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Design and Implementation of The Smart Weighing Precision Livestock Monitoring Technology based on the Internet of Things (IoT)

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Abstract— **The traditional approach to weight measurement, which measures each sheep individually, is time-consuming, and sometimes, human error triggers other issues, such as data validation, sheep classification, etc. Most farmers or breeders nowadays still manage their livestock traditionally, which is inefficient. We proposed that the Livestock Live Monitoring System is designed to collect measured data in real-time and display data in graphics; these models combine Bluetooth Low Energy as a wearable sensor to identify animals and Smart Weight Measurement to deliver weight and health data to the cloud system. This system aims to measure livestock and store the data in the server application so livestock monitoring can be done in real-time and remotely. The technology used in this system is ESP32, Load Cell, Bluetooth Low Energy, and Message Queue Telemetry Transport Protocol. Wearable devices act as an identification tag for livestock, and a smart weight scale is used to weigh the livestock and integrate it with the system. Two sheep are used as experiment objects, and their measured weight is compared to their weight when measured traditionally using a conventional scale. Based on the experiment, the weight data measured using the system has an accuracy of 99.82% for sheep number 1 and 99.17% for sheep number 2. This proposed system provides many benefits, including real-time livestock monitoring, cost efficiency, and an efficient feeding system for sheep using weight data.**

Keywords— **Internet of Things; smart weight scale; bluetooth low energy identification; weight data; sheep classification.**

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I. INTRODUCTION

Based on The United Nations Committee on World Food Security, people must have access to sufficient and safe food supply [1]. Sheep are a necessary source of food production worldwide [2]. Indonesia's sheep population reached nearly 18 million, based on the Indonesian Statistical Centre (Badan Pusat Statistik) in 2021. The largest population contributor is from West Java Province, which has 12,246,608, or 68.4% of the total sheep population [3]. Sheep are one type of animal widely enjoyed in Indonesia for their meat, clothing, gloves, and other leather crafts [4]. In Indonesia, sheep are mostly found in West Java, Central Java, or East Java, where most of the population still lives in rural areas with many farms and stock breeding. Despite the many sheep produced in Indonesia, farmers still use conventional systems for breeding and producing sheep. They still monitor, feed, clean, and traditionally weigh the sheep. They do use tools, but they do not use the newest technology to maintain their farms. The traditional way does provide some benefits to farmers. Because they do not use many high-technology tools, their operation cost is inexpensive, so they can maintain a high-profit margin from selling sheep.

Moreover, they can easily operate their farms without the necessary skills required for the current technology [5]. Still, there are disadvantages to operating a farm traditionally. A farm requires human resources to maintain it because each farm usually has thousands of sheep, making it difficult to manage a farm for only one or two people. Several tasks are difficult to perform with basic tools, such as counting sheep, weighing sheep, and sheep identification. Therefore, Indonesia's farms require new technology to become more efficient.

The evolution of technology in Indonesia is as up to date as possible. Although Indonesia's technology use is behind that of some other countries, Indonesia's government and researchers are striving to keep up with the pace of technology. The Internet of Things (IoT) is one technology that is currently used. It is already massively used in several developed countries, but in Indonesia, it has only just been introduced to the people, though its popularity has increased field[6]. IoT is one of many technologies developed to adapt to the new digital area, and it can help society overcome the difficulties of the digital era. The advancement of IoT allows for connecting several devices to store data in the cloud. IoT and the development of technology can be applied to many sectors, such as the farm and livestock sectors.

There have been new developments in livestock technology, specifically for livestock live monitoring, which can change traditional livestock farming to make it more optimal and cost-effective for farmers, such as by reducing crop waste. The goal is to create technology for farmers to generate messages on different platforms to notify farmers using data. The product is helpful for farmers, property owners, and investors by providing them with real-time data through website applications (tracking, weight, healthcare, and live view) for livestock. The proposed product utilizes ESP32, Bluetooth Low Energy (BLE), Weight Scale Smart, and live data, which can be monitored via the MQTT protocol and then viewed on the site application, allowing farmers to manage crops in this new age of agriculture [7]. The evolution of the broadband cellular network, which is 5G technology, also has a role in this technology to establish connections between devices while still maintaining a rapid data transfer. Nano-enabled sensors are also an important topic in this article, which discusses challenges and upcoming developments [8]. This technology can be combined to create a new livestock live monitoring integrated system.

An IoT is a network of sensors, controllers, operators, and objects that communicate using technologies, such as local area networks or the internet, creating an intelligent, automated, and information-driven system. Accordingly, the core function of IoT is to connect devices that initially function independently and to obtain effective information about each unit so that it can be controlled in a unified manner. IoT devices have a traceability, or tracking, function, which works with tracking and surveillance activities to prevent robberies and wild attacks [9]. These portable sensors can monitor an animal's health status, such as temperature, and can track and identify the animal. The power source is alkaline batteries, which do not have a long lifetime, so the farmer needs to replace the batteries every couple of months. Livestock industries have tremendous potential for these parameters, which are also important for maintaining healthy livestock [8].

There is an alternative to measuring weight using the digital image processing method active geometry contour to classify sheep by weight by capturing images of the sheep [10]. This alternative gives a weight estimation accuracy of 73.82%. Research has been conducted in Thailand to estimate pig weight with digital image processing using an artificial intelligence data sampling collection through image capturing with a high-quality digital camera, which is then compared with manual weight measurements. A detection rate of 87.15% was achieved [11]. The primary concern regarding IoT devices is available data versus the goal of the approach, with the primary goal of precision livestock farming being to improve animal health and welfare [12]. The condition of livestock areas can be automatically or manually controlled according to the information obtained. Sensors, such as accelerometers, can be used to monitor animal movement and health. Animal weight information is also sent to applications to classify animals by weight, as mentioned [13]. In doing so, productivity is increased, and livestock can be cared for more quickly [12]. Animal counting by capturing images has been deployed [14], [15]. Sheep identification using facial images has an accuracy of 80 percent, and kinship detection has an accuracy of 68 percent [16].

The size of the sensors depends on the target animal and how to make it comfortable for an animal. Heavy wearable sensor devices cause animals to stress and cause the animal's health to decrease slowly. For example, if a chicken weighs 2-3 kg, the sensor weight should be less than 50g. Sheep have a body weight of around 30-60kg, so the sensor weight should be less than 700g. Energy efficiency is also a primary concern, as the lifetime of a sensor depends on the battery type. Battery specifications are important to consider. Current sensors have a low power consumption when using different features, such as hibernate power mode. The features can be utilized using small-size batteries, such as coin cells; hence, the devices have a longer lifetime. This is also a primary topic of research aiming to determine how to reduce battery size to increase a device's lifetime.

The traditional approach to weight measurement, which measures each sheep individually, is time-consuming, and sometimes, human error triggers other issues, such as data validation, sheep classification, etc. The proposed Livestock Live Monitoring System is designed to collect measured data in real time and to display data in graphics. The sheep is attached to wearable tracking devices that are connected to BLE. The Livestock Live Monitoring System can track each sheep's unique ID on the User Application. The data that the farmer receives is used for weight and sheep quality classification.

The literature review is essential better to understand the scope and related field of research. Based on the research objective, the articles that are considered to be reviewed are articles with topics around livestock monitoring, smart farming, and any IoT related such as BLE and RFID. Although wearable sensors, RFID, Bluetooth Low Energy, mathematical prediction estimation, and digital weight measurement have been applied to solve the smart farming industry, these approaches encounter many challenges in real settings. The proposed models combine Bluetooth Low Energy as a wearable sensor to identify animals and Smart Weight Measurement to deliver weight and health data to the cloud system. In the end, the farmers will be presented with data to classify the animals, an efficient feeding system, and the average weekly growth for each animal, including the animals' health.

More importantly, everything can be done in real-time and remotely as long as the farmer can access the internet. There are three class classifications for livestock standards based on weight. Class A is livestock that weighs from 35 to 40 kg. Class B is livestock that weighs from 30 to 35 kg. Class C is livestock that weighs from 24 to 30 kg. There are also two other classes, which include the special quality class that weighs above 40 kg and the unclassified class that weighs below 24 kg. The data from the livestock are collected and filtered automatically by the application and forwarded to the application server/database. The livestock application server is synched to the website application so that the owner can access the data and review the data visualization from the livestock. Some of this data can be analyzed, determined, and transformed into simple and useful information. We designed the devices to be integrated and to provide data visualizations to farmers. The final data shared by the application provide a detailed analysis of the quality of the livestock. This research contributed to collecting the weight data and analyzing the livestock every day for about five months before being sold to the market.

II. Material and Methods

This section discusses many key aspects of the livestock surveillance system using integrated sensors. The system produces two types of data: sheep identification by the BLE system and the smart weight scale to measure the weight of sheep. The data is collected at each custom measurement period, then transmitted and published to the MQTT broker via a Wi-Fi connection.

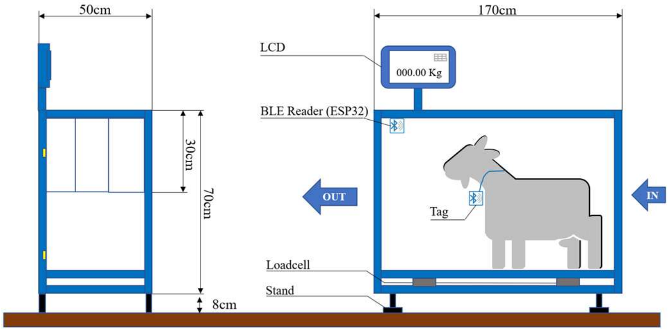

Fig. 1 Device Design

The device design is shown in Figure 1 for the system, these scales are integrated with BLE, and the application is used for the live surveillance system. BLE allows for communicating using multiple sensors with low energy consumption; however, the system does not provide information about battery life. Based on several findings regarding the sheep tracking system, this BLE integrated system is believed to provide major benefits.

A. BLE Identification

BLE technology was used in this study for wearable devices because it has a low power consumption. The IoT solution can reduce the cost of livestock monitoring, which is quite cost-efficient to have the capability to monitor the physical parameters of an animal farm continuously [13]. BLE technology is a wireless connection to deliver data from IoT devices [17].To identify an animal, this portable device employs an RFID tag [12]. The RFID devices are replaced by BLE devices, which are monitored by an application, and it has more features using machine learning to analyze the guided path tomography images [18]. The device then investigates smart scale measurements using calibrated load cells and additional sensor biometrics to identify the weight data. Data collected from the load cells are then sent to an Android application [19].

The developed system uses ESP32, which has BLE embedded. BLE is activated on the ESP32 module to detect and localize Bluetooth transmission devices, such as wearable devices, which are placed indoors or outdoors according to the strength of the signal received by the transmitter device. Bluetooth emits BLE signals on multiple occasions. Nearby devices, including BLE-activated sensors, can detect these signals. The continuous signal broadcast through BLE contains a unique identifier (MAC address). This ID code is sent regularly, along with other data, according to the BLE communication protocol used. The smart scale enabled BLE to communicate with a dedicated preconfigured service while within range of BLE, receive and analyze the BLE signal in livestock. Detection between a BLE sensor and an intelligent scale can enable proximity depending on the location services, such as whether BLE and a device are within reach. With several BLEs strategically placed in one space, communication between two or more BLEs and a wireless device can be used to position the multiliterate RSSI device. In this application, BLE as ID automatically identifies a tag to measure sheep's weight. The frequency bands are defined at 2400 – 2438.5 Megahertz. The materials list is shown in Table I. This device uses ESP32, which has a functional BLE embedded in the system and a sensor for body temperature.

TABLE I
Material for BLE Module

No	Component Name	Description	Quantity
1	ESP32	Microcontroller	2
2	Connecting Wires	Jumper	20
3	Breadboard	Project Board	1
4	GY-906-BAA	Temperature Sensor	1

Temperature sensors are used to measure the temperature of the sheep's bodies. The Network Time Protocol (NTP) is a network protocol used to synchronize time between computing systems on a packet-switched variable latency data network. Each time the BLE receiver receives a new BLE message, it asks the NTP server for the date and time of the last measurement received.

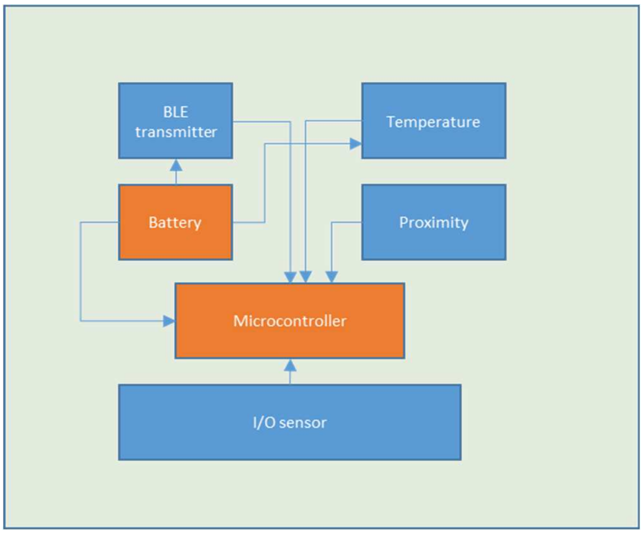

Fig. 2 Wearable device using the BLE diagram

The diagram of the wearable device using BLE is shown in Figure 2. The figure illustrates the connection between the temperature sensor, the proximity, and the BLE transmitter to the microcontroller ESP32. The microcontroller controls the data from sensors sent via the BLE transmitter to the smart weight scale as tag IDs, and then the data ID and the sheep's weight is sent to the cloud via the MQTT protocol.

B. Proposed Experimental Area

The livestock area investigated was Jonggol, where farmers still operate farms traditionally. In this area, a five-hectare paddock is used to keep the sheep inside the area and avoid any health hazards. This area is relatively flat, and it has a power source and an internet connection available 24 hours per day.

Figure 3 shows two types of areas: open and closed. The open livestock area is only used in the daytime and has the capacity for around 500 sheep, sufficient to ensure the sheep receive direct sunlight. The closed livestock area has food and water. This area has six rooms, and each room has a capacity of 20 sheep. In total, the closed area can contain about 240 sheep. This area is also where the sheep rest at night.

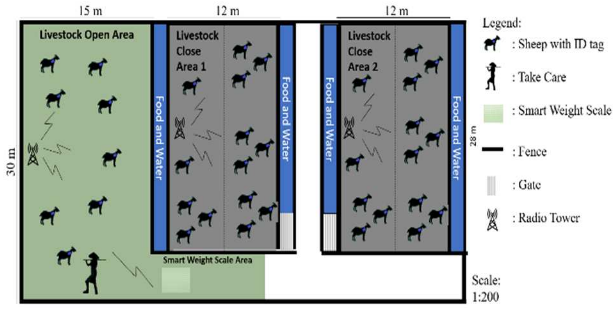

Fig. 3 Proposed Experimental area

C. Battery

The battery, as a power source, is critical for wearable devices. Several types of batteries can be used depending on the battery slot and application. The lithium battery is commonly used to save memory backup in microcomputers. The shape and size are similar to the coin battery or the button cell.

D. MQTT Protocol

MQTT defines two kinds of network entities. A message broker and a certain number of clients. A MQTT broker is a server that receives customer messages and then forwards them to the appropriate destination customers. A MQTT client is any device, from a microcontroller to a whole server, which runs an MQTT library and connects to a MQTT broker on a network.

The information is organized according to the subject hierarchy. When a publisher has new data for distribution, it sends a check message with the data to the connected broker. The broker then distributes the information to customers. The publisher does not require information about the number or location of subscribers. Thus, it is not necessarily set up with publisher data.

There is a subscription for the broker to receive a stored message. The broker preserves the message as a normal MQTT with a true flag. The broker stores the latest message kept and chooses the selected topic. All clients who registered for the topic template will receive the saved message. The broker keeps one message per topic, allowing for the most up-to-date value rather than waiting for the publisher's next update. Clients only interact with one broker, but one system can have several broker servers that exchange data based on their current subscriber's topics. MQTT uses the TCP protocol for transmitting data. MQTT sends a credential login using clear text and includes no security or authentication measures.

E. GATT Protocol

The GATT protocol is an abbreviation for the Generic Attribute Profile. This protocol allows for transferring data between two BLEs. This concept is referred to as services and characteristic general attributes standards on Bluetooth technology.

The client is a gadget that sends broadcast messages, which the GATT then orders, requests, and accepts. The server is a widget for receiving broadcast messages and returning replies, showing the value of data delivered between the client and the server.

Some service and characteristic values are used for administrative purposes. Bluetooth identification and serial numbers are shown as standard characteristics. The universally unique identifier (UUID) identifies services, attributes, and descriptors. The UUID of the characteristic is read by specifying the value and some information from Bluetooth. Write operations always identify the feature through the handle but have the choice of whether a server response is necessary or not.

F. The Real-Time Data Visualization

The livestock lives monitoring website application allows the users, such as buyers, investors and owners, and the farmer administrator, to view the measurement data of their wearable devices. The author decided to build a website application to access field data anytime. It provides different services called real-time data, ringing alerts for wearable devices and history, and the administrative interface. This website application displays any data information that can be exported.

Automatic weighing system (AWS) has gradually replaced manual weighing to reduce cost and casualties. Nevertheless, the existing AWS has limited weight monitoring and prediction capability. To address the deficiency of the existing AWS, industry 3.5 has developed a data-driven framework for weight monitoring and prediction to support smart production for poultry farming [20]. Weight estimation has been widely investigated. In particular, fitting a mathematical function or algorithm is often used to model the growth based on the characteristics of the animals. Previous research has developed various methods and algorithms such as the Gaussian mixture model, bootstrapping, resampling, and weight mean technique to estimate the current weight of animals on the farm via big data, including electronic signals collected from the multiple sensors in the farm. The system performances have good accuracies in weight measurement [21].

The Internet of Things offers several innovative capabilities and features but is prone to security vulnerabilities and risks. These vulnerabilities must be studied to protect these technologies from being exploited by others. Message Queuing Telemetry Transport (MQTT) is an application layer protocol vulnerable to various known and unknown security issues [22].

The main purpose of the real-time data section is to display sheep ID with weight data measured. The feature ring button is available to identify the sheep ID in the field and is displayed as an interactive marker. The user and administrator can review the table that lists and confirms all the current alerts. The website application can calculate the data received to extract relevant information. The weight data are converted to sheep classifications in the table and displayed on the website. There is a history section to check sheep growth data and then to store the data.

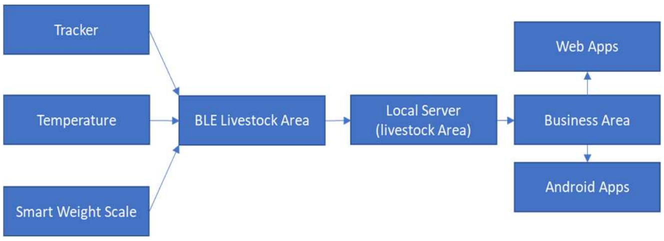

Fig. 4 Block diagram of system

Figure 4 shows the block diagram of a system. The data generated by the devices must be stored to be accessible to end-users. The website application delivers a simple network architecture using two application servers and a database server.

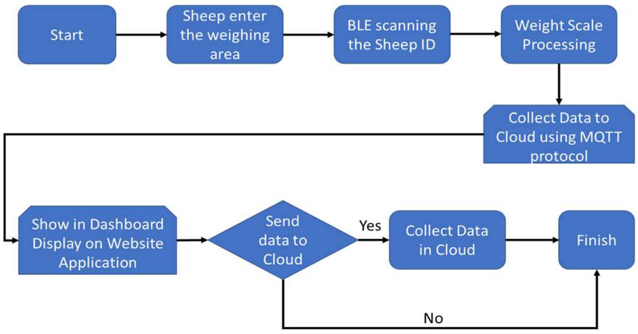

Fig. 5 Flowchart

The supervision software is available as a website application to visualize the position of the devices, data-data sensors, smart weight scale, etc. Figure 5 shows the process of obtaining weight data from the sheep and sending the data to the application, where the data are then shown on the application dashboard with a good representation and interface. The prototype of the wearable device is used for a system that is integrated with BLE technology. The wearable device on the sheep uses BLE as identification.

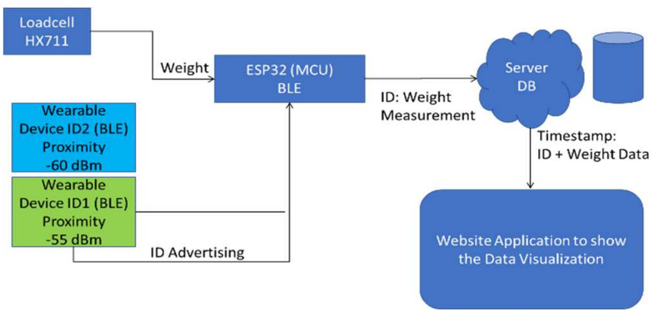

Fig. 6 Two devices as a tag ID

The wearable device functions as a tag identification that will be combined with weight data later. The communication between ESP32 (smart weight scale) is used as a tool to measure the precision of data with the wearable device using the received signal strength indicator (RSSI) levels. The RSSI level should be less than or equal to -55 dBm. Figure 6 shows that the other BLE RSSI level is -60 dBm, less than -55 dBm. The data gathered is transferred to the server via the MQTT protocol and shown as visualization data on the website application.

Livestock monitoring using wearable sensors and Radio-Frequency Identification (RFID) for real-time monitoring has been done in another research [23][24]. The RFID sends the data through an open-source platform called Think Speak. Think Speak, as an IoT platform will receive the data and present the data to the farmer so that easy monitoring can be done remotely[13]. RFID can estimate the quantity of food ration for the livestock in the cow-feed alley. The use of RFIS represents an interesting solution for both the quantity of food ratio and the evaluation of the residual food in the feed alley [25].

Livestock monitoring, especially for pig farms, is considered in another research. BLE tags are used for identifying pig location and pig counting[26]. The data from the field are collected by the BLE tags and analyzed. BLE communication is used for animal identification inside the area. The RSSI level received is calculated and processed through some algorithm to determine the animal's location. The algorithm proposed by the other research has considered the use of BLE for smart farming applications, especially to monitor animals on the farm [27].

G. Smart Weight Scale

This device is based on the weight scale using the measuring cell of the HX711 and ESP32 modules. The load cell sensors can measure any weight up to 200 kg. The display indicates the measured weight. The smart weight scale also measures and sends output and timestamp data, which is then synchronized by the server to analyze which ID passes the smart weight scale at a specific time. The classification of the sheep can be made based on the data that is integrated with other devices.

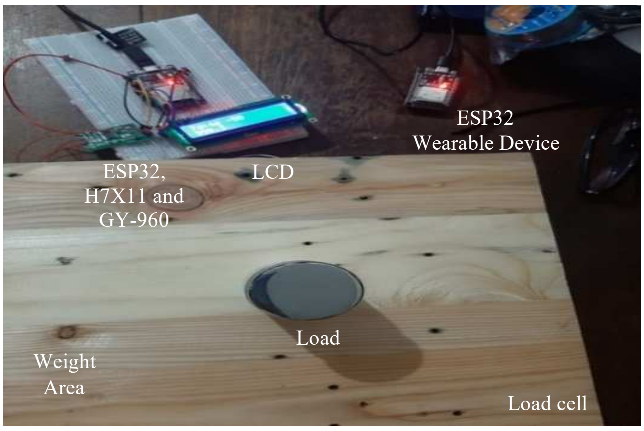

Fig. 7 Smart weight scale

This unit connects the 200kg measuring cell to the ESP32 with the HX71 in Figure 7 HX711 is a precision 24-bit analog digital converter designed from weight scales and industrial control applications to interact directly with a bridge sensor. The H7X11 cell is used to recover measurable data from a cell of measurement and a strain gauge. The electronic scale uses a load-sensing device to measure the weight produced by the load. In this case, most weighing cells use the strain gauge method to convert the pressure to an electrical signal. These weighing cells are fitted with four strain gauges plugged into a wheat stone bridge formation. The list of materials is given in Table II.

TABLE II
MATERIAL FOR SMART WEIGHT SCALE

No	Component Name	Description	Quantity
1	ESP32	Microcontroller	1
2	LCD display	LCD Display	2
3	Load Cell	100 Kg	4
4	H7X11	24 Bit Module	2
5	Lithium Battery	Battery	4
6	Push Button	Tact Switch	2
7	Connecting Wires	Jumper	15
8	Breadboard	Project Board	2

The device displays the measured weight on the LCD monitor and sends the data to the server. The measurement cell is a type of transducer, such as a power transducer. It converts a resistance, such as voltage, compression, pressure, or torque, into an electrical signal, which can be measured and standardized. When the force exerted on the cell of measurement increases, the electric signal changes proportionately. Load transducers are used to measure weight. The measuring cells are generally comprised of a spring element. Upon which strain gauges have been placed. The spring element is generally steel or aluminum. As the spring element name suggests, the steel is slightly deformed under a load but then returns to its initial position, reacting elastically with each load. These minor modifications can be achieved with strain gauges. Finally, the strain gauge's strain is interpreted by analytical electronics for weight determination.

III. Result and Discussion

To assess the basic concept of the proposed method, the IoT-based BLE as a wearable device was tested with a label ID. First, an experiment with the prototype was conducted to receive data from the wearable devices using BLE as wearable devices. The data were sent via the MQTT protocol and then sent to the website application.

A. Duration Test Result

The test compares measurements using manual digital and smart weight measurements. After manually weighing the sheep, the weights are added to the Excel file. Smart Weight Measurement is automatically data recorded and sent to the website application. Table III shows the comparison of manual and smart weight tests. The duration test for two sample IDs (ID1 and ID2), that test repeated 30 times and recorded the data. Figure 8 shows that the manual measurement has different data measurement between both sample's ID. There is additional time to record it and collect it manually by a farmer. Figure 9 shows that the smart measurement has the same data measurement between both samples' IDs. The Smart Measurement will send the data automatically to the website application.

TABLE III
DURATION FOR A WEIGHT TEST

Manual Weight Test			Smart Weight Test		
Test	Sample		Test	Sample	
	ID1	ID2		ID1	ID2
1	174 s	174 s	1	13 s	14 s
2	173 s	171 s	2	13 s	14 s
3	174 s	172 s	3	13 s	12 s
4	179 s	181 s	4	12 s	14 s
5	174 s	174 s	5	12 s	14 s
6	174 s	173 s	6	12 s	12 s
7	171 s	173 s	7	13 s	13 s
8	173 s	179 s	8	12 s	12 s
9	171 s	172 s	9	14 s	14 s
10	179 s	171 s	10	12 s	13 s
11	174 s	171 s	11	12 s	12 s
12	174 s	182 s	12	12 s	12 s
13	174 s	174 s	13	13 s	12 s
14	174 s	171 s	14	12 s	14 s
15	181 s	171 s	15	13 s	12 s
16	171 s	173 s	16	13 s	13 s
17	174 s	173 s	17	13 s	12 s
18	174 s	174 s	18	14 s	13 s
19	176 s	179 s	19	12 s	14 s
20	172 s	174 s	20	14 s	13 s
21	177 s	174 s	21	13 s	14 s
22	173 s	171 s	22	12 s	14 s
23	174 s	181 s	23	14 s	12 s
24	174 s	174 s	24	13 s	14 s
25	172 s	172 s	25	12 s	14 s
26	179 s	171 s	26	13 s	13 s
27	173 s	173 s	27	14 s	13 s
28	174 s	178 s	28	14 s	14 s
29	181 s	172 s	29	12 s	12 s
30	173 s	172 s	30	13 s	14 s

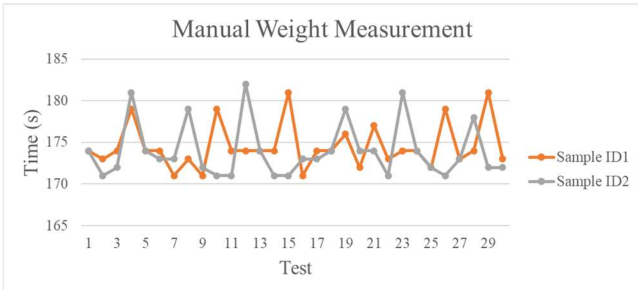

Fig. 8 Manual weight measurement test

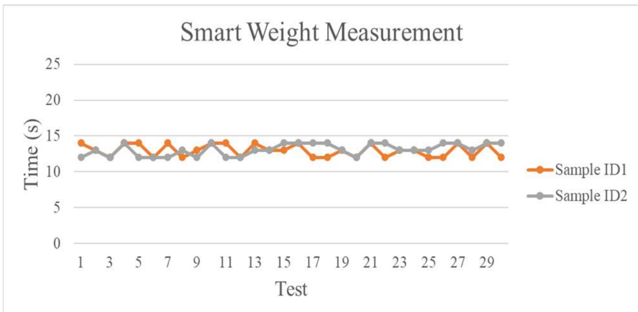

Fig. 9 Smart weight measurement test

B. RSSI Level Test Result

The smart weight scale identifies the Bluetooth ID using the RSSI level power on ESP32. ESP32 Bluetooth has eight transmit power levels, corresponding to -12 to 9 dBm of transmit power.

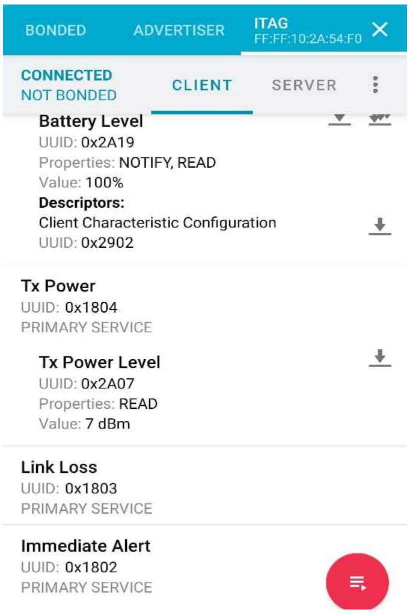

Fig. 10 Wearable devices transmit power information

Figure 10 shows the BLE's transmission strength as a wearable device is 7 dBm. In a wireless sensor network, the wearable device is a radio device that uses BLE, and signal strength and quality are measured in dBm. These data are detected on the smart weight scale. The RSSI level value is supposedly a negative dBm. The values near 0 dBm are categorized as strong signals. ESP32 typically does not recognize signal force lower than -95 dBm. Table IV shows the calculation of the RSSI level power for a dBm value.

TABLE IV
DURATION FOR WEIGHT TEST

No	RSSI Level	Distance	Success Rate
1	-23.6270	0.046 m	100%
2	-38.7536	0.098 m	100%
3	-53.4166	0.204 m	100%
4	-59.8924	0.282 m	0%
5	-66.3764	0.431 m	0%
6	-73.6129	0.560 m	0%
7	-78.2465	0.706 m	0%
8	-86.3369	1.058 m	0%
9	-91.4763	1.368 m	0%
10	-95.2127	1.649 m	0%

Here, the Friis transmission formula used to calculate the RSSI level versus distance is [28]:

$$P_r^{[dBm]} = P_t^{[dBm]} - 20 \times \log\left(\frac{4 \times \pi \times d}{\lambda}\right) \quad (1)$$

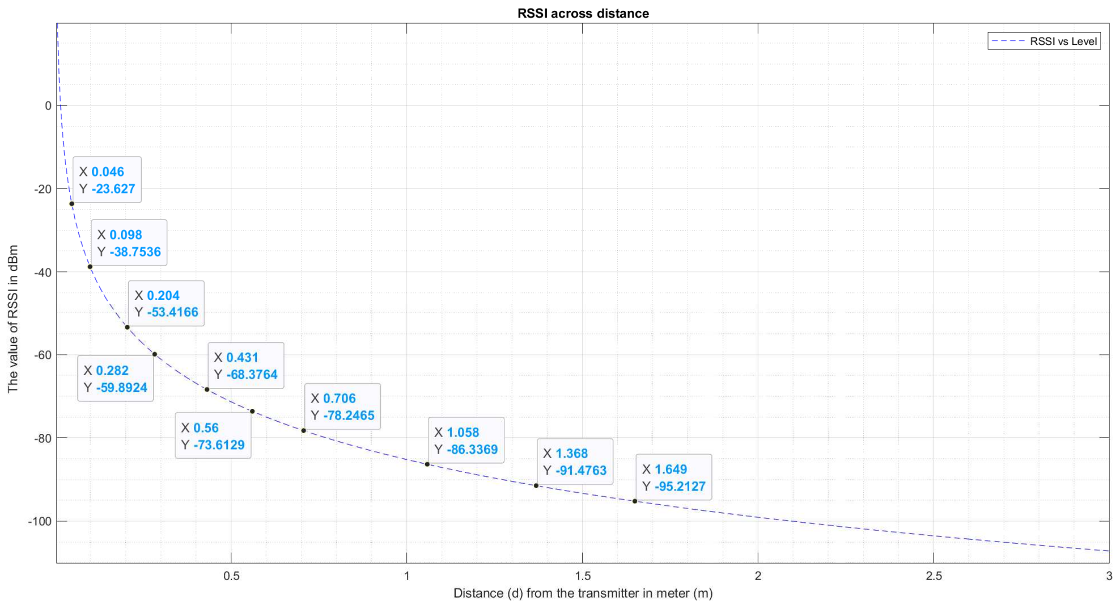

Fig. 11 RSSI level power versus distance by plotting various points

The plotted RSSI level identifies the maximum distance to reach the smart weight scale where the wearable device that ranges as far as 1.649 meters has the RSSI level power value of -95.2127 dBm, as shown in Fig. 11. The Smart weight scale measures and send the data when the RSSI level more than -53.4166 dBm with wearable devices. The distance between smart weight scale and the tag ID is about 0.2 meters or 20 cm. RSSI level threshold is more than -55dBm to filter noises from other BLE devices and select the nearest BLE device for identification.

C. Delay Test Result

This test is conducted to measure the delay of the system network. This test is to observe the effect of distance of transmission time. The scenario for placing the BLE device on the sheep and the ESP32 on the smart weight measurement system is by what is with what is shown in Table 5. Each distance scenario sent data with the distance being 0.046, 0.098, 0.204, 0.282, 0.431, 0.560, 0.706, 1.058, 1.368, and 1.649 meters. The average delay up to 0.204 meters has the data request time out (RTO) due to RSSI level threshold setting. The test result is shown in Table V.

The average delay is about 2 seconds due to the distance too close between BLE devices. The discovery latency has been derived as the performance measures of the neighbor discovery process similar to the actual study reported in [29] and the technical specification of the ESP32 analysis[30]. Based on delay, the network quality is suitable for real-time system requirements referring to ITU-T standard [31]. Meanwhile, for distances of more than 0.204 m, the system does not send and receive the data.

TABLE V
DELAY TEST RESULTS

No	Distance (m)	Average delay (ms)
1	0.046 m	9.498
2	0.098 m	9.508
3	0.204 m	37.912
4	0.282 m	RTO
5	0.431 m	RTO
6	0.560 m	RTO
7	0.706 m	RTO
8	1.058 m	RTO
9	1.368 m	RTO
10	1.649 m	RTO

D. Accuracy Weight Test Result

This test is to confirm the accuracy of the smart weight measurement working properly. When a sheep with a wearable device moves to the smart weighing area, the display shows the sheep's weight, which is about 34.76 kg based on Figure 12.

Fig. 12 Result ID 1 with the smart weight scale


Fig. 13 Result ID 1 with the weight scale standard

The sheep move to the standard weight scale for the weight value. The sheep with the ID1 measure on the standard weight scale weighed about 34.70kg, as shown in Figure 13. The weight accuracy between the smart weight scale and the standard weight scale was 99.82%. Another sheep with a wearable device moves to the smart weighing area. The display shows the sheep's weight to be about 72.99kg, as shown in Figure 14. The sheep then moves to the standard weight scale for the weight value. The sheep with ID2 measured on the standard weight scale weighed about 73.60kg, as shown in Figure 15. The weight accuracy between the smart weight scale and the standard weight scale was 99.17%.

Fig. 14 Result ID 2 with the smart weight scale


Fig. 15 Result ID 2 with the weight scale standard

The data is visualized as graphical time and weight, as shown in Figure 16, which is then delivered to the server, where analysis and synchronization with wearable devices are performed so that the data have the same location data as the smart weight scale. This study focused on the real-time monitoring of livestock using a website application. There are sheep classifications based on the weight data, including temperature, movement, and visualization. Livestock Live Monitoring is designed and developed to optimize and reduce onsite resources, enable sheep tracking, and obtain real-time weight data to monitor livestock. This wearable device and livestock live monitoring has a high cost per sheep. In addition, issues occurred when sending data from the local server to the end customer because the system still uses an ISP with a low bandwidth due to the 5G network not being available. Figure 16 shows the data representation as weekly and monthly with graphics of time and weight. The data is easily accessed and used by buyers or investors to review. The data indicate sheep growth per day, which impacts sheep weight.

Fig. 16 Dashboard Website Application

Figure 17 shows the data representation as the data indicate significant changes week by week. Livestock Live Monitoring has a good integrated system with a local server to send data to the website application. It should be integrated with an IoT system on a 5G network to improve data transfer.

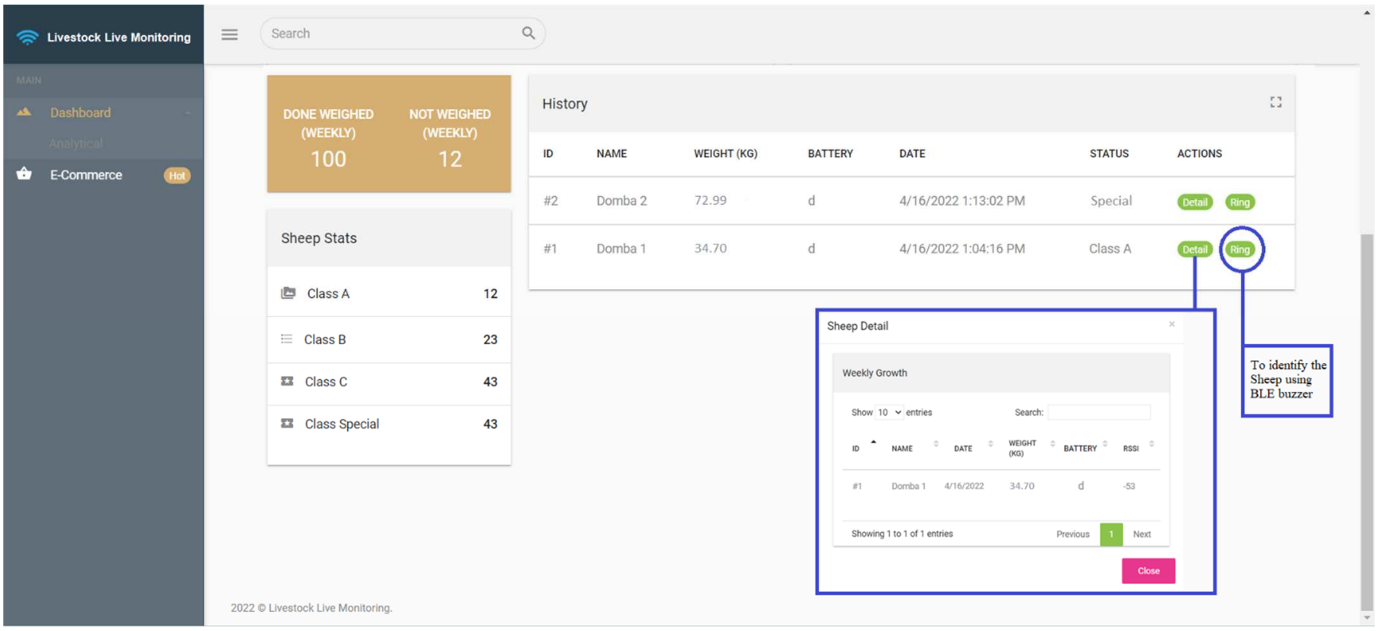

Fig. 17 Weight measurement

Compared to the previous studies which consider RFID as an identification tag in smart farming, a different approach approached is considered in this research. This research considers Bluetooth Low Energy as a solution to deliver sensor data from wearable devices and trigger smart weight measurement. Between the two approaches, the previous study has an issue with delivering sensor data from the wearable device because using the RFID-based system can only deliver information regarding animal identification [13]. Whereas the method proposed by this research is integrated with a smart weight scale so not only information on animal identification can be gathered, but also the weight of each animal.

The accuracy of this research can be compared to another previous research. Other research uses mathematical calculation and digital imaging to measure animal weight and achieve accuracy of 73.826 %, 87.15 %, and 95 %, respectively [11], [12], [18]. Based on the results presented in this paper, the proposed method achieves an accuracy of up to 99.82 %, which is better than another previous research.

The main objective of this research is to propose a system combining other technologies such as BLE as a wearable sensor for animal identification and Smart Weight Measurement to deliver weight and health data to the cloud system. In the end, all the data gathered will be processed and displayed to the user via the website application. Compared to other research, the proposed system has more functionality and better accuracy to be used for livestock monitoring.

IV. Conclusion

Technology and IoT are crucial to many new applications. New IoT devices can be developed with the right technological choice and a proper design. This paper proposes a system consisting of wearable devices integrated with BLE technology and Smart Weight Scale for farm applications. This system can measure and identify livestock in real-time with data visualization that can be accessed in the website application. BLE technology is important due to its long lifetime and cost efficiency. The area chosen for the experiment is a good possibility for the use of BLE due to the proximity of the livestock area being close to the installed smart weight scale. BLE is the best choice to achieve the power and cost efficiency research objective due to its low power consumption and low cost. It is more efficient than the traditional way, which requires resources to monitor the sheep individually and record data manually. The advancement of IoT makes it possible for devices to communicate with each other and to provide data in real-time.

Based on the experimental results, the accuracy of the weight data measured was 99.82% for ID1 and 99.17% for ID2 of the devices. The website application can classify the sheep class based on the data, and the owner or investor can monitor livestock data in real-time. Based on one month of research and experiments, the average daily growth of a sheep was about 150-200 grams, and the average monthly growth of a sheep was about 5 to 7 kilograms, which is the expected growth for a sheep to attain a class A classification, the classification over three to five months. The website application is also able to provide data in real-time. This proposed system design provides many benefits, including the real-time monitoring of livestock and an efficient feeding system for sheep using weight data.

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