An IoT-Enabled Smart System Utilizing Linear Regression for Sheep Growth and Health Monitoring

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Abstract

The global livestock industry faces significant pressures from climate change, land constraints, and rising consumer demand, necessitating greater efficiency and sustainability in production. To address these challenges, there is a critical need for accessible, data-driven tools; however, accessible and individualized tools for monitoring the growth and health of livestock like sheep remain underdeveloped, limiting farmers' ability to transition from reactive to proactive management. This study developed and validated an Internet of Things (IoT) smart system for monitoring sheep using an Arduino and ESP32 platform equipped with a DHT22 sensor for temperature and humidity and a load cell for weight. Weekly weight data from 15 sheep were collected over a six-month period. Simple linear regression was then applied to model the individual growth trajectory of each animal. The IoT system was successfully implemented and deployed in a farm setting. The primary finding was that individualized linear regression models provided a highly accurate method for tracking sheep growth, with R^2 values consistently exceeding 99% for most animals. The system effectively delivered real-time reports on growth trajectories and health-relevant environmental conditions (e.g., temperature and humidity) to a smartphone interface, confirming its practical utility. The primary implication of this research is a validated framework for practical and interpretable precision livestock farming. The system empowers farmers to shift from reactive to proactive management by using individualized growth curves as baselines for early problem detection. This dual-function system enhances productivity through precise growth tracking while supporting animal welfare via environmental monitoring, offering a valuable tool for modern, sustainable sheep farming.

Keywords: Growth Modeling, IoT, Linear Regression, Precision Livestock Farming, Smart Farming

1. Introduction

The global livestock industry confronts numerous challenges that threaten both food security and environmental sustainability, including the impacts of global climate change, the reduction of available agricultural land, and increasing consumer demand for high-quality products [1], [2]. This situation is intensified by a projected 60% increase in global demand for animal products by 2050 [3], driven by population growth, urbanization, and rising incomes [4], [5]. This rising demand puts immense pressure on production efficiency and sustainable practices, especially given the decreasing availability of arable land for quality forage [6]. Furthermore, the structural transformation towards larger, concentrated farms can exacerbate resource competition and environmental degradation [3]. These intersecting pressures create a critical need for innovative solutions that can enhance farm productivity and enable proactive health management to ensure the industry's viability and sustainability.

These combined pressures create significant hurdles for farmers and the livestock industry. Environmentally, the livestock sector contributes significantly to greenhouse gas emissions and occupies substantial agricultural land—indeed, 77% of arable land is dedicated to livestock production [7], underscoring the necessity for innovative, sustainable practices and technologies. Economically, farmers often struggle with balancing financing between input

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costs, operational expenses, and often low product selling prices. Thus, making efficiency and sustainability paramount for profitability and business survival. Adopting advanced systems, such as automatic milking, decision support systems [8], [9], and advanced feeding systems [10], may enhance productivity and resource efficiency while addressing these pressing sustainability concerns.

Technological advancements, particularly in the IoT and wireless control systems, are crucial for modernizing agriculture and animal husbandry, leading to the development of sophisticated and modern tools. The development of this technology has encouraged human life to be more practical, economical, and efficient, and these rapid technological developments must be utilized, studied, and applied in everyday life [11]. The integration of IoT into livestock management facilitates real-time monitoring of animal health, behavior, and environmental conditions, thereby enhancing animal welfare and farm efficiency [12], [13]. IoT, in particular, facilitates enhanced data collection, remote monitoring, and smarter decision-making in various fields, including animal husbandry. For example, systems leveraging Global Navigation Satellite System (GNSS) and LoRaWAN technology have demonstrated significant improvements in locating and monitoring livestock, addressing challenges such as inadequate supervision and environmental ruggedness [14].

One of the technological advances that has been applied is in the field of control with the application of the internet of things; currently, with wireless network technology that has grown rapidly, the problem of distance and time can be solved [15]. The use of a controller system can make performance in terms of distance and time more effective. Wireless technology is a key media that can be utilized in improving work efficiency [16], providing various functions and facilities that can be used as a sophisticated control and communication medium [17]. Seeing the progress of wireless technology, it is plausible that in the future various kinds of electronic devices can be controlled through wireless technology [18], [19]. For instance, wireless technology can be applied to livestock growth monitoring systems [20], and the application of technology in controller systems can provide signals through sensors to users [21]. Furthermore, Internet of Things technology is capable of sending data captured by sensors to smartphones [22].

Moreover, cloud computing technologies paired with IoT enable proactive health monitoring, allowing for timely interventions based on data insights [23]. The implementation of AI algorithms further enriches these systems, analyzing biometric data for predictive insights into livestock health and productivity [24], [25]. This technological fusion not only boosts operational effectiveness but also meets the growing demand for sustainable livestock production amidst global challenges [26], [27]. Thus, these advancements not only revolutionize traditional practices but also play a pivotal role in enhancing food security.

Effective, data-driven monitoring of sheep growth and environmental conditions is crucial for improving productivity, ensuring animal welfare, and maintaining farm viability. Integrating advanced monitoring systems using IoT technology can provide real-time data on sheep health, growth metrics, and environmental parameters, leading to improved management practices and timely interventions [28]. The ability to collect and analyze this data allows farmers to make informed choices, optimizing resource use and livestock productivity. Key challenges in sheep farming include health issues like coccidiosis, which can significantly impact productivity; thus, prevention is vital for stable output and animal welfare [29]. Additionally, understanding and mitigating the effects of climate change is essential, as environmental stressors such as heat can hinder growth, especially in poorly managed conditions [30].

Addressing these needs, the current study introduces the "Smart System for Monitoring the Growth and Health of Modern Sheep Animals." This system leverages IoT technology by utilizing an Arduino Microcontroller [31] and module as a data processing center [32], along with sensors to detect pen temperature, humidity [32], and animal weight [33]. The analytical core of the system involves applying linear regression models to the collected data from 15 farm animals that will be monitored, aiming to provide a practical solution for enhanced efficiency and sustainability in sheep farming.

This research aimed to design and implement an IoT-based system for real-time monitoring of sheep weight, pen temperature, and humidity using sensors such as the DHT22 and load cells. A further objective was to develop and evaluate individualized linear regression models to characterize sheep growth trajectories based on weekly weight data collected from the 15 monitored animals. Additionally, the study sought to assess the system's capability to provide actionable insights to farmers through a smartphone-based reporting interface, which can be monitored directly. This study contributes a practical demonstration of an integrated IoT system for individualized sheep growth monitoring. The key contribution lies in the application of simple linear regression models to provide highly accurate growth trajectories for individual animals within the study cohort, offering a valuable tool for on-farm management. The system also provides real-time environmental data, specifically temperature and humidity, to support animal welfare by minimizing heat and humidity in the pen, thereby aiming to prevent disease and support the growth process.

2. Literature Review

2.1. IoT in Smart Agriculture and Livestock Farming

The evolution of "smart farming" signifies a shift towards integrating advanced technologies to enhance agricultural productivity and sustainability, largely driven by the IoT which facilitates real-time data collection and analysis [34], [35]. This technological integration allows for precise monitoring in both crop and livestock management, fundamentally reshaping agricultural operations. In livestock farming, IoT applications are crucial for monitoring diverse parameters such as animal activity, health indicators, and location, providing farmers with comprehensive operational overviews and enabling early disease detection and effective management strategies [36], [37]. Furthermore, the application of machine learning through IoT enhances livestock production by predicting critical indicators like fertility and dietary needs, thereby improving overall animal welfare and economic viability.

A key aspect of IoT's role is fostering automation and optimizing resource management through networked sensors and actuators, which enhance decision-making and operational efficiency in areas like irrigation and crop monitoring [38]. In animal husbandry, real-time monitoring systems utilize wireless sensors to gather critical data on environmental conditions, animal behavior, and health statuses, such as temperature, heart rate, and activity levels, often tracked via wearable devices [39]. This data aids in mitigating disease risks, improving yield, and informing decisions about feeding, veterinary care, and overall herd management [40], [41]. IoT solutions also contribute to resource management, such as optimizing water use through smart irrigation systems and improving feed efficiency, which is vital for sustainability, particularly in resource-scarce regions [42], [43].

The synergy between IoT, AI, and advanced telecommunications protocols like MQTT optimizes data flow and analysis, enabling farmers to derive actionable insights from vast datasets for predictive modeling and strategic decision-making [44], [45]. As agriculture digitizes, cybersecurity measures are essential to protect sensitive data handled by these interconnected systems [46]. Concurrently, educational initiatives are important to enhance digital literacy among farmers, encouraging the adoption and effective use of these smart farming technologies [47], [48]. This holistic approach, integrating advanced technology with informed practices, paves the way for a more resilient, sustainable, and profitable agricultural future.

2.2. Sensor Technology and Wireless Communication in Monitoring Systems

WSNs and specific sensors for parameters like temperature, humidity, and load have become integral to advancing agricultural and environmental monitoring. These networks, comprising spatially distributed sensors, gather crucial environmental data, enabling real-time monitoring and data transmission that drive precision agriculture and conservation efforts [49], [50]. The historical development of WSNs has been spurred by the demand for remote data collection, with technological progress leading to low-power, high-efficiency sensor nodes suitable for diverse deployments [51]. For instance, temperature and humidity sensors are vital for assessing conditions critical to crop health, guiding decisions on irrigation, pest control, and fertilization to optimize yield and reduce waste [52], while load cells assist in monitoring structural health of farm equipment and storage facilities, ensuring optimal conditions and preventing spoilage or malfunctions [53], [54].

The evolution of wireless communication technologies is fundamental to the efficacy of these IoT-based monitoring systems, ensuring efficient, reliable, and secure data transmission across WSNs [51]. Protocols such as Wi-Fi, LoRa, NB-IoT, and ZigBee cater to specific needs like data bandwidth, power consumption, and coverage area, with LoRaWAN being particularly effective in agricultural settings requiring long-range, low-power communication, especially in remote areas [55], [56]. This robust wireless communication facilitates the transfer of real-time sensor data to cloud platforms where advanced analytics, including machine learning and big data processing, can yield

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insights into crop health, environmental changes, and potential threats, enabling timely interventions [57]. This continuous flow of information establishes a valuable feedback loop and historical dataset, informing future strategies and enabling a shift from reactive to predictive agricultural management [58].

The integration of WSNs and wireless communication underpins a transformative, data-driven approach to farming and resource management, fostering high levels of automation in processes like irrigation and fertilization based on real-time data analytics [56]. Continuous monitoring also extends to agricultural infrastructures like greenhouses, ensuring optimal conditions for crop quality and yield [59]. As sensor technology advances, with hybrid sensors measuring multiple parameters simultaneously, and network protocols evolve to handle greater data volumes with low latency, the role of WSNs in agriculture is set to expand further, enhancing productivity and promoting sustainable practices [60].

2.3. Previous Work on Sheep Monitoring

Recent advancements in sheep monitoring have significantly leveraged IoT and sensor technologies to enhance animal welfare and operational efficiency. Research by [61] underscores the potential of IoT in livestock management, particularly through real-time behavioral analysis and health monitoring. Their work explores how data from wearable sensors, tracking activity patterns, feeding behavior, and social interactions, can predict animal behavior and identify stress indicators, enabling timely interventions to improve well-being and farm sustainability. This approach aligns with the broader goal of creating a connected ecosystem where data-informed decisions optimize livestock welfare and productivity.

Complementing these findings, [62] have advanced wearable stress monitoring systems for livestock using multi-sensor IoT frameworks. These systems allow for the continuous assessment of various physiological parameters such as heart rate, temperature, and activity levels, offering a holistic view of a sheep's health and stress state. The real-time tracking of such indicators enables producers to proactively adjust environmental conditions, feeding regimens, or handling methods to mitigate stress, thereby improving overall herd health and welfare. This responsive farming approach, prioritizing animal well-being, also addresses productivity concerns by preventing declines associated with stress-related problems.

The collective insights from these studies exemplify the substantial progress in livestock monitoring through IoT and sophisticated sensor technologies. The shift towards data-driven decision-making, as highlighted by [63], allows for a more informed and technology-augmented approach to traditional farming practices. By harnessing the full scope of IoT systems, farmers can engage in proactive management, ensuring the health and productivity of their livestock while aligning with broader sustainability goals in agriculture [61]. This convergence of technology and farming practices signals a new era in livestock management, where data-driven insights are central to shaping the future of sheep husbandry.

2.4. Application of Regression Models in Agricultural/Biological Systems

Regression analysis serves as a foundational statistical tool in agricultural science, animal science, and biological growth modeling, enabling researchers to understand and predict complex relationships between variables. Its applications are diverse and critical for optimizing productivity and sustainability. For instance, regression models provide a robust framework for understanding the ecological conditions necessary for enhancing soil health, such as assessing the impact of management factors on soil organic matter [64] and clarifying complex soil interactions to inform sustainable management [65]. Similarly, multiple regression has been used to evaluate the entire agricultural product industry chain, elucidating how different elements within the ecosystem interact to affect productivity [66]. In environmental science, linear and multivariate regression models are essential for assessing the ecological impacts of farming, such as exploring nitrogen and phosphorus emissions from integrated crop-animal systems [67].

Within the specific domain of animal and plant science, regression is instrumental for modeling growth and productivity. Techniques such as support vector regression have been effectively used to correlate various growth factors associated with livestock, linking classical statistical methods with advanced computational tools to analyze complex biological systems [68]. This approach allows for a more nuanced understanding of how different stimuli and stressors affect animal welfare and development. As agriculture faces increasing pressure from challenges like climate change, complex forms of regression are also being applied to examine the interactions between agricultural practices, technology, and environmental sustainability, supporting the development of more resilient systems [69]. These applications highlight the indispensable role of regression in providing quantitative insights into the biological processes that underpin modern agriculture.

2.5. Identifying the Gap

The review of current literature highlights significant strides in applying IoT technologies and various analytical models to enhance smart farming practices, particularly in livestock management [34]. WSNs and specific sensors for environmental and physiological monitoring are well-established, offering robust data collection for precision agriculture [49]. Furthermore, regression analysis, from simple linear models to more complex multivariate and machine learning-enhanced techniques, has been extensively utilized to understand crop yields, soil health, and animal growth [64]. Previous work on sheep monitoring specifically has explored IoT for tracking welfare, behavior, and stress, often incorporating machine learning or multi-sensor frameworks [61].

While these studies demonstrate sophisticated approaches, a discernible gap exists regarding the practical implementation and validation of simple, yet highly interpretable, individualized growth models for sheep using accessible IoT technology. Much of the advanced research leans towards complex, "black box" models that, while powerful, may not be practical for on-farm decision-making where understanding the reason for a prediction is as important as the prediction itself [70]. For the specific goal of creating an actionable baseline for an individual animal's growth, a simple linear model is not only sufficient but arguably optimal. Its transparency allows farmers to easily understand the expected growth trajectory and intuitively grasp the magnitude of any deviation, a critical feature for making confident management decisions. There remains a need to validate this straightforward approach within an easily deployable IoT system, particularly for farming contexts where resource availability or technical expertise for complex systems might be limited. This study aims to address this niche by focusing on the development and application of an IoT-based system for robust individual animal growth trajectory modeling in sheep using simple linear regression. The emphasis is on creating a practical, interpretable solution that leverages accessible technology to provide accurate, individualized growth insights. By concentrating on this specific application, the research seeks to offer a valuable tool for on-farm management that, while data-driven, remains straightforward for end-users to understand and act upon, thereby complementing existing research that often explores more complex or broader monitoring paradigms.

3. Methodology

3.1. System Architecture and Components

The smart system developed in this study is engineered to provide users with crucial information via smartphones, facilitating the monitoring of environmental conditions pertinent to livestock health and tracking weight data for assessing growth [71]. The system's architecture is fundamentally based on IoT technology, integrating various hardware and software elements into a cohesive monitoring solution. At its core, an Arduino Microcontroller and an ESP32 Dev Module function as the primary data processing and instruction centers, orchestrating the system's operations based on sensor inputs and pre-programmed logic [32]. For user interaction and immediate data display, a 16x2 LCD screen is utilized. The key sensory apparatus comprises a DHT22 Sensor, selected for its reliability in detecting ambient temperature and humidity, and an HX711 Module connected to a 50kg capacity LoadCell for accurate weight measurement [33]. Power is distributed through an Adapter/Power Supply, and the entire assembly is supported by electrical components and connectors housed within a central panel box. A water storage container is also integrated, with a mechanism allowing for remote water provision. Additionally, a camera was included for manual, real-time visual inspection by the farmer via the smartphone app but was not integrated into the automated data collection and analysis pipeline. The system's microcontrollers are programmed using Arduino 1.6.10 Software [31].

3.2. Experimental Setup

The research was conducted utilizing a cohort of 15 sheep, which served as the subjects for monitoring growth and health-related environmental parameters. To ensure consistency and gather sufficient longitudinal data for analysis, the monitoring and data collection activities were carried out over a continuous six-month period, which commenced in January 2023 and concluded in June 2023. Throughout this duration, all 15 sheep were housed and managed under consistent farming conditions to minimize variability arising from external factors. This included adherence to a specific and uniform feeding regime for all animals, which consisted of fermented tempeh waste, fermented corn waste, and, on occasion, grass. This controlled experimental setup was designed to ensure that the data collected on growth and environmental responses were primarily attributable to the monitored variables and the inherent characteristics of the animals.

3.3. Data Collection

The data collection process was meticulously designed to capture accurate and timely information relevant to sheep growth and the ambient conditions of their environment. For the primary purpose of growth modeling, each of the 15 sheep was weighed individually once per week throughout the entire 6-month study period. These weight measurements were performed using digital scales that were specifically designed and calibrated to ensure accuracy and precision in weighing livestock [71]. To facilitate individual tracking and data integrity, each sheep was assigned a unique label or identity tag. An example of this weekly weight data collection protocol, specifically for the month of January, is presented in table 1. Concurrently, environmental data, specifically the ambient temperature and humidity within the livestock cages, were continuously collected using the deployed DHT22 sensors [32]. All data streams, encompassing the individual sheep weights and the corresponding environmental parameters, were systematically logged and stored in a central database, which was directly integrated with the system's hardware tools to ensure seamless and reliable data capture and retention. This comprehensive data collection formed the empirical basis for the subsequent regression analysis.

3.4. Data Analysis using Linear Regression Model

Regression analysis is generally employed to determine the influence between one or more predictor variables and a responsive variable. The fundamental simple linear regression model is expressed as shown in equation (1).

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{1}$$

Where based on equation (1), Y is the response variable, β_0 is a constant or intercept which is the intersection point between the Regression line and the Y axis on the Cartesian ordinate, X is a predictor variable, and β_1 is the direction coefficient. For situations involving high correlation between predictor variables, the ridge regression method can be utilized. This method introduces a constant (c) on the diagonal of the matrix, affecting the regression parameters to produce biased estimates but with minimum variance. A general form for multiple linear regression is shown in equation (2).

$$y = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \epsilon_i \tag{2}$$

In equation (2) it is explained that Y_i is a dependent variable, X_{ki} is an Independent Variable, $\beta_1, .., \beta_k$ is a Regression Parameter, and ϵ_i is a Nuisance Variable. The linear regression model can also be expressed in matrix form as depicted in equation (3), with the matrices defined in (4).

$$Y = X\beta + \epsilon \tag{3}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}; X = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1k} \\ 1 & x_{12} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \ddots & x_{nk} \end{bmatrix}; \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix} dan\ \epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix} \tag{4}$$

In this particular study, simple linear regression (of the form Y=ax+b, analogous to equation 1) was employed to model the growth trajectory (weight, Y) of each individual sheep over time (weeks, X). This specific approach was selected for its interpretability, ease of implementation within the developed IoT context, and its demonstrated efficacy in capturing the consistent linear growth trends observed in the individual animals during the study period. A distinct linear regression model was fitted for each of the 14 sheep that survived the duration of the study, using their collected weekly weight data. To provide a summary overview of the cohort's growth trend, the slope (a) and intercept (b)

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coefficients derived from these 14 individual sheep growth models were averaged. This averaging process resulted in the general formula for cohort growth. Similarly, the reported R^2 for this general formula represents the average of the R^2 values obtained from the individual models. The focus of this research, as mentioned in the system identification, is specifically on the growth of sheep as determined by their weigh-ins to observe the growth rate.

3.5. System Operation and Reporting

The smart system developed for this research functions in both manual and automatic operation modes. The Arduino microcontroller and ESP32 module act as the central instruction unit, managing system commands based on signals received from the various sensors. The system is designed to transmit sensor values—including temperature, humidity, and weight—to users' smartphones. This provides real-time data for monitoring the health (via environmental conditions) and growth of the livestock. An important operational limitation is that if the smart system process is disrupted, it cannot be remotely maintained or controlled; in such scenarios, its functionality is limited to sending the data captured by its implanted sensors.

3.6. Research Stages

The research was systematically conducted through several defined stages, as illustrated in figure 1. The first stage was Problem Formulation, identifying and defining the problem to be addressed by the integrated smart system. This was followed by the Determination of Objectives, where clear objectives and the overall direction for the smart system research, focusing on the application of IoT technology, were established. The third stage was Literature Study, involving a comprehensive search for reference data from journals, the internet, and books related to smart systems for livestock growth and development. The fourth stage, Data Collection, concerned obtaining sensor data from the smart system, which served as the primary material for monitoring the growth and health of the farm animals. The fifth stage was Implementation, where the produced smart system was analyzed to evaluate its effectiveness in monitoring livestock growth and health through linear regression. The final stage, System Testing, involved evaluating the smart system to identify and address any operational problems or issues that arose during its operation.

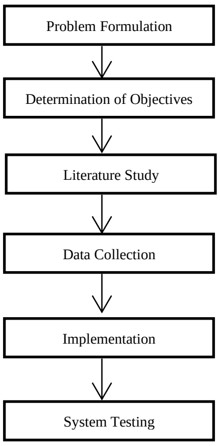

Figure 1. Research Method Flowchart

4. Results and Discussion

4.1. Implementation of the IoT-Based Monitoring System

The smart system for monitoring sheep growth and health, as detailed in the Method section, was successfully constructed and fully deployed within the operational livestock pen environment. The physical hardware was installed to ensure continuous and reliable data acquisition. The central panel box, serving as the nerve center of the system, was securely mounted. From this hub, sensors were strategically placed: DHT22 sensors were positioned to capture representative ambient temperature and humidity within the sheep pens, while the custom-built weighing station with its integrated load cell was installed for easy and regular access. The automated water dispensing unit was also connected and calibrated. This complete installation created an active operational setting, enabling the system to begin its primary function of collecting real-time data on both environmental conditions and key livestock growth parameters throughout the entire six-month study.

4.2. Collected Data Overview

Over the six-month study period, weekly weight data was collected for all 15 sheep. A sample of the raw weight data, illustrating the weekly measurements for the month of January, is presented in table 1.

Table 1. Sheep weights for the month of January

No	Data	Tag	1st Week	2nd Week	3rd Week	4th Week
1	A	581	3.15	3.9	4.3	5.05
2	B	582	3.05	3.8	4.6	5.35
3	C	583	3.18	3.9	4.55	5.28
4	D	584	3.28	4.1	4.7	5.53
5	E	585	3.25	4.2	5.2	6.15
6	F	586	3.05	3.8	4.55	5.3
7	G	587	4.38	5.6	6.87	8.1
8	H	588	4.68	5.8	6.8	7.93
9	I	589	4.33	5.2	6.1	6.98
10	J	590	4.58	5.9	7.1	8.43
11	K	591	5.33	6.5	7.8	8.98
12	L	592	4.75	6.3	7.9	9.45
13	M	593	3.08	3.9	4.5	5.33
14	N	594	3.2	4.2	5	6
15	O	595	3.27	4.1	4.7	5.53

At the conclusion of the study, the cohort was grouped into four distinct weight ranges, as detailed in table 2, which shows the final distribution of the animals based on their weight. One sheep (Tag 595, 'O') died due to disease during the study and was therefore excluded from all regression analyses.

Table 2. Sheep Weight Range Distribution

Weight Range	Number (head)	Sheep Name
10 Kg < Weight ≤ 15 Kg	1	C
15 Kg < Weight ≤ 20 Kg	9	A, B, D, E, F, I, M, and N
20 Kg < Weight ≤ 25 Kg	4	G, H, J, and K
25 Kg < Weight ≤ 30 Kg	1	L

The DHT22 sensor continuously collected data on ambient temperature and humidity within the livestock pens throughout the study. These values were displayed in real-time on the system's LCD screen and transmitted to the user interface, as shown later in the system reporting output.

4.3. Sheep Growth Modeling Results

Linear regression analysis was performed on the weekly weight data for each of the 14 surviving sheep. Figure 2 provides a comparative visualization of the individualized linear regression models for four selected sheep, each representing a different growth pattern observed in the study. The solid lines depict the calculated 24-week growth trajectories, while the circular markers represent the actual weight data collected during the first four weeks. This graph effectively illustrates the significant variation in growth rates among individual animals and visually confirms the strong fit of the linear models to the initial observed data for each distinct trajectory.

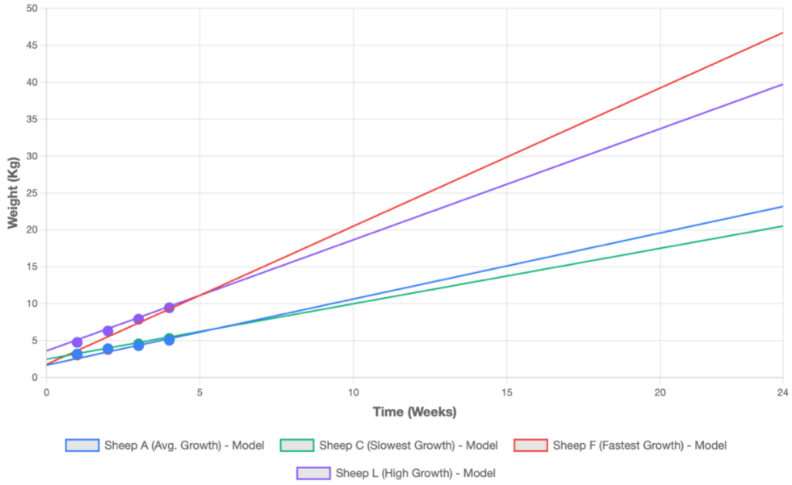

Figure 2. Comparative Growth Trajectories of Selected Sheep

As a representative example from the analysis, the model for Sheep A (Tag 581) produced the linear regression equation Y=0.8958x+1.6775, with a corresponding R^2 accuracy of 0.9951, or 99.51%. Based on this model, the estimated weight for Sheep A at the end of the 6-month period (24 weeks) was calculated to be 23.1767 Kg. The individual regression formulas and R^2 accuracy values for all 14 sheep are presented in table 3.

Table 3. Livestock Growth Regression Models

No	Sheep	Code	Formula Regression	Accuracy
1	A	581	Y = 0.8958x + 1.6775	99.51%
2	B	582	Y = 0.9071x + 1.705	99.62%
3	C	583	Y = 0.7515x + 2.4794	99.14%
4	D	584	Y = 0.9453x + 1.8881	99.69%
5	E	585	Y = 1.0177x + 2.0775	99.96%
6	F	586	Y = 1.8733x + 1.775	99.55%
7	G	587	Y = 1.1754x + 3.4339	98.90%
8	H	588	Y = 1.1489x + 3.6081	99.60%
9	I	589	Y = 1.0278x + 2.8909	99.65%
10	J	590	Y = 1.3878x + 3.1706	99.38%
11	K	591	Y = 1.1725x + 4.2669	99.72%
12	L	592	Y = 1.5055x + 3.6063	99.20%
13	M	593	Y = 0.9731x + 1.6644	99.82%
14	N	594	Y = 1.1332x + 1.7238	99.73%

To further validate the fit of the individual linear regression models, a residual analysis was performed. Figure 3 shows the residuals (the difference between actual and predicted weight) for the first four weeks of data for the same four representative sheep. The plot shows that for most measurements, the residuals are small and randomly scattered around the "Zero Error" line. This lack of a discernible pattern in the errors indicates that the simple linear model is an appropriate fit and is not systematically over or under-predicting the weight, which further strengthens the conclusion of high model accuracy based on the R^2 values.

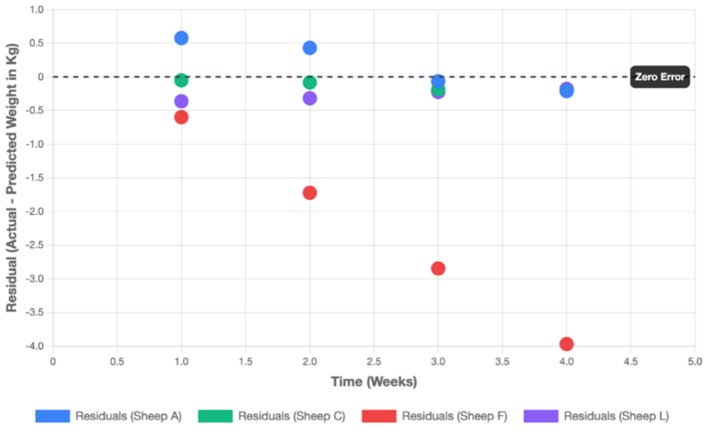

Figure 3. Residual Analysis Graph

To provide a summary descriptor of the cohort's overall growth tendency, a general formula was derived by averaging the slope (a) and intercept (b) coefficients from the 14 individual regression models. This resulted in the general cohort growth equation Y=1.065x+2.569. The average of the individual model R^2 values was 99.53%. The operational flow of the system is governed by two core algorithms. The logic for the IoT device itself, responsible for data gathering and transmission, is outlined in algorithm 1. This process involves a continuous loop of reading sensor data, formatting it into a standardized payload, and transmitting it wirelessly to the backend server for processing and storage.

Algorithm 1. IoT Device Data Collection and Transmission

```
PROCEDURE Main_Loop
  Initialize_Sensors(DHT22, Load_Cell)
  Initialize_WiFi_Connection()
  LOOP indefinitely
    temp_celsius     ← Read_Sensor(DHT22_temperature)
    humidity_percent ← Read_Sensor(DHT22_humidity)
    weight_kg        ← Read_Sensor(Load_Cell)
    data_payload ← Format_JSON({
      "device_id": "SHEEP_PEN_01",
      "temperature": temp_celsius,
      "humidity": humidity_percent,
      "weight": weight_kg,
      "timestamp": Get_Current_Time()
    })
    IF WiFi_Is_Connected() THEN
      Send_Data(data_payload)
    ELSE
      Attempt_Reconnect_WiFi()
    END IF
    WAIT for interval (e.g., 60 seconds)
  END LOOP
END PROCEDURE
```

The logic for the user-facing smartphone application is detailed in algorithm 2. This procedure is triggered upon receiving new data for a specific animal. It retrieves that animal's unique regression model, calculates its expected weight for the current week, and compares it to the actual weight to determine any deviation. This deviation is then displayed to the user, with an alert triggered if it surpasses a predefined threshold.

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Algorithm 2. Smartphone Application Logic for Growth Deviation Alert

```
PROCEDURE On_Receive_New_Data(sheep_ID, current_weight)
  model ← Get_Model_Parameters(sheep_ID)
  current_week ← Get_Current_Study_Week()
  expected_weight ← (model.slope * current_week) + model.intercept
  deviation ← current_weight - expected_weight
  deviation_percent ← (deviation / expected_weight) * 100
  Update_UI(sheep_ID, current_weight, expected_weight, deviation_percent)
  IF ABS(deviation_percent) > 5.0 THEN
    Display_Alert("Warning: Sheep " + sheep_ID + " is deviating from expected growth.")
  END IF
END PROCEDURE
```

The IoT system was configured to embed the derived linear regression models, using them as baselines for monitoring purposes. A key result of the implementation was the system's ability to successfully transmit signals from the hardware devices to a mobile user interface. This interface provided real-time reports on the health and development of the sheep, forming the core of the smart system application. The mobile application displayed outputs such as live camera feeds for visual inspection, as well as quantitative data reports. These reports included ambient temperature and humidity readings from the pens, alongside other relevant sheep data outputs, allowing for continuous and remote real-time monitoring of the animals and their environment. This functionality confirmed that the system could effectively close the loop from data collection to user-friendly information delivery.

4.4. Interpretation of Key Findings

Consistent with findings in other livestock growth studies that show predictable development patterns in young animals, the results presented in table 3 demonstrate that simple linear regression is a highly effective model for tracking the growth of individual sheep during this specific life stage. The extremely high R^2 values, consistently above 99% for most animals, indicate that a linear model can explain nearly all the variance in weight gain over the six-month period. This suggests that under the controlled feeding and environmental conditions of the study, the growth of young sheep follows a strong and predictable linear trajectory. This finding is significant because it validates the use of a straightforward, interpretable statistical method for creating reliable, individualized growth baselines for each animal, which is a foundational aspect of precision livestock farming [33]. An important observation from the original data analysis was that the minor differences in weight gain between sheep were not attributed to the consistent feeding regimen but rather to biological factors, specifically the litter size from which the lambs were born. The system's ability to collect precise, individual weight data allowed for this level of insight, demonstrating that the IoT application provides value beyond simple data logging. It enables farmers to identify and understand the sources of variance within their flock, which can inform breeding strategies and management decisions.

4.5. Practical Implications for Farm Management

The true value of this smart system lies in its practical application for on-farm management. By implementing individualized regression models, the system moves beyond simply recording a sheep's current weight. It allows a farmer to compare the animal's actual weight against its own established, predictable growth curve. This enables a farmer to detect significant deviations from an animal's personalized trajectory via the smartphone interface (figure 3). Such deviations can serve as a powerful early warning for potential health issues or inadequate nutrient intake, prompting targeted intervention long before problems become visually apparent. This aligns with the concept of building digital representations to bring the farmer closer to the animal [33]. Furthermore, the system contributes directly to preventative health management. While this study did not develop a quantitative health model using regression, the continuous monitoring of temperature and humidity provides actionable environmental data. By receiving real-time reports on pen conditions, farmers can proactively manage the environment to reduce heat stress

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and mitigate conditions favorable to disease [72]. This function addresses the health monitoring aspect of the study's goal by providing a tool for maintaining a healthy and productive environment for the livestock.

4.6. Limitations of the Study

Despite the positive results, several limitations must be acknowledged. First, the quantitative modeling was confined to growth metrics; no predictive health models were developed from the collected environmental or physiological data. No predictive health models were developed using the environmental or weight data. Second, the study was conducted on a limited sample size of 14 sheep in the final analysis, within a single farm and under a specific feeding regime. Therefore, the specific model parameters (slope and intercept) may not be directly generalizable to other sheep breeds, ages, or farming conditions without further validation. Finally, the camera's separate operation from the main data-logging application limits the potential for integrated, multi-modal analysis in this iteration of the system.

4.7. Future Work

Based on the findings and limitations of this study, several avenues for future research are apparent. A logical next step would be to validate the individualized modeling approach on a larger and more diverse sheep population, encompassing different breeds and management systems, to confirm its broader applicability. Future work should also focus on developing multivariate regression models to quantitatively assess the influence of temperature and humidity on variables such as daily weight gain or feed conversion efficiency, though this will require more intensive data collection to avoid overfitting and ensure model robustness. The implementation of automated anomaly detection algorithms could enhance the system by providing real-time alerts to farmers when a sheep's growth deviates significantly from its predicted trajectory, which will necessitate defining appropriate and dynamic thresholds for what constitutes a significant deviation to avoid false positives. Finally, integrating the camera feed with image analysis software could provide new data streams on animal behavior, posture, or physical condition; however, this presents significant challenges in data storage and the computational power required for real-time image analysis, creating a more comprehensive but technically demanding monitoring tool for precision livestock farming.

5. Conclusion

This study successfully developed and validated an IoT-based smart system for monitoring sheep growth and health-related environmental conditions. The primary achievement was the demonstration that simple linear regression provides a highly accurate and reliable method for modeling the individual growth trajectories of sheep over a six-month period, with R^2 values consistently exceeding 99% for most animals. The implemented system effectively collected real-time weight, temperature, and humidity data and delivered actionable reports to users via a smartphone interface, confirming the feasibility of the proposed architecture for on-farm use. The main contribution of this research lies in its validation of a practical, interpretable, and accessible data-driven approach to precision livestock farming. Compared to more complex machine learning approaches that focus on behavior or stress, the proposed system demonstrates that a simple, interpretable linear regression model provides exceptional accuracy for the specific, high-value task of growth monitoring, offering a practical entry point for data-driven farm management. By creating individualized growth models, the system empowers farmers to shift from reactive to proactive management. Deviations from an animal's established growth curve serve as crucial early indicators for potential health or welfare issues, enabling targeted and timely interventions. This dual functionality enhances productivity through precise growth tracking while concurrently supporting animal welfare through preventative environmental monitoring. In conclusion, this research serves as a successful proof-of-concept for applying fundamental data science models within a practical IoT framework to solve real-world agricultural challenges. It establishes a strong foundation for future enhancements, including the development of multivariate models that incorporate environmental data, the implementation of automated anomaly detection, and the integration of multi-modal data streams, such as camera feeds for behavioral analysis, to create an even more comprehensive and powerful smart farming solution.

6. Declarations

6.1. Author Contributions

Conceptualization: S.E., P.S., H.M.; Methodology: S.E., H.M., A.T.; Software: S.E.; Validation: A.T., G.W.W.; Formal Analysis: S.E.; Investigation: S.E., P.S.; Resources: G.W.W.; Data Curation: S.E.; Writing – Original Draft Preparation: S.E.; Writing – Review and Editing: P.S., H.M., A.T., G.W.W.; Visualization: S.E.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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