]
105. Putra, B.T.W.; Rocelline, L.A.; Syahputra, W.N.H. Embedded system in handheld water turbidity meter for smallholders. *Microprocess. Microsyst.* **2022**, *93*, 104603. [CrossRef]
106. Chiu, M.C.; Yan, W.M.; Bhat, S.A.; Huang, N.F. Development of smart aquaculture farm management system using IoT and AI-based surrogate models. *J. Agric. Food Res.* **2022**, *9*, 100357. [CrossRef]
107. Tamim, A.T.; Begum, H.; Shachcho, S.A.; Khan, M.M.; Yeboah-Akowuah, B.; Masud, M.; Al-Amri, J.F. Development of IoT Based Fish Monitoring System for Aquaculture. *Intell. Autom. Soft Comput.* **2022**, *32*, 55–71. [CrossRef]

108. Dupont, C.; Wussah, A.; Malo, S.; Thiare, O.; Niass, F.; Pham, C.; Dupont, S.; Le Gall, F.; Cousin, P. Low-cost IoT solutions for fish farmers in Africa. In Proceedings of the 2018 IST-Africa Week Conference (IST-Africa), Gaborone, Botswana, 9–11 May 2018; p. 1.
109. Reduan, A.; Sani, M.M.; Kutty, S.B.; Isa, N.M.; Yusof, Y. Design of an IoT Water Quality Monitoring System for Tropical Fish Aquaclture. *Int. J. Acad. Res. Bus. Soc. Sci.* **2021**, *11*, 173–1783.
110. Mamunur Rashid, M.; Nayan, A.A.; Obaidur Rahman, M.; Afrin Simi, S.; Saha, J.; Kibria, M.G. IoT based Smart Water Quality Prediction for Biofloc Aquaculture. *arXiv* **2022**, arXiv:2208.08866.
111. Susanti, N.D.; Sagita, D.; Apriyanto, I.F.; Anggara, C.E.W.; Darmajana, D.A.; Rahayuningtyas, A. Design and Implementation of Water Quality Monitoring System (Temperature, pH, TDS) in Aquaculture Using IoT at Low Cost. In Proceedings of the 6th International Conference of Food, Agriculture, and Natural Resource (IC-FANRES 2021), Tangerang, Indonesia, 4–5 August 2021; pp. 7–11.
112. Gao, G.; Xiao, K.; Chen, M. An intelligent IoT based control and traceability system to forecast and maintain water quality in freshwater fish farms. *Comput. Electron. Agric.* **2019**, *166*, 105013. [CrossRef]
113. Hassan, W.; Føre, M.; Ulvund, J.B.; Alfredsen, J.A. Internet of Fish: Integration of acoustic telemetry with LPWAN for efficient real-time monitoring of fish in marine farms. *Comput. Electron. Agric.* **2019**, *163*, 104850. [CrossRef]
114. Kalantar, S.; Jafari, M.; Hashemipour, M. Energy and load balancing routing protocol for IoT. *Int. J. Commun. Syst.* **2023**, *36*, e5371. [CrossRef]
115. Padmapriya, N.; Ananth Kumar, T.; Aswini, R.; Rajmohan, R.; Kanimozhi, P.; Pavithra, M. IoT Based Energy Optimization in Smart Farming Using AI. In *Hybrid Intelligent Approaches for Smart Energy: Practical Applications*; Wiley: Hoboken, NJ, USA, 2022; pp. 205–223.
116. Pedditi, R.B.; Debasis, K. Energy efficient routing protocol for an IoT-based WSN system to detect forest fires. *Appl. Sci.* **2023**, *13*, 3026. [CrossRef]
117. Tupe, U.L.; Babar, S.D.; Kadam, S.P.; Mahalle, P.N. Research perspective on energy-efficient protocols in IoT: Emerging development of green IoT. *Int. J. Pervasive Comput. Commun.* **2022**, *18*, 145–170. [CrossRef]
118. Hashmi, S.A.; Ali, C.F.; Zafar, S. Internet of things and cloud computing-based energy management system for demand side management in smart grid. *Int. J. Energy Res.* **2021**, *45*, 1007–1022. [CrossRef]
119. Garrido-Zafra, J.; Gil-de-Castro, A.R.; Savariego-Fernandez, R.; Linan-Reyes, M.; Garcia-Torres, F.; Moreno-Munoz, A. IoT cloud-based power quality extended functionality for grid-interactive appliance controllers. *IEEE Trans. Ind. Appl.* **2022**, *58*, 3909–3921. [CrossRef]
120. Germer, M.; Marschner, U.; Richter, A. Energy harvesting for tire pressure monitoring systems from a mechanical energy point of view. *IEEE Internet Things J.* **2022**, *9*, 7700–7714. [CrossRef]
121. Akan, O.B.; Cetinkaya, O.; Koca, C.; Ozger, M. Internet of hybrid energy harvesting things. *IEEE Internet Things J.* **2017**, *5*, 736–746. [CrossRef]
122. Hentati, A.; Jaafar, W.; Frigon, J.F.; Ajib, W. Analysis of the interdelivery time in IoT energy harvesting wireless sensor networks. *IEEE Internet Things J.* **2020**, *8*, 4920–4930. [CrossRef]
123. Rehbein, J.A.; Watson, J.E.; Lane, J.L.; Sonter, L.J.; Venter, O.; Atkinson, S.C.; Allan, J.R. Renewable energy development threatens many globally important biodiversity areas. *Glob. Chang. Biol.* **2020**, *26*, 3040–3051. [CrossRef] [PubMed]
124. Şen, Z. Innovative methodologies in renewable energy: A review. *Int. J. Energy Res.* **2019**, *43*, 5621–5658. [CrossRef]
125. Sarker, M.R.; Riaz, A.; Lipu, M.H.; Saad, M.H.M.; Ahmad, M.N.; Kadir, R.A.; Olazagoitia, J.L. Micro energy harvesting for IoT platform: Review analysis toward future research opportunities. *Heliyon* **2024**, *10*, e27778. [CrossRef] [PubMed]
126. Tairab, A.M.; Wang, X.; Zhang, Z.; Hao, D.; Abdelrahman, M.; Salman, W.; Ali, A. The Nexus of IoT technology: A renewable multi-module energy harvester for self-powered on railway. *Sustain. Mater. Technol.* **2023**, *38*, e00752. [CrossRef]
127. AWS Official Documentation, Overview of AmazonWeb Services, Whitepaper. April 2021. Available online: https://d1.awsstatic.com/whitepapers/aws-overview.pdf (accessed on 5 April 2024).
128. Jabeen, F.; Khan, Z.U.R.; Hamid, Z.; Rehman, Z.; Khan, A. Adaptive and survivable trust management for Internet of Things systems. *IET Inf. Secur.* **2021**, *15*, 375–394. [CrossRef]
129. Mohammed, S.A.; Mahmood, M.R. Security in Ambient Intelligence and Internet of Things. In *Ambient Intelligence and Internet of Things: Convergent Technologies*; Wiley: Hoboken, NJ, USA, 2022; pp. 81–123.
130. Lv, Z. Security of internet of things edge devices. *Softw. Pract. Exp.* **2021**, *51*, 2446–2456. [CrossRef]
131. Ziegeldorf, J.H.; Morchon, O.G.; Wehrle, K. Privacy in the Internet of Things: Threats and challenges. *Secur. Commun. Netw.* **2014**, *7*, 2728–2742. [CrossRef]
132. Available online: https://azure.microsoft.com/en-in/products/iot-hub (accessed on 20 April 2024).
133. Available online: https://aws.amazon.com/iot/ (accessed on 20 April 2024).
134. Giannino, F.; Esposito, S.; Diano, M.; Cuomo, S.; Toraldo, G. A predictive Decision Support System (DSS) for a microalgae production plant based on Internet of Things paradigm. *Concurr. Comput. Pract. Exp.* **2018**, *30*, e4476. [CrossRef]
135. Kleanthous, N.; Hussain, A.J.; Khan, W.; Sneddon, J.; Al-Shamma'a, A.; Liatsis, P. A survey of machine learning approaches in animal behaviour. *Neurocomputing* **2022**, *491*, 442–463. [CrossRef]