DEVELOPMENT OF A CLOUD-BASED IOT SYSTEM FOR LIVESTOCK HEALTH MONITORING USING AWS AND PYTHON

by

Harini Shree Bhaskaran

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Dalhousie University is located in
Mi'kma'ki, the ancestral and unceded
territory of the Mi'kmaq.
We are all Treaty people.

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Abstract

This study develops a cloud based IoT system for monitoring the health of livestock using Amazon Web Services and Python, addressing the increasing demands of digital agriculture. As the number of IoT devices in agriculture proliferates, issues of scalability and computational load have become prominent, necessitating efficient and scalable solutions. This research introduces a cloud-based architecture aimed at enhancing Livestock Health Management.. This system is designed to track critical health indicators such as movement patterns, body temperature, and heart rate, utilizing AWS for robust data handling and Python for data processing and real-time analytics. The proposed system incorporates Nb-IoT technology, which is optimized for low-bandwidth, long-range communication, making it suitable for rural and remote farming locations. The architecture's scalability allows for effective management of varying numbers of IoT devices, which is essential for adapting to changing herd sizes and farm scales. Preliminary experiments conducted to assess the system's performance have demonstrated its durability and effectiveness, indicating a successful integration of AWS IoT Cloud services with the deployed IoT devices. Furthermore, the study explores the implementation of predictive analytics to facilitate proactive health management in livestock. By predicting potential health issues before they become apparent, the system can offer significant improvements in animal welfare and farm efficiency. The integration of cloud computing and IoT not only meets the growing technological needs of modern agriculture but also sets a new benchmark in the development of sustainable farming practices. The findings from this research could have broad implications for the future of livestock management, potentially leading to widespread adoption of technology-driven health monitoring systems in agriculture. This would help in optimizing the health management of livestock globally, thereby enhancing productivity and sustainability in the agricultural sector.

Keywords: Cloud Computing; IoT; Livestock Health Management; Predictive Analytics; AWS.

List of Abbreviations Used

AI	Artificial Intelligence
API	Application Programming Interface
ASF	African Swine Fever
AutoML	Automated Machine Learning)
AWS	Amazon Web Services
BLE	Bluetooth Low Energy
CNN	Convolutional Neural Network
CO2	Carbon Dioxide
CPU	Central Processing Unit
DB	Data Base

EC2	Elastic Compute Cloud
ELB	Elastic Load Balancer
Env	Environment
FIS	Fault Injection Service
GDP	Gross Domestic Product
GPS	Global Positioning System
GPU	Graphical Processing Unit
GSM	Global System for Mobile Communications
HR	Heart Rate
IAM	Identity and Access Management
ICT	Information and Communication Technologies

iOS	iPhone operating system
IoT	Internet of Things
JSON	JavaScript Object Notation
kHz	Kilo Hertz
KMS	Key Management Service
LCD	Liquid-Crystal Display
LHM	Livestock Health Monitoring
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
LPWAN	Low Power Wide Area Networks
MB	Mega Byte

ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
NAS	Network Attached Storage
NB-IoT	Narrow Band Internet of Things
NodeMCU	Node microcontroller Unit
NoSQL	Not only SQL or Non-SQL
NVMe	Non-Volatile Memory express
OTA	Over The Air
PLF	Precision Livestock Farming
RCNN	Region-based Convolutional Neural Network
RDS	Relational Data Base

RFID	Radio Frequency Identification
RMSE	Root Mean Square Error
S3	Simple Storage Service
SAN	Storage Area Network
SDK	Software Development Kit
SMS	Short Message Service
SNS	Simple Notification Service
SSDs	Solid State Drives
SSL	Secure Sockets Layer
SVM	Support Vector Machine
TCP	Transport Control Protocol

TLS	Transport Layer Security
VPC	Virtual Private Network
WAF	Web Application Firewall
Wi-Fi	Wireless Fidelity
WSN	Wireless Sensor Network

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Chapter 1 Introduction

The Canadian agricultural sector, particularly in Nova Scotia, is significantly driven by animal husbandry, which not only supports the livelihoods of farm families and sustains rural communities but also enriches cultural diversity and promotes social cohesion. This sector is a cornerstone of the provincial economy, evidenced by the steady growth in GDP contributions from agriculture, forestry, fishing, hunting, and related industries over the past decade. Notably, aquaculture and animal production have seen increases of 17.9% and 3.2%, respectively, underpinning their importance to the economic landscape of Nova Scotia (Aquaculture Statistics - Government of Nova Scotia, Canada, 2023).

The LHM systems are crucial in this context, where sustainability, agility, and precision are paramount. As of 2023, the dairy sector alone in Nova Scotia generated $33.5 million, underscoring the necessity for advanced technological solutions to optimize productivity and profitability (Aquaculture Production Quantities and Value, 2024).

Historically, LHM has relied on intermittent manual observations, which often result in delayed responses to health issues and inefficient farm management. The advent of integrated modern technologies, including IoT and cloud computing, offers transformative potential for real-time, proactive animal health monitoring. This shift not only promises to enhance animal welfare but also to improve the operational efficiency of farms (Mana et al., 2024), (Kumar Mohanty et al., 2024).

This research is positioned to further these advancements by proposing a scalable Cloud-based IoT architecture aimed at refining the precision and efficiency of real-time LHM. Incorporating technologies such as Narrowband IoT (Nb-IoT) enhances connectivity, extends battery life, and ensures robust data transmission even in remote settings, which is crucial for extensive farming operations (Dangana et al., 2021).

1.1Technological Innovations in Livestock Health Monitoring

Traditional methods for LHM are labor-intensive and often inefficient. For example, behavioral observations critical for managing reproductive health can consume up to 30% of labor resources on commercial farms (Handa & Peschel, 2022), (Racewicz et al., 2021). These methods underscore significant inefficiencies in resource allocation and highlight the critical need for automated and precise monitoring systems that can significantly reduce labor costs and improve health detection rates (Mancuso et al., 2023).

PLF tools represent a leap forward in managing animal health. These systems utilize advanced sensors and data analytics to provide real-time insights into animal behavior and health. PLF tools help overcome the limitations of human observation, facilitating early detection of health issues and more efficient herd management (Odintsov Vaintrub et al., 2021). Various PLF tools and the corresponding findings to support early detection of diseases in swine is outlined in Table 1.

Table 1 PLF Tools and early disease detection in swine.

Journal	Technology	Findings
(Kashiha et al., 2014)	Camera (2D and 3D) to capture behavior and physiology	Image analysis translates the acquired images into indices of distribution (animal location and proximity) and activity (animal position and movement).
(Kongsro, 2014), (K. Kollis et al., 2007), (Tscharke & Banhazi, 2013)	Camera (2D and 3D) to capture behavior and physiology	Images have also been used to estimate the weight of swine.
(J. Lee et al., 2016), (Lao et al., 2016)	Camera (2D and 3D) to capture behavior and physiology	Recording aggressive behaviour, walking patterns, sow posture and behavior patterns during lactation period.
(Manteuffel et al., 2017)	Microphones to analyse sounds	Indicate stress or illness
(Silva et al., 2008)	Microphones to analyse sounds	Respiratory diseases.

(Sellier et al., 2014)	Infrared Image and Thermistor (Temperature)	Measures accurate body temperature.
(Foerschner et al., 2018)	RFID	Monitor pig feeding and drinking behaviour

As the global population is projected to reach 9.7 billion by 2050, the demand for animal products is expected to surge, necessitating a 70% increase in global food production, with meat demand alone expected to rise by over 50% (Beryl Odonkor et al., 2024). The livestock industry's expansion has been rapid, fueled by globalization and increasing consumer demands across diverse markets. However, this growth brings challenges concerning sustainability, environmental impacts, and animal welfare, making it imperative to balance increasing meat production with responsible farming practices to ensure long-term industry viability (Aquilani et al., 2022), (Daszkiewicz, 2022), (Tripathi et al., 2018), (Ominski et al., 2021).

1.2 Internet of Things and Sensor Technologies in Livestock Health Management

The IoT framework for LHM integrates various components essential for effective health monitoring. Sensors like accelerometers and temperature sensors are deployed extensively to monitor vital physiological parameters such as heart rates and body temperatures, which are indicative of the animals' general health (Tan et al., 2021a). These sensors provide a continuous stream of data, which is crucial for timely interventions. Moreover, communication technologies such as ZigBee, RFID, Bluetooth, and Wi-Fi play pivotal roles in the efficient transmission of this data (Pozo et al., 2021).

Despite the advancements, certain limitations persist with technologies like ZigBee, which currently supports monitoring only one animal at a time. In contrast, integrating LoRaWAN and NB-IoT has shown promise in enhancing data transmission efficiency, demonstrating low operational costs and extended communication ranges, even in complex environments. The amalgamation of NB-IoT and lora technologies is particularly advantageous, offering extended transmission distances and reduced operational costs. These features are essential for large-scale farm applications, where traditional cellular communications may prove less energy-efficient and more costly (Rojas-Downing et al., 2017), (Al-Samman et al., 2022).

Additionally, incorporating cloud services in LHM provides enhanced data management, real-time analysis, scalability, and improved decision-making. Continuous collection and analysis of health data from IoT sensor can detect health issues early, enabling timely interventions. Immediate alerts about abnormal conditions such as changes in body temperature, heart rate, or activity levels are sent to farmers and veterinarians to respond quickly to potential health problems. Moreover, cloud platforms provide scalable framework that can handle huge volumes of data from numerous devices. Hence data from a large farm can swiftly scale their data storage and processing capabilities up or down depending on the requirement without significant investment in physical hardware.

1.3 Gaps in the Current Knowledge Landscape

The adoption of advanced technologies in LHM on small-scale farms faces specific challenges. Research focusing on these barriers and developing tailored solutions is crucial for wider technology adoption (Kleen & Guatteo, 2023). While the immediate benefits of technology adoption in LHM are evident, there is a notable gap in literature concerning the long-term impacts on livestock health, farm sustainability, and economic viability. Longitudinal studies are required to provide deeper insights into these aspects (Bonato, 2010). The ethical implications of deploying advanced technologies in livestock monitoring remain under-explored. Issues such as data privacy, animal welfare, and societal impacts need comprehensive examination to ensure responsible technology implementation (Nasirahmadi et al., 2015). The existing literature often focuses on specific regions or countries, lacking a global perspective that accounts for varied agricultural practices, socio-economic factors, and environmental conditions. Developing universally applicable LHM strategies requires a broader understanding of these global dynamics (Fan & Li, 2018).

The overall objectives of the study are,

1) To develop a Cloud-based IoT architecture that enhances real-time monitoring and management of livestock health.

2) To create a collaborative web-based platform that serves as a nexus for interaction among farmers, researchers, and regulatory bodies, fostering a community of practice that enhances knowledge exchange and supports sector-wide improvements.

3) To utilize advanced data analytics, powered by Python, for robust data processing and interpretation, enabling precise health assessments and predictive analytics for proactive farm management.

1.4 Cloud-Based System in Animal Husbandry

The goal of smart animal farming is to harness the potential of cloud computing technology and internet to give a boom in the pasturage (Yang et al., 2020). Cloud technology offers a network of remote servers hosted on the internet for the purpose of storing, managing, and processing massive volumes of data to facilitate data-driven farming. This ability to store and manage huge volumes of data, cost effectiveness and remote accessibility makes it optimal solution for addressing the challenges faced by the agricultural sector . A Livestock monitoring system is a cutting-edge solution architected and developed using sensors, GPS, etc., and integrating all these with a network protocol for communication. This monitoring system enables farmers to remotely check their farms and take actions immediately.

1.4.1 Amazon Web Services for Cloud Deployment in Livestock Health Monitoring

Leveraging Amazon AWS for cloud deployment in LHM provides several critical advantages. AWS offers unparalleled scalability, allowing the system to handle data from numerous IoT devices without performance degradation, even as the number of devices increases (Goudarzi, Ilager, & Buyya, 2022). This flexibility is crucial for adapting to varying farm sizes and the dynamic nature of livestock operations. AWS ensures high availability and reliability, with services distributed across multiple geographic regions and availability zones. This redundancy minimizes the risk of downtime and data loss (Malhotra et al., 2023), ensuring continuous monitoring and prompt responses to any health issues in the livestock. S3 automatically replicates data across multiple servers and data centers, ensuring that data is available even if a server or data center fails. Enabling versioning in AWS S3 helps keep track of changes to objects over time that helps overcome accidental overwrites or corruption. S3 cross region replication allows to store backups in different geographic location.

Security is a paramount concern in any cloud deployment, and AWS provides robust security features, including encryption, access control, and continuous monitoring to safeguard sensitive data (Abdulsalam & Hedabou, 2021). Compliance with industry standards and regulations is also easier with AWS's comprehensive suite of compliance certifications. Cost efficiency is another significant benefit. AWS's pay-as-you-go pricing model, Al Moaiad et al., (2024) allows for cost-effective scaling, reducing the need for large upfront investments in physical infrastructure. This model ensures that resources are used efficiently, and costs align with actual usage, which is particularly beneficial for small and medium-sized farms.

Integration capabilities are a strong suit of AWS, facilitating seamless interaction between various services such as AWS IoT Core, DynamoDB, and Amazon Pinpoint. This integration enables the creation of a cohesive and efficient system that supports real-time data processing, storage, and communication. Moreover, AWS's extensive global infrastructure provides low-latency access and fast data processing, crucial for real-time health monitoring applications where timely interventions can significantly impact animal welfare.

1.5 Livestock Health Monitoring

LHM is of utmost importance when overall farm management is considered. It is essential to maintain proper check of the livestock since good health and well-being of livestock are mandatory for sustainable production of milk. It also paves way for farmers to have a check on the animal behaviour, identifying early signs of disease detection (Humboldt-Dachroeden & Mantovani, 2021). Timely intervention helps prevent the spread of diseases within the herd. This not only saves individual animals but also the whole livestock population. In addition to this, healthy breed can be utilized for breeding to get best traits acquired (Barrett et al., 2020). Another most important reason is that quality and safety of food to consumers (Sharif et al., 2024). Healthy livestock produce high-quality products which is highly essential for maintaining consumer demands. It avoids diseases spreading from animals to humans (Perry et al., 2018). Furthermore, by monitoring key health metrics farmers can optimize breeding programs, selecting healthier animals with desirable traits to improve the overall herd's genetics (Sellier et al., 2014). Besides, this health monitoring also helps understanding the movement pattern such as grazing, rumination and idling behaviors (Iqbal et al., 2023).

1.6 Narrow-Band Internet of Things

The research proposes Nb-IoT and LoRaWAN as part of the system's design for its ability to handle long range ow-bandwidth communication efficiently, and LoRaWAN for its cost-effectiveness and scalability in large-scale deployments. Nb-IoT is a wireless IoT that works on the principle of LPWAN technology, providing a greater volume of devices to share bandwidth than traditional cellular networks like 2G, 3G, and 4G. The unused frequencies within a carrier's licensed bands are utilized by these devices, thereby consuming less power than many other types of networks (IoT Communication Protocols with Measurements for NB-IoT - Expert Guide, 2024). Since the NB-IoT networks use narrower frequency band, it allows a larger volume of devices to occupy one of the network's "cells." This enhances coverage by repeating transmissions and increasing the receiver's ability to resolve messages (Narrowband – Internet of Things (NB-IoT) | Internet of Things, 2024). While the system follows a strategic approach, the proposal included simulations and theoretical analyses that explored how these technologies could enhance the system performance. The proposal outlined how Nb-IoT and LoRaWAN could be integrated and tested in future work, providing a framework for real-world application and be evaluated under real world conditions to validate the effectiveness.

Advantages of using Nb-IoT includes:

- Low power consumption: Nb-IoT is designed specifically for low-power applications, enabling devices to operate for extended periods on minimal battery power. This efficiency is crucial for IoT devices that need to function in remote or hard-to-reach areas without frequent maintenance. It reduces the need for frequent battery replacements, lowers operational costs, and supports long-term deployments in agricultural settings.

- Power Saving Mode (PSM): Power Saving Mode is a feature that allows Nb-IoT devices to enter a deep sleep state when not actively transmitting or receiving data. During PSM, the device consumes very little power, extending battery life significantly. This enhances the overall efficiency of the system by minimizing power consumption during idle periods, making it ideal for applications with infrequent data transmission.

- Extended Discontinuous Reception (eDRX): Extended Discontinuous Reception allows Nb-IoT devices to stay in a low-power mode while periodically waking up to check for incoming data. This extended sleep period between check-ins helps conserve energy. It reduces power consumption further by increasing the time between device wakeups, which is beneficial for devices that do not require constant data communication.

- Efficient Spectrum Use: Nb-IoT operates in licensed spectrum bands, which ensures more reliable and interference-free communication compared to unlicensed bands. It uses a narrow bandwidth (e.g., 180 kHz) to transmit data, optimizing spectrum efficiency. This minimizes interference and maximizes the use of available spectrum, resulting in more reliable and consistent data transmission.

- Ubiquitous Coverage and Connectivity: Nb-IoT is designed to provide coverage in challenging environments, including rural and remote areas, by leveraging existing cellular networks. Its signal can penetrate deep into buildings and underground structures. It ensures reliable connectivity even in areas with poor network coverage, making it suitable for agricultural applications where connectivity may be a challenge.

- Low Cost: The cost of deploying and maintaining Nb-IoT devices and infrastructure is relatively low compared to other communication technologies. This cost-effectiveness is partly due to the use of existing cellular networks and the low power requirements of the devices. Reduces the overall cost of deploying IoT solutions, making it accessible for large-scale and budget-sensitive applications in agriculture.

- Strong Signals: Nb-IoT provides strong and stable signal reception even in areas with weak cellular coverage. Its design allows for reliable communication over long distances and through obstacles. Improves the reliability of data transmission and reception, ensuring consistent performance in diverse and challenging environments.

- Good Battery Life: The combination of low power consumption, PSM, and eDRX contributes to extended battery life for Nb-IoT devices. Devices can operate for several years on a single battery charge in many cases. Reduces maintenance efforts and costs associated with battery replacement, particularly in remote or inaccessible locations.

Nb-IoT is more advantageous than the other wireless communication technologies in the context of livestock health monitoring. ZigBee and Bluetooth technologies are better for short-range, low-power applications (Huircán et al., 2010). In contrast LoRaWAN offers long-range and low-power benefits but with limited data rates and infrastructure needs. Hence, incorporating Nb-IoT in the system design shall be more suited providing a good balance of range, power efficiency, and cost, especially in rural and remote areas.

1.7 Agile Methodology

The proposed research follows the principles of Agile Methodology that has dynamic phases called sprints. In contrast to other models in software development, Agile method is flexible, efficient and follows an iterative approach thus ensuring requirement satisfaction (What Is Agile Methodology? (A Beginner's Guide), 2024). The various phases of Agile method are elaborated in the subsequent paragraphs.

1.7.1 Requirements

The primary step of any successful architecture lies in the ideation stage. This serves as a foundation to build the LHM system pertaining to the satisfy the following parameters (Davis & White, 2020a). The LHM model that is based on AWS Cloud architecture and IoT must be a very secure system as it stores and monitors private data. Hence this should prevent breaching data through unauthorised access. Any robust model must be handled easily and efficiently without much human interference (Nsabagwa et al., 2019). This architecture complies to this as troubleshooting takes place to isolate fault thereby not breaking the operation of the entire system. It should meet the changing demand by allocating or removing resources depending on the incoming traffic from the system. The model is flexible to changing herd size thereby not incurring more cost. The architecture must be able to run through its complete lifecycle. All the desired services and components must be available 24/7.

1.7.2 Planning

A crucial step in modelling this architecture, is the planning phase which involves deploying the technological stack for the application. The various features to be included in the LHM is outlined as follows:

Feature 1: A secure model that prevents unauthorised access.

Feature 2: Model that works seamlessly irrespective of resources being coupled or decoupled.

Feature 3: It must handle increase or decrease in traffic.

Feature 4: Must allow more than 500 IoT sensors to operate simultaneously.

Feature 5: The framework must be accessible in remote areas.

Feature 6: Identify any anomalies in the behaviour of animals.

Feature 7: Perform analytics and create visualizations from the collected data.

Feature 8: SMS notification to farmers and concerned authorities, vet.

Feature 9: Record and store the event.

Feature 10: Distributed storage.

1.7.3 Designing

Any cloud-based model must comply to the five pillars of well-architected framework to have satisfied the requirements of the proposed work. This involves the framework to perform the necessary actions as coded and must be flexible to changes. The system must anticipate failures, learn, and recover from it (Manvi & Krishna Shyam, 2014). The proposed model must have a strong secure system to protect the data when in transit or at rest. It should also anticipate any security events to ensure that the proposed work functions effectively and efficiently as expected. Correct usage of resources. It must be cost-efficient and avoid unnecessary expenditure.

1.7.4 Developing

The technology stack is determined based on the features that are necessary to build the LHM. This includes a variety of AWS Services, software tools and technologies which are deployed during the development phase. The overall performance of a model depends on the efficiency of the components selected and their effective utilization. Hence choosing the right technology infrastructure is of utmost importance to achieve desired results. Various AWS Services, software tools and technology used in developing this model are outlined as follows:

i. Infrastructure: To satisfy the requirements mentioned as step 1, the proposed model is built on AWS Cloud infrastructure as it provides secured access management, cost effective and flexible resource allocation. In addition, it also offers a well-developed edge computed service that allows resources it to coupled or decoupled alongside the other required IoT services.

ii. Programming Language: Python is a high-level programming language that offers high readability, supports multiple programming paradigm with a vast number of libraries . It is essential in this framework as it has an excellent SDK for developing cloud-based services (The Role of Python in Cloud Computing: Scaling Applications and Services | MoldStud, 2024). This is used for the development of software deployed in IoT devices, and AWS Lambda functions, which are used as data processing triggers for AWS data pipelines.

iii. AWS Services: The smart LHM architecture built in AWS combines the various AWS serverless services that performs individual and independent task.

1.7.5 Testing

Data load testing ensures the system's readiness to handle large data volumes continuously while maintaining acceptable levels of average latency and error counts. Data integrity testing verifies that data is correctly populated across all locations and that insertion events occur in the proper sequence. Functional testing guarantees proper data acceptance, processing, and retrieval under high loads. Stress testing evaluates the system's durability, scalability, and performance. Security and access control testing ensures that only authorized users can access the ingested data. In terms of evaluating results, test completion and success criteria are assessed by analyzing test logs and various performance metric charts.

1.7.6 Deploying

During deployment, the architecture utilizes Terraform for provisioning resources in the AWS infrastructure. Hashicorp Terraform is employed to create, modify, and provision these resources using JSON configuration files. Commands are then executed to adjust the infrastructure according to requirements, with Terraform's robust capabilities available to restore infrastructure state if necessary.

Chapter 2 Literature Review

2.1Introduction

Livestock products comprise the world's agricultural production that include foods derived from animals, non-food items (like hides), production inputs (like fertilizer for crops), and other non-market uses (like culture). Amidst, the United States and Canada are regarded as major agricultural powers, with Canada producing the seventh most pork (Kappes et al., 2023).

Conventional methods employed for monitoring livestock health, particularly in discerning animal behavior, have been noted for their prolonged nature (Geers, 1997) elucidated in their research that the identification of mounting behavior alone engrosses a substantial proportion, amounting to roughly 30% of the labor invested in commercial farming enterprises. This revelation accentuates the considerable temporal investment demanded by a singular facet of behavior recognition within livestock husbandry systems. Additionally, (Cheon et al., 2023) underscored that the ongoing surveillance of mounting behavior contributes significantly, up to 20%, to instances where estrus, a pivotal indicator of reproductive well-being evades detection. This signals a discernible deficiency in conventional monitoring methodologies, potentially resulting in missed opportunities for timely intervention and management.

Furthermore, the challenge transcends individual behaviors to encompass broader herd management practices. As elucidated by (Anzai & Hirata, 2021) another study the laborious task of monitoring individual cattle within expansive herds for critical activities such as estrus identification poses a substantial operational impediment. These revelations collectively underscore the inefficiencies inherent in traditional LHM techniques, underscoring the urgent imperative for more streamlined and automated solutions to mitigate labor burdens and enhance the precision of behavioral discernment in livestock stewardship.

Digital technologies are reshaping various industries, including agriculture, by harnessing technology to streamline processes and increase productivity. This transformation will help swine farms manage resources and operations more effectively. In 2050, there is a projected 63% increase in worldwide demand for meat and 30% increase in demand for dairy products due to population growth and economic development.

The rising demand for quality pig products worldwide shows that the swine industry is crucial to food security and nutrition (Tummaruk et al., 2023). Swine reproductive management affects farm sustainability, herd productivity, and breeding efficiency. Pig farmers still struggle to maximize reproductive success and resource use. Conventional methods often rely on experience and intuition, which can lead to poor choices and breeding inefficiencies (Stødkilde et al., 2023). Pork farms and industry owners struggle to monitor farm operations and swine herd health and behavior.

The worldwide pork market is rising to meet animal protein demand, leading to larger swine farms. Swine production is changing the climate and affecting the environment, animal welfare, and human health, including zoonosis and antibiotic resistance. Swine farms' success depends on pigs optimal growth and health, which modern farming practices can provide (Davis & White, 2020). Consequently, the swine health issues go undetected until the severity increase causing causalities and high-cost treatment. This statistical trend necessitates the paradigm shift from traditional agricultural methodologies to modern agricultural models.

2.2 Digital Livestock Farming

It is predicted that the global population will reach 9.7 billion by 2050 (United Nations, High-Level Summits and Conferences 2022, n.d.) and hence the demand for animal products will increase. This projection that global food demand will surge by 70% by 2050, with meat demand expected to rise by over 50%, underscores the significant challenges facing the agricultural sector in the coming decades (Mc Carthy et al., 2018), (Fletcher et al., 2024).

The burgeoning demand for meat and associated products has propelled the global livestock industry into rapid expansion. This surge stems from globalization that has enabled the industry to tap into new markets and meet diverse consumer demands. However, amidst this growth, concerns loom over sustainability, environmental impact, and animal welfare. Balancing the imperative to meet escalating meat demand with the need for responsible practices is crucial for ensuring the long-term viability of the livestock industry and global food security (Tan et al., 2021).

This also induces negative impact on the environment and biodiversity (Wang, et al., 2021) (Bahar et al., 2020) (Houghton et al., 2017) that includes the loss and degradation of forests globally and some troubles. Thus, it implies that, in addition to produce more animal products, this livestock sector must also incorporate more efficient and sustainable production programs.

In traditional livestock farming, decisions are frequently made solely based on the producer's experience. This approach relies heavily on the accumulated knowledge and intuition of the farmer, honed over years of hands-on involvement in the industry. While this experiential wisdom can be valuable in navigating various aspects of livestock management, such as breeding, feeding, and health care, it also presents limitations. Without incorporating data-driven insights or adopting modern technologies, traditional methods may lack precision and efficiency. This synergy between traditional knowledge and modern advancements holds promise for ensuring the resilience and competitiveness of the livestock farming sector in the face of evolving challenges and opportunities.

The integration of digitalization in LHM has marked the onset of new era of efficient and smart animal farming in multiple aspects ranging from the general well-being to advanced applications (Fuentes et al., 2022). The farmers and veterinarians is benefitted from this better farming yield because of this improved animal health. The predictive analytical models embedded with machine learning (giving sense to machines) has helped better decision-making and has enabled farmers to derive most out of their farms (Melak et al., 2024).

Management of individual livestock through automated, continuous, and real-time monitoring of the health, welfare, production/reproduction, and environment impact using sensor technologies, related algorithms and interfaces is defined as PLF. In this aspect, different technologies are deployed to monitor the livestock which can be broadly categorised as wearables Bonato (2010) and non-wearables Yin et al., (2023). Animal wearables are devices designed for direct attachment to animals, including collars and patches, enabling the monitoring of movement trajectory and health status (Neethirajan, 2020). These wearables collect data on various physiological parameters such as heart rate, breathing rate, skin temperature, and activity levels. By analyzing this data, researchers and veterinarians can gain insights into the animal's well-being, identify abnormal patterns indicative of health issues, and track changes over time. Animal wearables offer a non-invasive and real-time method for continuous health monitoring, facilitating early detection of problems and informed decision-making for animal care and management (Herlin et al., 2021).

2.3 Advent of Internet of Things and Sensors

The rapidly growing IoT, is revolutionizing many industries, including agriculture. Livestock farming stands to benefit greatly from the implementation of IoT technology. There is enormous increase in the numbers of techniques proposed to implement IoT based solutions in livestock farming. To enhance the quality and proliferation of farming and agricultural productivity, researchers have focused on sensor networks and artificial intelligent based farming methods. In a study conducted by Varun Mhatre to classify the health status of dairy cows, the IoT sensors are used to capture body temperature, heart rate, humidity, and rumination rate at regular intervals to predict the milk yield which serves as an important parameter for health status classification (Mhatre et al., 2020).

G. Lee et al., (2022) used IoT devices to monitor and count pigs in a pigsty. The pigs' ears were fitted with BLE tags. The BLE tag signals were detected by wireless broadband leaky coaxial cable antennae, which then sent them to the central controller where the primary controller sends data to the server. An experiment was carried out consisting of 60 pigs where the system is assisted in pig identification and tracked pig movement. The pig's details couldn't be accessed via a mobile or web interface which posed a limitation to the developed model. To avoid piglet death due to pig crushing, Chen et al., (2021)developed an IoT-based piglet screaming detection technique.

The farrowing houses in this system are equipped with a microphone, an IP camera, a temperature sensor, a floor vibration sensor, and a water drop. The IP camera records video and sends it to the server using an Ethernet cable. Before sending data to the server, the sensors collect and send environmental data, such as floor vibration. An Nvidia geofence 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. The piglet sounds were classified by the authors using a CNN model. The system detects piglet crushing early on and activates actuators. S. Lee et al., (2019) 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. Image processing and deep learning techniques (tinyyolo3) are used to identify pigs. The TinyYOLO3 is a simplified neural network architecture that is compact, efficient version of YOLOv3, designed for environments where speed and resource efficiency are critical. 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.

The geophone sensors are used by (Bonde et al., 2021) 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. Y. R. Chen et al., (2020) 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 & Kaiwman, (2022) 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 specific 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., (2017) 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. S. Lee et al., (2019) 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., (2022) 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. Dineva

& Atanasova, (2021) developed a scalable LHM system that uses AWS Greengrass, an edge computing resource combined with lora technology. Further, the study by Dutta et al., (2022)focuses on development and deployment of “MOOnitor”, a neck mounted intelligent IoT device for cattle monitoring. It uses temperature sensor, GPS, accelerometer, and GSM module facilitating classification of salient activities of cattle.

Information and communication technology (ICT)-based smart swine farming, considering auto-identification, remote monitoring, feeding behavior, animal rights/welfare, zoonotic diseases, nutrition and food quality, labor management, farm operations, etc., with a view to improving meat production from the swine industry (Mahfuz et al., 2022).

In research conducted by (Unold et al., 2020)automated dairy cow health evaluation system was developed based on IoT to measure rumination, feeding, sleeping and movement of the dairy cows. This involves sensors including rumination sensor, accelerometer, and Wi-Fi. Further IoT application in cow health monitoring, milk processing, and secured transportation was efficiently carried out using the BLE and ZigBee technology by (Alonso et al., 2020).

It can be summarized that the broader hierarchy comprises of three fundamental components. Primarily, that involves the use of IoT to monitor, control and track the health status of the livestock. Under distinct conditions, different sensors including accelerometer sensors, temperature sensors have been installed in the animal to record the heart rate, temperature, and other health-related factors. Conclusively, communication protocols such as ZigBee, RFID, Bluetooth, and Wi-Fi are used for data transmission.

The studies indicate that the functionalities of the Zigbee module is restricted and allows the monitoring of only one livestock at a time. Several studies revealed that the combination of LoRaWAN and NBIoT improves low-cost data transmission. For instance, Zhang et al., (2019), performed a systematic approach to incorporate this technique to Information Monitoring System where, “the communication distance in a complex environment is up to 1.6 km, the minimum working current is 2 ma, and the system communication packet loss rate is approximately 3%”. In a further review, Tang et al., (2019) and colleagues investigated a case study involving a fault indicator in Electricity Distribution Network, used the same methodology and found consistent evidence of reduced operation cost.

Previous studies have shown that ZigBee and Bluetooth are short-range radio technologies and are not suitable for long-range transmission scenarios. 2G, 3G, 4G, and other solutions based on cellular communication can provide a wider coverage, but they consume too much energy and increase the operating costs. The advantage of this approach is that the combination of NB-IoT and lora not only improves transmission distance but also reduces the operating costs of the WAN information monitoring system.

2.4 Cloud Computing in Animal Farming

Using this technology and combining it with the benefit of IoT, (Park & Park, 2020) developed livestock monitoring method that uses WSN and data being managed over Cloud. This helped management of grazing cows across different locations.

Cloud based cattle monitoring system using GPS and LoRaWAN technology to monitor cattle movement is designed by Joshitha (Joshitha, Kanakaraja, Bhavani, Raman, & Sravani, 2021). This concept was extended with the inclusion of drones for aerial monitoring of farm animals by (Behjati, et al., 2021). Dwyer et al., (2015), developed a web page for animal monitoring using IoT and Cloud for understanding the animal behaviour. A similar model to monitor the feed and deploy a scalable IoT platforms integrated with cloud; tested against a batch of pigs at their fattening stage was performed by (Mateo-Fornés et al., 2021).
Various others conducted research that assess the health, behaviour, stress, emotion, feed monitoring with the help of Cloud, IoT and WSN technologies (Dineva et al., 2021).

2.5 Data-driven decision making in Swine Industry

Data-driven decision making at pig farms means that decisions that are made will depend on predictions made using the information gathered at the farm and across the supply chain (Ahmed et al., 2021). To perform successful predictions and help in decision making, data analytics and ML techniques can be used. Recently, ML models are being used to predict various variables of interest to decision making, such as sales and feed performance (Javaid et al., 2022).

With the implementation of more sensors and data sources, more possibilities arise for using ML in information systems. Manufacturing companies are often focused on static explanatory models, but there are many opportunities in predictive modelling where ML can be used and improve the decision-making processes (Flath & Stein, 2018). For example, ML is used to predict limb conditions of pigs, using data collected at farm Liang et al., (2020) predicted ASF outbreaks, using ASF outbreak data and the WorldClim database provides high-resolution climate data, including variables like temperature, precipitation, and humidity. In this context, the meteorological data is used to identify environmental factors that could influence ASF outbreaks (Bakoev et al., 2020).

Chapter 3 Materials and Methods

3.1 Ethical Declaration

The empirical data supporting this study was generously provided by my distinguished colleagues at Wageningen University & Research and is linked to an independent, prior experiment. The study in question was authorized by the Central Committee on Animal Experiments (CCD) and the Animal Experiments Department (IVD) of the Netherlands, ensuring that the ethical standards and optimal procedures were followed. The Department of Animal Sciences of the Care of Animals Used for Scientific Purposes (CARUS) at Wageningen University & Research carefully reviewed and approved any additional, non-invasive treatment of animals for the current study. For this investigation, the appropriate approval number is 20210521ADP (Neethirajan, 2023).

3.2 Study Design and Animal Housing: A Methodological Approach

50 male piglets (Tempo × Topigs Norsvin TN70), weighing an average of 25 kg and born about nine weeks ago, participated in the long-term study. Rooms 14 and 15 of Wageningen University & Research's CARUS facility served as the home for these piglets. Six piglets, ranging in age from 86 to 108 days, were selected from this cohort to undergo a thorough examination of their behavioural and physiological adaptations. Acclimatization took place throughout the first week, giving the piglets time to become used to their new surroundings, food, and care routine. Measuring 2.86 by 1.16 meters, each pen was large enough to accommodate two piglets and was furnished with all the

necessities, including toys. Lights were kept on from 7:00 to 19:00, and the room temperature was adjusted to suit the demands of the piglets. A particular eating schedule was followed with water always available.

3.3 Data Collection

Data used in this study is collected from already mounted Zephyr bio harness belt application on a Topigs Norsvin TN70 piglet (Figure 1) in a swine farm. The design structure, layout, and equipment of the sensor installed on the pig can be found in (Figure 2 and 3) illustrate two components of a single system. This system automates the process of data collection and transmits these data to the system. The used approach represents a non-invasive method for data collection.

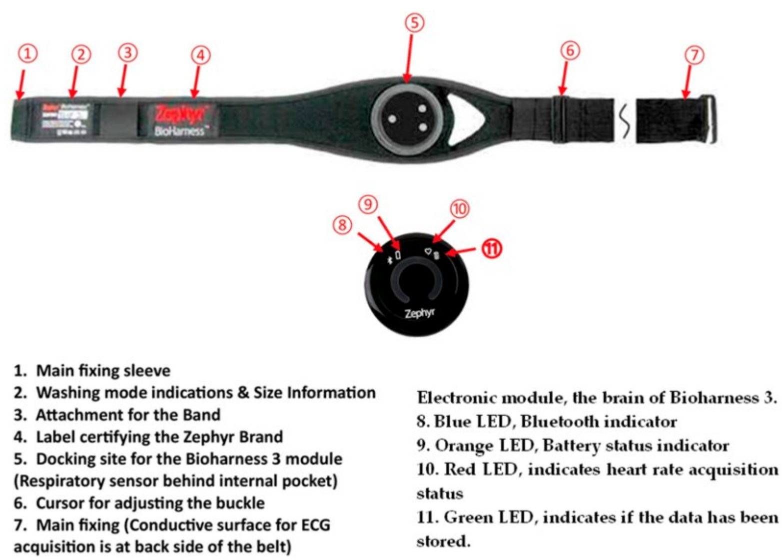

Figure 1 Photograph of the Zephyr bio harness multimodal sensor platform used for data collection from Topigs Norsvin TN70 piglets.

Figure 2 Overhead view portraying the Zephyr bio harness 3.0 strap's arrangement around the piglet's chest, reinforced with a Vetrap bandage.

Figure 3 Side perspective showcasing the piglet wearing the Zephyr bio harness.

3.4 Dataset

The sensor data collected are in a raw format, hence it is necessary to analyze and format the data into usable form for developing a custom ML model. The methods, process, and approaches to understand how the data from IoT devices is processed and modelled and integrate this trained ML model into production environment along with other AWS services. To ensure a robust and comprehensive analysis, the original dataset was augmented using Mockaroo, a tool that allows for the generation of realistic and structured data. The original dataset consists of data collected from sensors and other monitoring tools in a pig farming environment. Key parameters include temperature, humidity, HR etc.

The individual analysis of data load which were used to test the load capacity of the model is discussed in the subsequent paragraphs. Case 1 (data volume 86.3 MB), this dataset contains the initially collected sensor data from the farms. The low load scenario represents a cleaned, preprocessed data with minimal external stressors. The data points incudes time stamp, temperature, humidity, animal activity levels etc. The Case 2 includes sensor data under medium load (data volume 258 MB) conditions, simulating a scenario with moderate external stressors such as increased animal activity and fluctuating environmental conditions. Here, the preprocessing task includes aggregation of data to hourly intervals for trend analysis. The Case 3 dataset captures sensor data under high load conditions (data volume 516 MB), that represent extreme scenarios including high heart rate, noisy data, and missing data points. Here, the primary task incudes removing outliers.

To enhance the dataset and facilitate more comprehensive testing and validation of the monitoring system, the original data was augmented using Mockaroo. This tool allowed for the generation of additional synthetic data that mirrors real-world scenarios and create more robust training sets for the model. The augmentation process involved increasing sample size to represent large herd size, adding variability to simulate health and behaviour patterns, introducing anomalies to represent spike in temperature or heart rate etc. This augmented dataset maintains the same structure and format of the original dataset with additional complexity and diversity.

To integrate this data with AWS, Amazon S3 is used for storing the data. Further, AWS Lambda was configured to preprocess and clean the data and Amazon Sage Maker to train the models using the processed data. Post this, the data is then stored in DynamoDB for historic data for future analysis. A larger and varied dataset improves the training process of ML models leading to better accuracy and reliability. The presence of synthetic anomalies allows for thorough testing of the system's ability to detect and respond to health issues. The augmented data enables the development of a scalable solution that can be adapted to different farm sizes and conditions. This approach ensures that the system is well-prepared to handle real-world scenarios and provide valuable insights to farmers.

3.5 Workflow

The methodology being considered is to gather unique characteristics of each pig, considering important health indicators. The dataset is then cleaned, preprocessed and transformed to a usable format that is suitable for training a machine learning model to accurately classify health status based on the animal's specifics and its environment. This leads to improved early detection of potential health problems and prevention of disease outbreaks in the livestock industry. The data acquired from the tripartite sensor is listed in Table 2. The collected data includes temperature, heart rate, breathing rate etc.

Table 2 Various parameters measured using the tripartite sensor installed on the body of the pig.

Features	**Meaning**
Time	Timestamp indicating the time of data collection
Animal	Identifier of the livestock being monitored (e.g., pig ID)
Activity	Description of the activity or behavior of the animal.
Date	Date of data collection.
Breathing Waveform	Data related to the breathing waveform.
HR (Heart Rate)	Heart rate of the animal.
BR (Breathing Rate)	Breathing rate of the animal.
Skin Temp	Skin temperature of the animal.
Posture	Posture of the animal.
Peak Accel	Peak acceleration experienced by the animal.
Battery Volts	Voltage of the device's battery.
Battery Level	Level of the device's battery.

Features	Meaning
BR Amplitude	Amplitude of the breathing waveform
BR Noise	Noise in the breathing waveform.
BR Confidence	Confidence level in the breathing rate measurement.
ECG Amplitude	Amplitude of the ECG waveform.
ECG Noise	Noise in the ECG waveform.
HR Confidence	Confidence level in the heart rate measurement.
HRV (Heart Rate Variability)	Variability in heart rate.
System Confidence	Overall confidence level in the system’s measurement
GSR (Galvanic Skin Response)	Galvanic skin response of the animal.
ROG State	State of the animal
ROG Time	Time related to the animal’s state.
Vertical Min, Vertical Peak	Minimum and peak values of vertical movement.
Lateral Min, Lateral Peak	Minimum and peak values of lateral movement.
Sagittal Min, Sagittal Peak	Minimum and peak values of sagittal movement.
Device Temp	Temperature of the device.
Link Quality, RSSI, TX Power	Quality of Link, RSSI (Received Signal Strength Indicator), and transmission power.

Features	Meaning
Core Temp	Core temperature of the device.
AUXadc1, AUXadc2, AUXadc3	Additional ADC (Analog-to-Digital Converter) readings.
R to R	R-to-R interval.
Vertical, Lateral, Sagittal	Movement data in different axes.
ECG Waveform	Data related to the ECG waveform

The list of services along with their features that are needed for the smooth functioning of this model are shown in Table 3.

Table 3 List of AWS services required to satisfy the feature requirements outlined in Planning phase.

Features	AWS Service
Feature 1 Secure model that prevents unauthorised access	AWS Device Defender,
Feature 2 Model that works seamlessly irrespective of resources being coupled or decoupled	AWS Greengrass
Feature 3 It must handle increase or decrease in traffic	Auto Scaling

Features	**AWS Service**
Feature 4 Must allow more than 200 IoT sensors to operate simultaneously	IoT Core Services
Feature 5 The framework must be accessible in remote areas	Nb-IoT protocol
Feature 6 Identify any anomalies in the behaviour of animals	AWS CloudWatch
Feature 7 Perform analytics and create visualizations from the collected data	AWS sagemaker, Quicksight
Feature 8 SMS notification to farmers and concerned authorities, vet	AWS SNS
Feature 9 Record and store the event	DynamoDB
Feature 10 Distributed Storage	AWS S3

Chapter 4 Results

4.1 Services used in Amazon Web Services Cloud

Using AWS serverless solutions, the proposed design for cattle farming in Figure 4 integrates a variety of services, encompassing development, computation, storage, databases, analytics, networking, mobility, management, IoT, business apps, and security. Essential components such as AWS IoT Core, Lambdas, DynamoDB, S3, Machine Learning, Notifications, Analytics, Logging, and User Identities were grouped together to establish a scalable and resilient monitoring system. These groupings were organized to meet the functional requirements outlined in Phase 2 of the Materials and Methods section. Furthermore, Phase 3 of the Materials and Methods section delineates the architecture in alignment with the fundamental principles of a well-structured design.

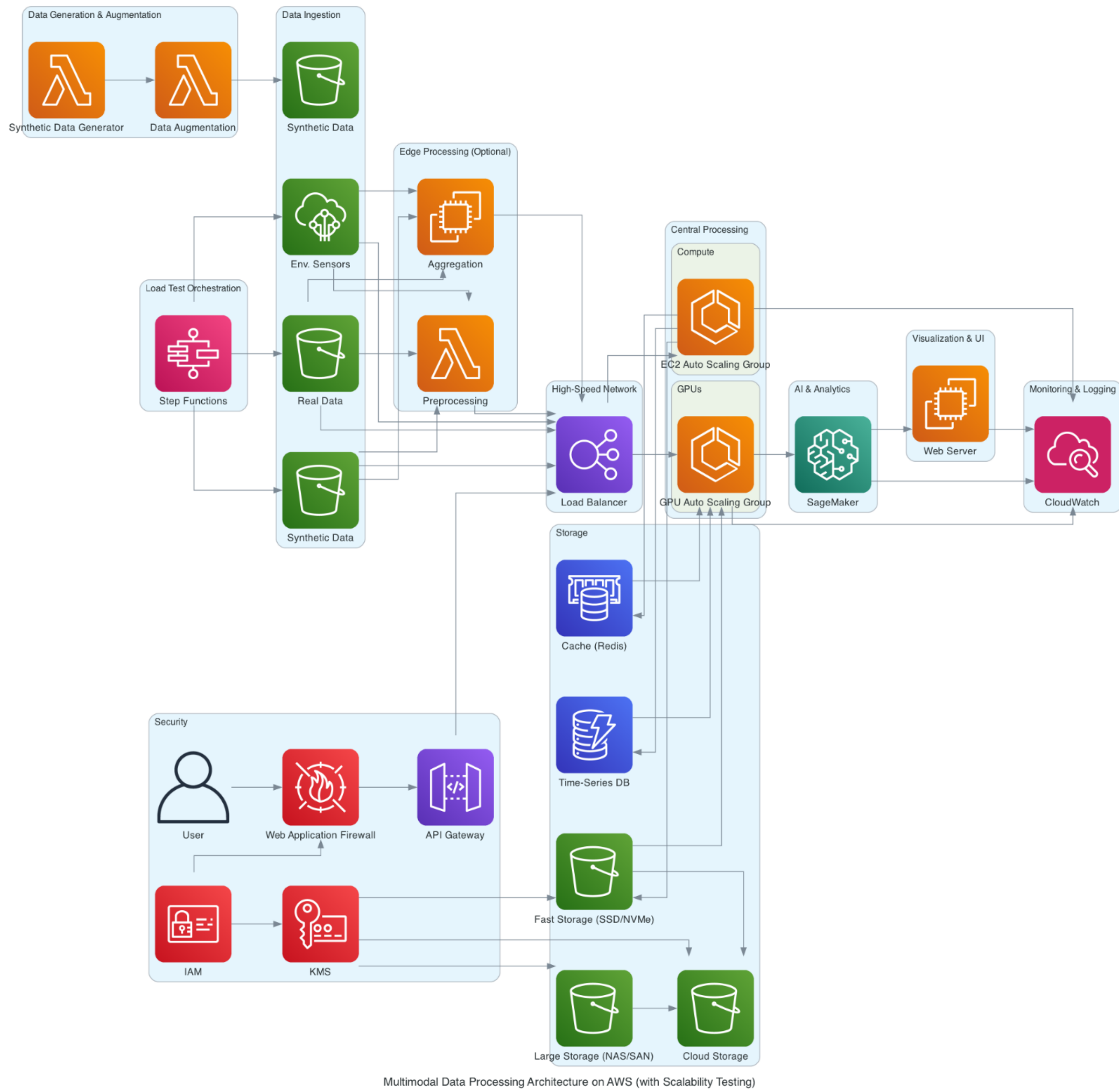

Figure 4 AWS Architecture depicting workflow of the model.

The overall framework scalability of the AWS services used is shown in Figure 5. This architecture includes Amazon S3 (Simple Storage Service) that is highly scalable by default and capable of storing virtually unlimited amounts of data. The automatic scaling feature allows S3 to automatically handle increased request rates and huge volumes of data without any manual intervention.

DynamoDB is a fully managed NoSQL database service that can handle massive scale and high throughput. It can automatically scale its read and write capacity to accommodate changes in traffic without performance degradation.

Amazon Sage Maker is a fully managed machine learning service that allows you to build, train, and deploy machine learning models at scale. It can scale horizontally to accommodate training and inference workloads across multiple instances.

AWS Lambda is a serverless compute service that automatically scales to handle incoming requests and can scale horizontally to handle increased concurrency as traffic grows.

It’s pay-per-use pricing model, allows users to scale efficiently based on actual usage without overprovisioning resources.

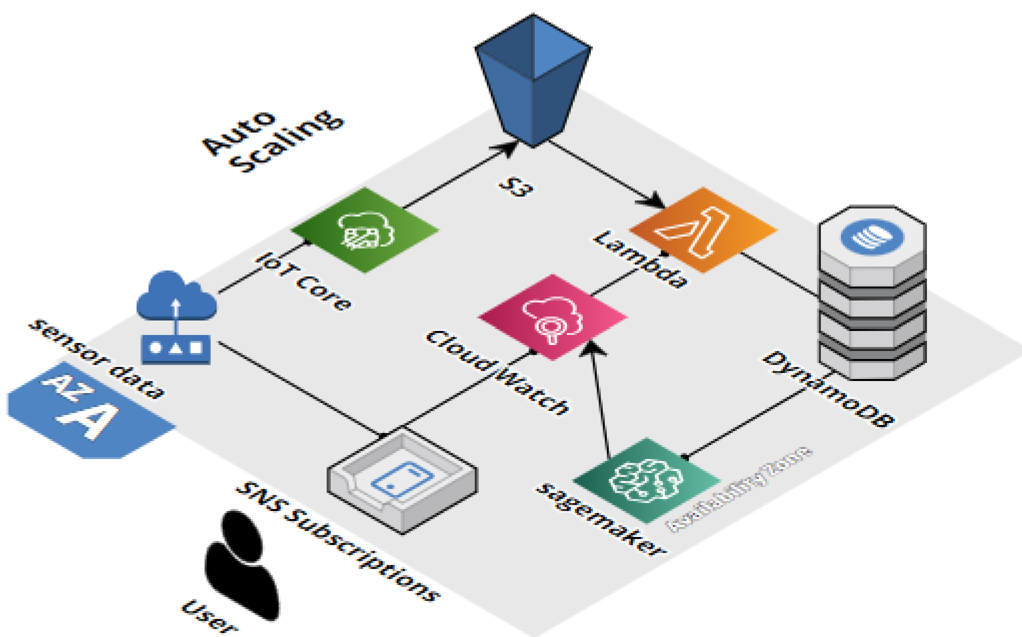

Figure 5 Scalability architecture of the AWS Services

4.1.1 Internet of Things Core Frame

The AWS IoT core consists of five services that maintain the needs of all IoT devices, connect to AWS cloud, manage devices, update over-the-air (OTA), and secure the IoT devices. It uses the scalability communication protocol to encrypt all communication and preventing third parties from reading or tampering with the data being transmitted. TLS encrypts the data being transmitted, ensuring that any sensitive information (e.g., health metrics, sensor data) cannot be easily intercepted or deciphered by unauthorized parties. This is particularly important when transmitting data over public or untrusted networks. It is done using certificates to authenticate the identity of the server (e.g., AWS). This ensures that the device or client is communicating with a legitimate server and not an imposter or attacker. The use of TLS in the system enhances trust and reliability. Farmers and stakeholders can be confident that the data being collected, processed, and analyzed is secure and has not been tampered with during transmission.

Services in this framework are rules, topics, shadow service, AWS IoT device defender, and AWS IoT device management. The Rules (Figure 6) enable the IoT devices developed for smart livestock to interact with AWS services (Pereira, et al., 2019).

Some of the rules used in the system are:

i. Filter incoming data from IoT devices.
ii. Simulating the IoT sensor (Figure 7)
iii. Separation and recording of data according to their type in various kinds of databases.

iv. Sending notifications to users in certain circumstances Figure 8 (for example, occurrence of abnormal events in the monitoring process)

v. Real-time processing of messages coming from multiple IoT devices.

vi. Setting alarms to notify the user when reaching predefined limits of certain parameters (for example, reaching a critical battery level of IoT devices, increase in HR of the animal Figure 9)

vii. Send the data from a Message Queuing Telemetry Transport (MQTT) message to a machine learning frame to make predictions based on the ML model.

viii. Send data to a dashboard.

SQL statement	SQL version
`SELECT HR FROM 'sensor/data' WHERE HR>150`	2016-03-23

Figure 6 SQL condition to trigger SNS if HR value exceeds a set threshold of150 from the topic sensor/data.

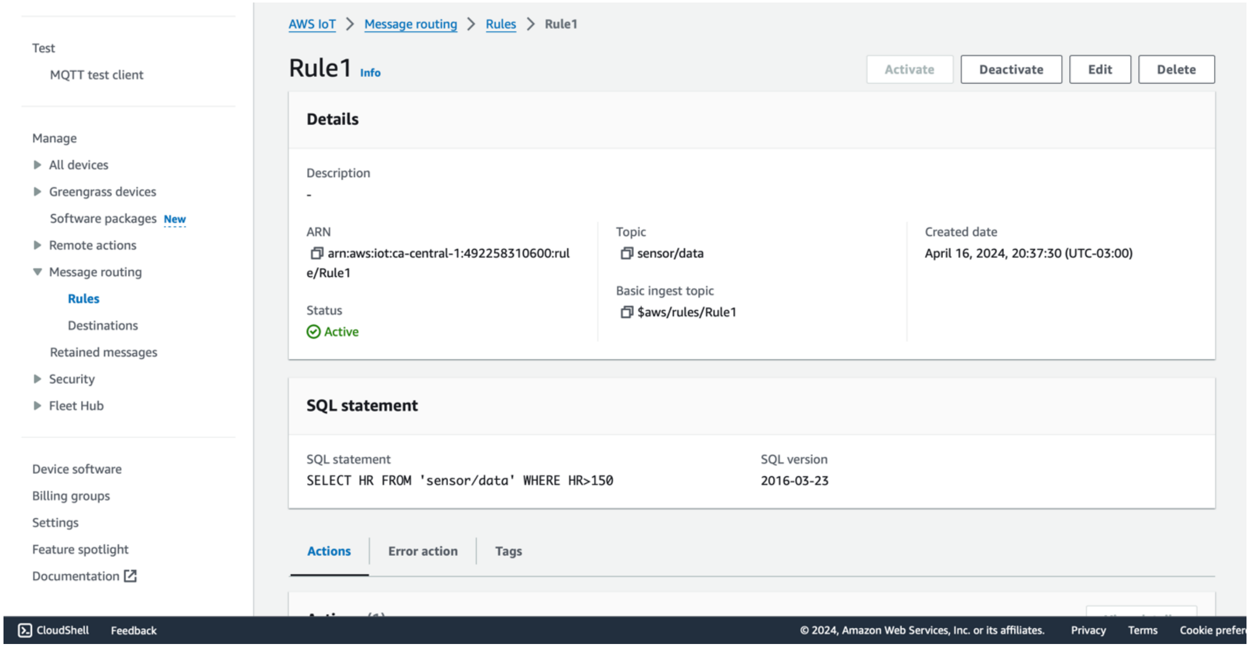

Figure 7 IoT Core Rule to trigger SNS if Heart Rate value exceeds a set threshold of 150 from the topic sensor/data.

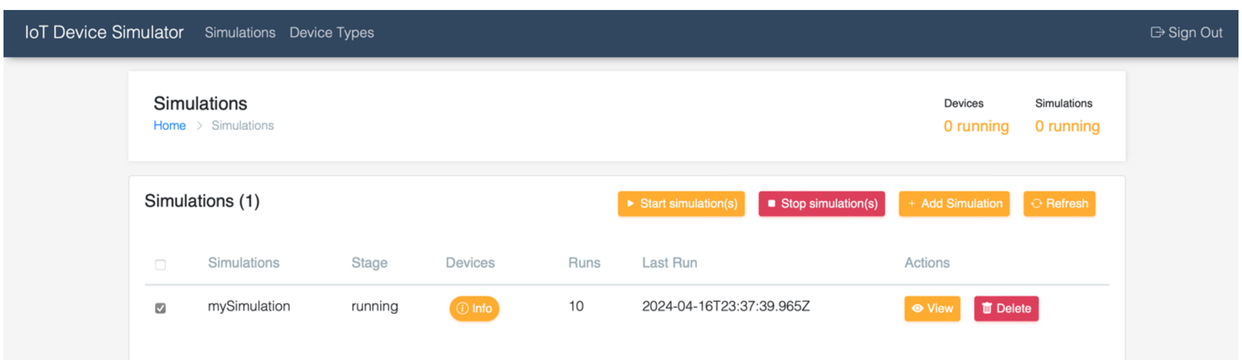

Figure 8 Simulating an IoT sensor to generate random values corresponding to the feature HR.

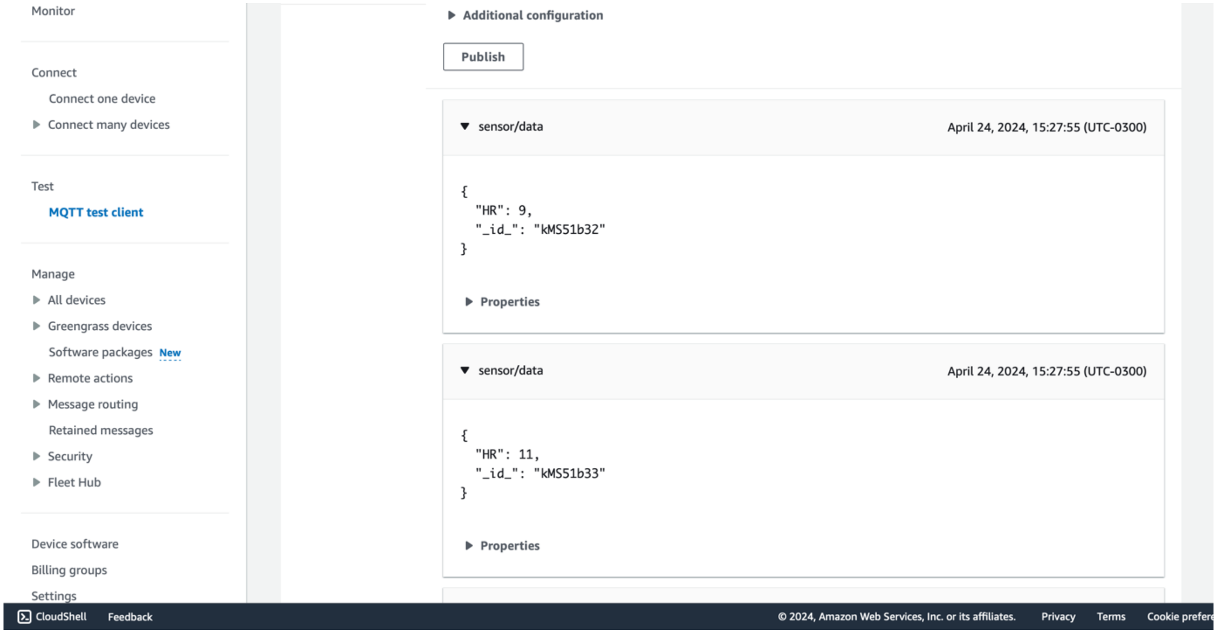

Figure 9 Filters data by the defined IoT Core Rule of HR greater than 150.

4.1.2 Lambda Frame

The Lambda function operates as a stateless code snippet, triggered by various sources both internal and external to AWS. It offers the capability to automatically scale applications without the need for capacity planning. Unlike an EC2 instance, a Lambda serves a singular purpose and runs for a short duration, typically a few minutes. It can scale rapidly to handle hundreds of instances with minimal platform maintenance. In the context of the livestock monitoring system described in this work, Lambda functions undertake the following tasks:

- Storing specific metadata, such as a unique ID, S3 bucket and key where the frame is saved, the approximate recording time, etc., to Amazon DynamoDB.
- Simulating IoT sensor behavior by adjusting random values to a specified frequency.

4.1.3 Data Storage

DynamoDB (Figure 10) is a serverless architecture are used to store events. Data from here is sent to real-time operational dashboard to provide insights. DynamoDB, with its high throughput and auto-scaling capabilities, efficiently handles large volumes of data from numerous IoT devices, ensuring the system remains responsive Firouzi & Farahani, (2020), Kumari et al., 2022). Its NoSQL design is ideal for diverse sensor data, and its high availability and durability provide robust data management. Seamless integration with other AWS services facilitates a cohesive IoT monitoring system, while low-latency operations ensure timely health interventions. Amazon Pinpoint enables effective communication and engagement through multichannel messaging, critical for real-time alerts and personalized notifications based on specific data points (Voutsas et al., 2024). Integration with AWS IoT Core and Lambda triggers real-time alerts for anomalies, supporting automated health checks and scheduled notifications. Detailed analytics on message delivery and user engagement refine communication strategies, ensuring critical alerts are promptly addressed. Pinpoint's scalability accommodates extensive livestock operations, offering targeted messaging for efficient health management. Together, DynamoDB and Amazon Pinpoint provide a robust, scalable, and efficient system for LHM, enhancing animal welfare and farm productivity through effective data management and real-time communication.

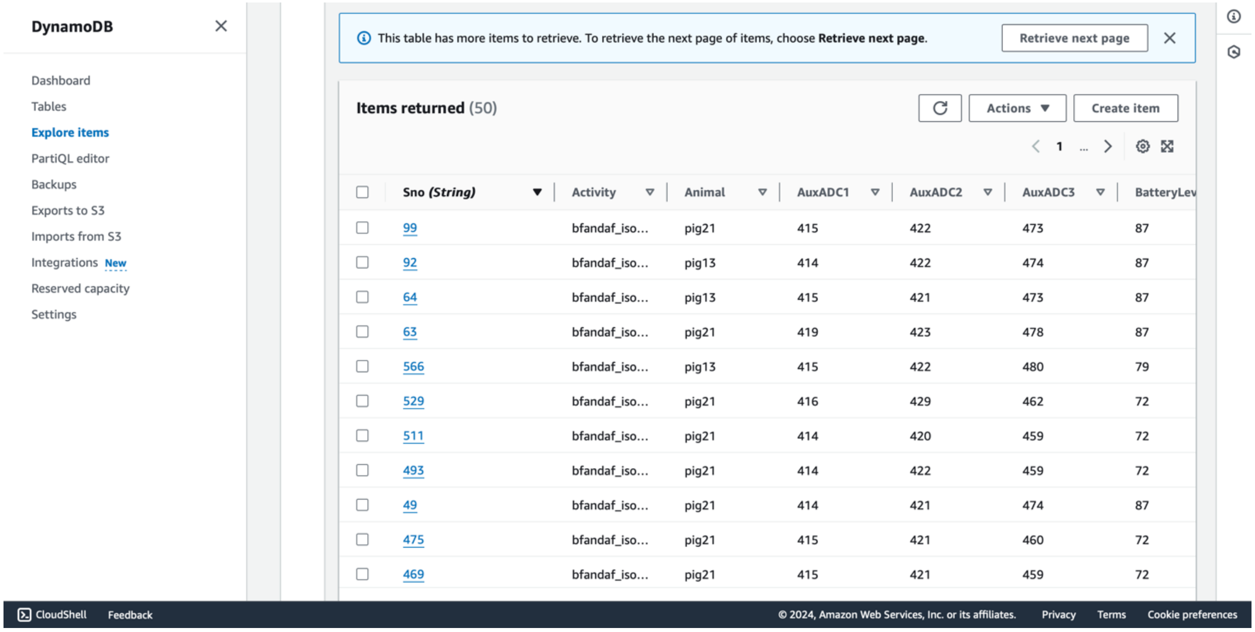

Figure 10 Filtered data from IoT Core is then stored in DynamoDB.

4.1.4 Notification Frame

Amazon Pinpoint, as a communication service, connects with users through various channels such as email, SMS, push, or voice (Figure 11). This service is used to personalise messages with the right content. It sends push notifications to the smart livestock application after pre-provided data that authorises pinpoint to send messages. The credentials that are provided depend on the operating system:

- For iOS applications, an SSL certificate is provided. The certificate authorises the pinpoint service for sending messages to the smart livestock apps.
- For Android applications, a web API key is provided. These credentials authorise the pinpoint service for sending messages to the smart livestock apps.

AWS AppSync takes care of managing and updating real-time data between web and mobile app and cloud. Additionally, it allows apps to interact with data on mobile devices when it is offline.

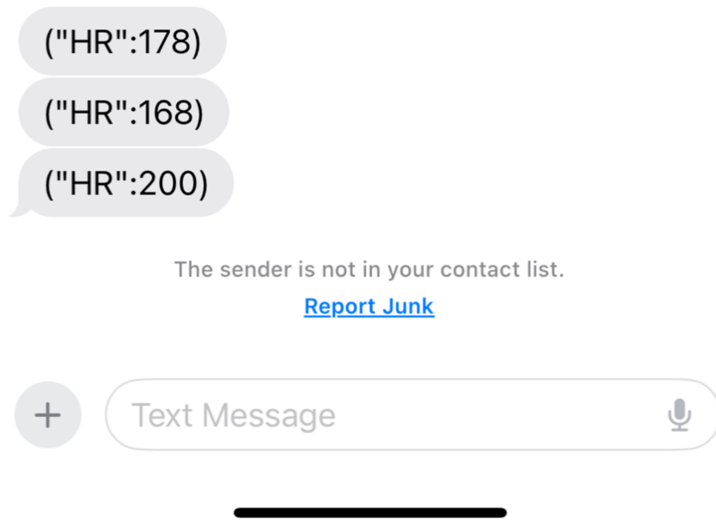

Figure 11 A screenshot representing IoT rule sending an alert to the user as the HR values exceeding the set threshold of 150.

4.1.5 Machine Learning Frame

Long-term unused data can be stored in S3 Glacier which is designed to store rarely used data. Since the data from S3 Glacier is not readily available it is archived. The unused data can be unzipped and moved to S3 bucket if required. The data from S3 is then used by Amazon Sage Maker to build, train, and deploy interface models. To predict the future health of the animals, the boosted decision tree algorithm was trained, which takes as parameters the animal's temperature, heart rate, isolation, and pairing. With these data, the model is trained to make a binary prediction of one of two classes: the animal has good vital signs, and the animal has poor vital signs. In addition to the classification of the health status of the animals, a regression is performed to predict, in the short-term, the future amount of milk that will be extracted from each animal. Linear regression is the algorithm trained with the historical data stored in the S3 Bucket. The trained models are deployed, and their self-learning continues through new data coming from the data stores frame.

Amazon SageMaker Autopilot is a feature that automates the process of building machine learning models by selecting the best prediction type and evaluating numerous model candidates. It begins by analyzing the dataset provided and automatically infers the appropriate type of prediction task, such as binary classification, multi-class classification, regression, or time series forecasting, based on the nature of the data.

Once the prediction type is determined, SageMaker Autopilot initiates a comprehensive AutoML process. This involves generating hundreds of different models, each using various machine learning algorithms and hyperparameter configurations. The AutoML cycle systematically tests these models to determine which combination of algorithms and hyperparameters yields the most accurate predictions for the given data.

Throughout this process, SageMaker Autopilot ensures that the model selection is data-driven, leveraging its ability to explore a wide range of possibilities that might be impractical to test manually. By evaluating and comparing these models against each other, it identifies the best-performing model that fits the data, providing a highly accurate solution tailored to the specific problem at hand. This automation not only accelerates the model development process but also enhances the reliability and precision of the final model, making it a powerful tool for data scientists and developers.

4.2 Execution Results

4.2.1 Internet of Things Device

A group of sensor groups, logical blocks, and power supply collected sensor readings from livestock for temperature, humidity, and heart rate. The communication in each livestock IoT device is device-to-edge using Nb-IoT (Lu et al., 2024). All IoT devices on a farm have strict firewall rules. The various sensor devices deployed are registered prior to initialization of the framework for security. Livestock IoT devices will not be able to communicate with each other on their farm or with other devices to ensure independent working of each sensor. In case the IoT device cannot connect to the IoT edge, or the data transmission is obstructed by any other reasons, the device can keep the sensor readings until the moment it reconnects. Then, the IoT device will send the up-to-date data.

4.2.2 Internet of Things Edge

The AWS IoT Core, which is an IoT open-source edge runtime and cloud service that helps to build, deploy, and manage device software (Ning et al., 2020). It was used to manage local processes, communicate, and synchronise certain groups of devices and exchange tokens between Edge and cloud, which acts as a hub or gateway in Edge. The communication is Edge-to-Cloud using TCP based protocols. It consists of MQTT Broker, Local Shadow Service, AWS Lambda, Meta Data, and Trained Models. AS IoT Core was used to perform the following tasks:

i. Processing of large data streams and automatically sending them to the cloud through Lambda functions (AWS Lambda).

ii. Lambda functions uses Nb-IoT protocol for connections between livestock IoT devices and cloud using device authentication and authorisation (Meta Data).

iii. Deployment of cloud-trained machine learning models for regression that predicts a percentage of the future power of the battery concerning the individual frequency and load of the monitoring livestock system (Trained Model).

iv. Updated group configuration with secured OTA software updates.

The developed framework is tested against three different sizes of data; The dataset contains 318713*44, 320713*44, and 322713*44 in scenarios 1,2 and 3 respectively.

The execution results from Lambda displaying a) Error count and success rate (%); b) Throttles; c) Invocations; d) Duration; e) Total concurrent executions; in three different scenarios of changing farm size are as follows.

It can be inferred from the Lambda metrics that a high success rate suggests that Lambda functions are functioning as expected and handling incoming requests effectively with increasing data load (Figure 12, Figure 13, Figure 14).

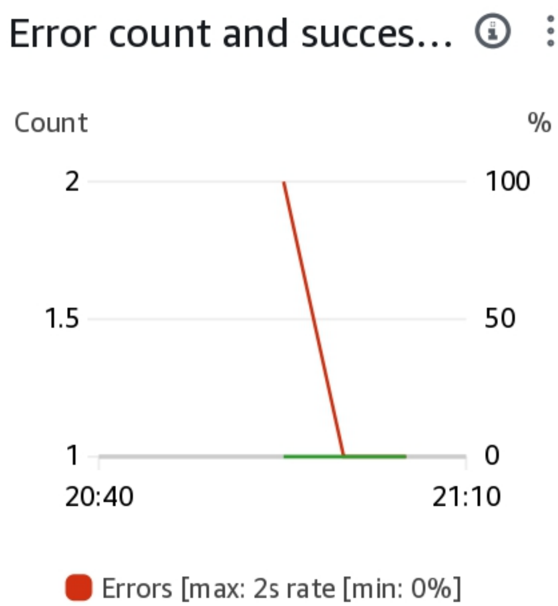

Figure 12 Lambda execution results the error and success rates when experiencing data load in Scenario 1.

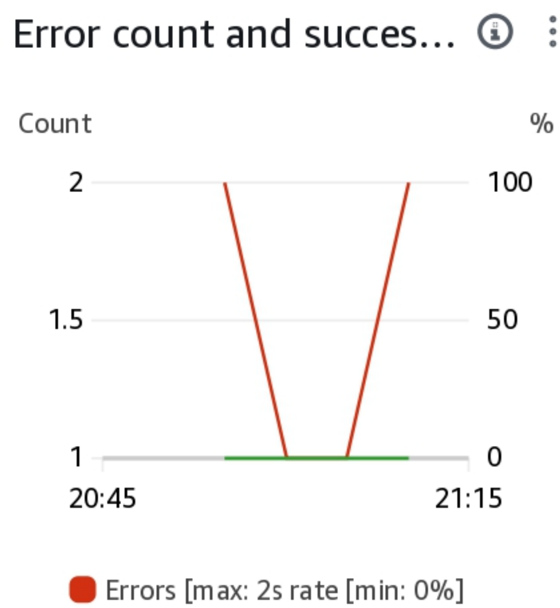

Figure 13 Lambda execution results the error and success rates when experiencing data load in Scenario 2.

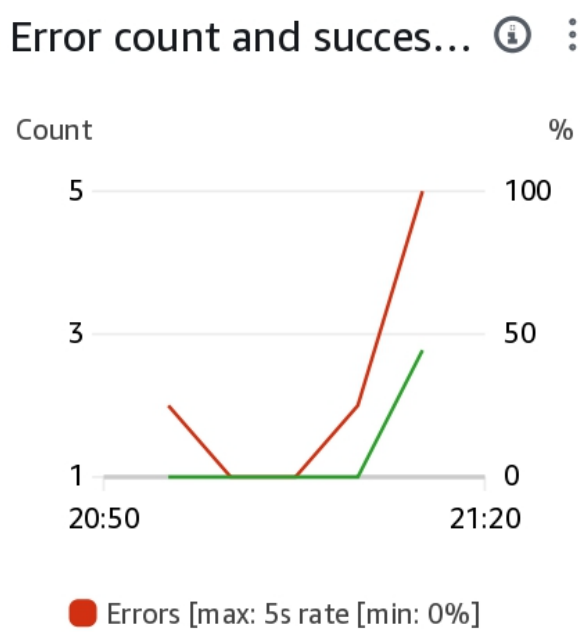

Figure 14 Lambda execution results displaying the error and success rates when experiencing data load in scenario 3.

Throttle lines (Figure 15, Figure 16, Figure 17) intersecting or crossing the x-axis indicate instances when Lambda invocations were throttled. The position of these lines along the x-axis corresponds to the timestamp or time period when throttling occurred.

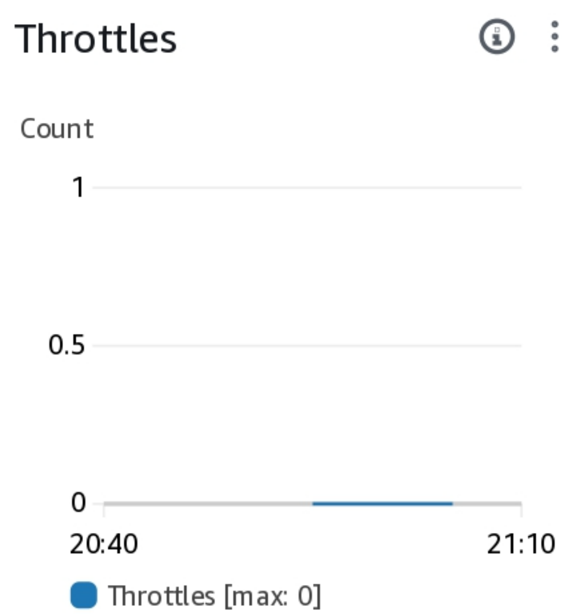

Figure 15 The count of throttles in Lambda function with small data load.

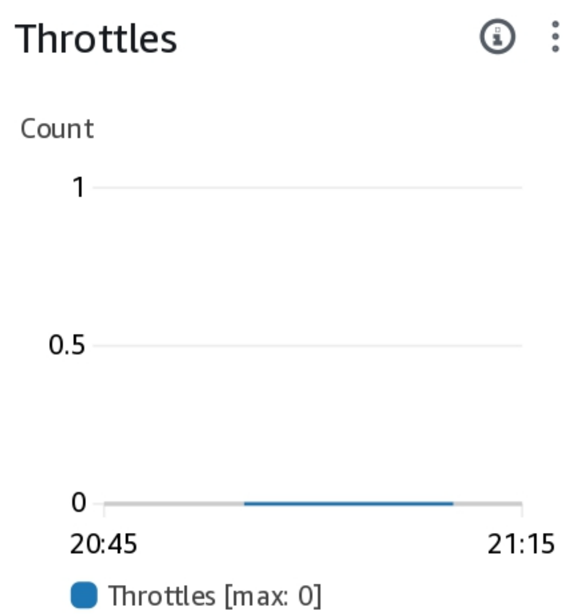

Figure 16 The count of throttles in Lambda function with medium data load.

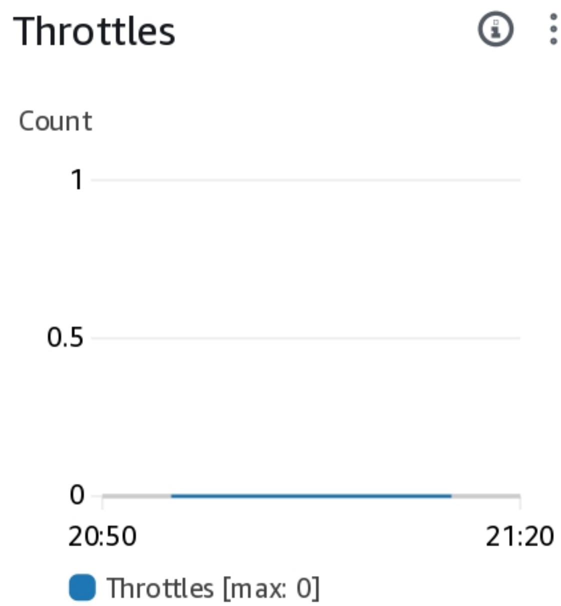

Figure 17 The count of throttles in Lambda function with large data load.

Figure 17 depicts that the Lambda function is operating efficiently and effectively, with no restrictions on the number of concurrent executions it can handle. It is also evident that the application can horizontally scale effectively to accommodate varying workloads without being hindered by concurrency limitations. AWS Lambda is utilizing the available resources (such as memory, CPU, and networking) to their fullest extent, maximizing the efficiency of your function executions. Figure 18, Figure 19, Figure 20 shows Lambda function is invoked automatically each time an AWS service is triggered. Here, the Lambda function serves as an event-driven, serverless compute service offered by AWS. Below are certain instances when the Lambda function is invoked when a corresponding AWS service is triggered.

Data Ingestion: For instance, whenever an IoT device such as sensor monitoring the livestock health, sends data to AWS through AWS IoT Core, this event triggers the Lambda function. The Lambda function then processes this incoming data, performs tasks such as data transformation or storage into S3. It automatically scales to accommodate incoming requests. As the number of invocations increases, AWS Lambda manages the allocation of resources to handle the workload efficiently.

Alerts and Notifications: If the system detects that certain health indicators (like temperature or heart rate) fall outside of predefined thresholds, this event triggers the Lambda function. The function sends an alert or notification to the farmer or initiate further analysis.

Data Analysis and Processing: Lambda is also triggered by scheduled events, such as periodically analyzing data stored in S3 or a database. For example, it might execute a predictive analytics model to identify potential health issues in livestock before they become severe.

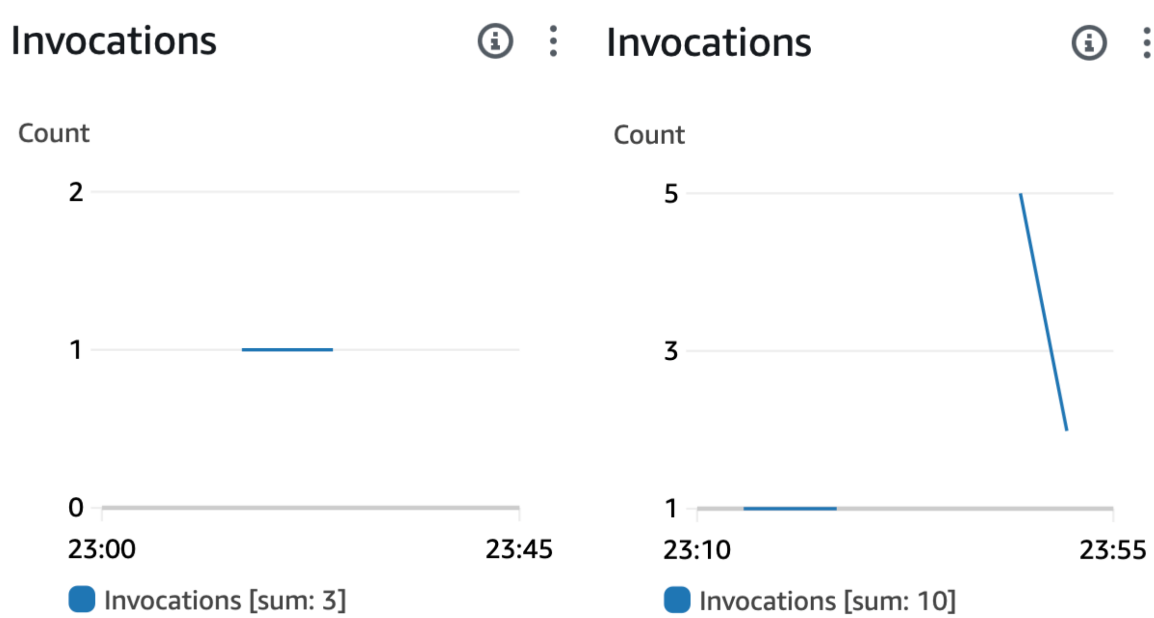

Figure 18 Examining Lambda in light data load.

Figure 19 Examining Lambda in moderate data load.

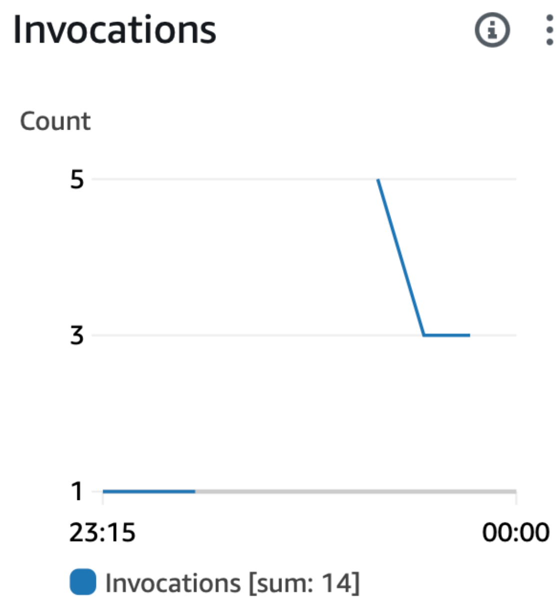

Figure 20 Examining Lambda invocations in heavy data load.

In AWS Lambda, "duration" refers to the time taken for a Lambda function to execute a single invocation from start to finish (Figure 21, Figure 22, Figure 23). It includes the time it takes to initialize the execution environment, execute the function's code, and handle any outgoing requests or asynchronous operations.

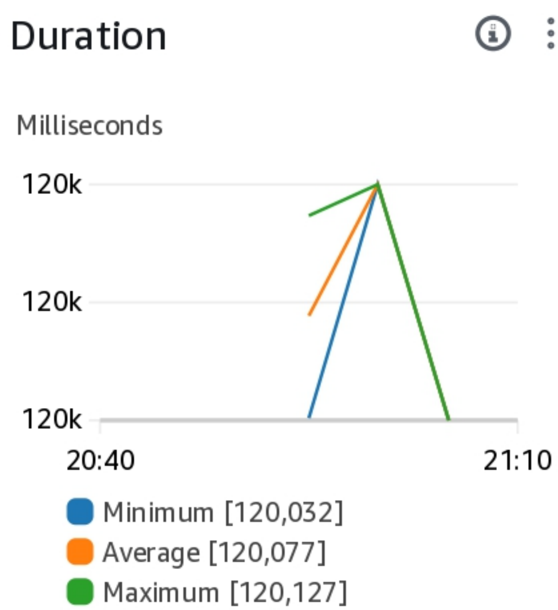

Figure 21 Duration variability in Case 1.

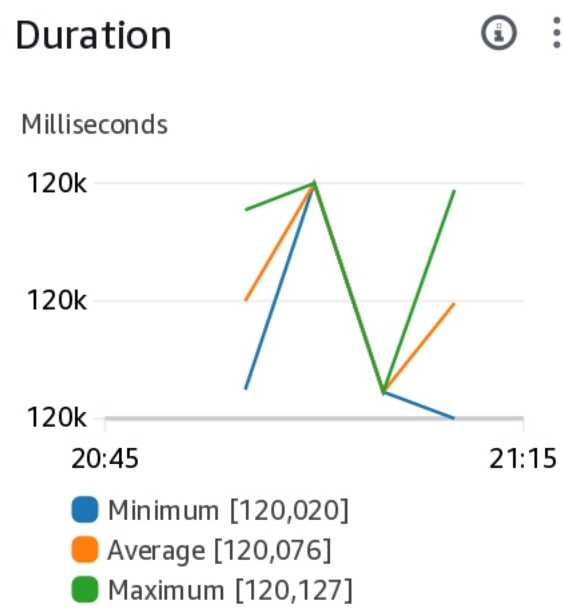

Figure 22 Duration variability in Case 2.

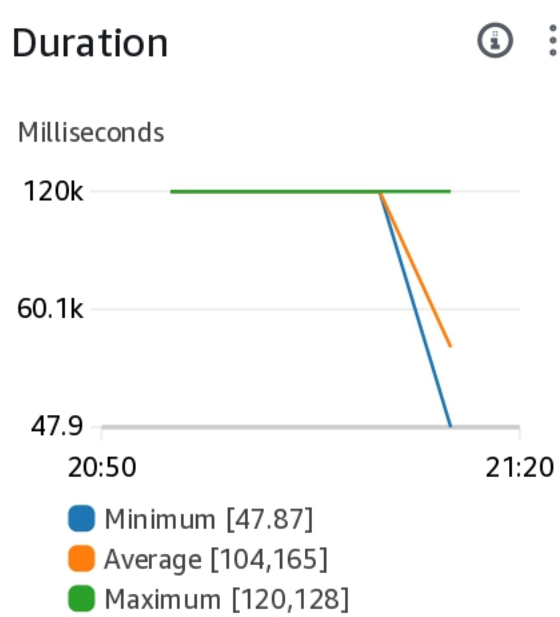

Figure 23 Duration variability in case 3.

Optimizing code, memory allocation, and concurrency settings can lead to improved performance, reduced costs, and enhanced user experiences in serverless applications.

Figure 24, Figure 25, Figure 26 depicts the total concurrent executions that occurred. Peaks in the graph represent times when the total concurrent executions reach their highest levels. This occurs during periods of high traffic, increased workload, or bursts of activity.

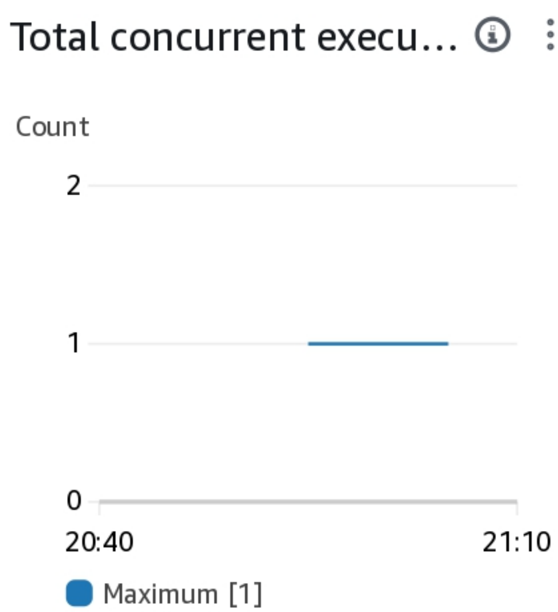

Figure 24 Total Concurrent Executions with small data size.

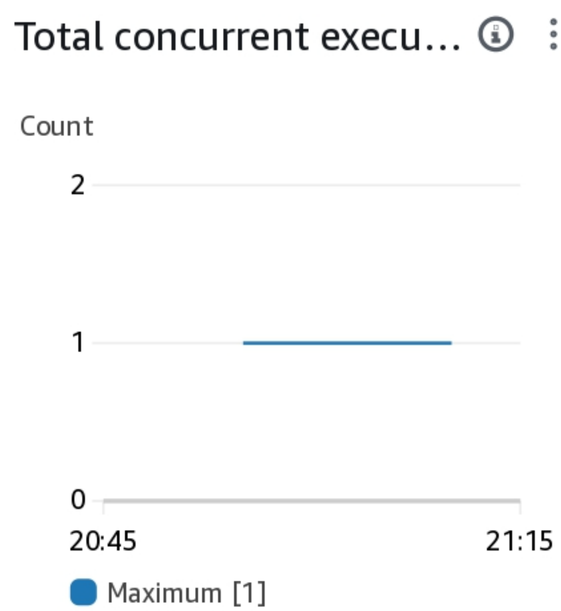

Figure 25 Total Concurrent Executions with medium data size.

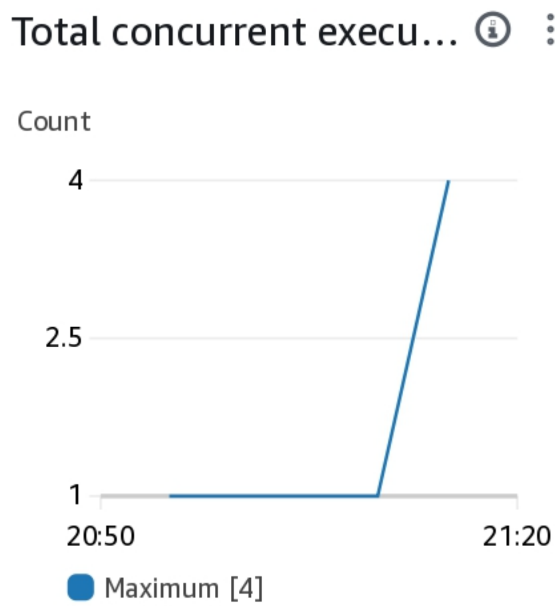

Figure 26 Total Concurrent Executions with large data size.

Built on the AWS cloud platform, which provides more than 200 services, is the smart livestock architecture. More than 20 management services, over 30 machine learning and data analytics services, and over 13 database and storage services are included in this list. This research's recommended architecture uses AWS serverless services to make it easier to create vital data pipelines that can effectively handle massive amounts of data from IoT devices. It also makes it possible to store large amounts of unprocessed raw sensor and image data on AWS S3 at a reasonable price while maintaining accessibility to both old and new data.

Figure 27 and Figure 28 displays the error and success rate recorded in Cloud Watch which is used to analyze the performance and reliability of the model.

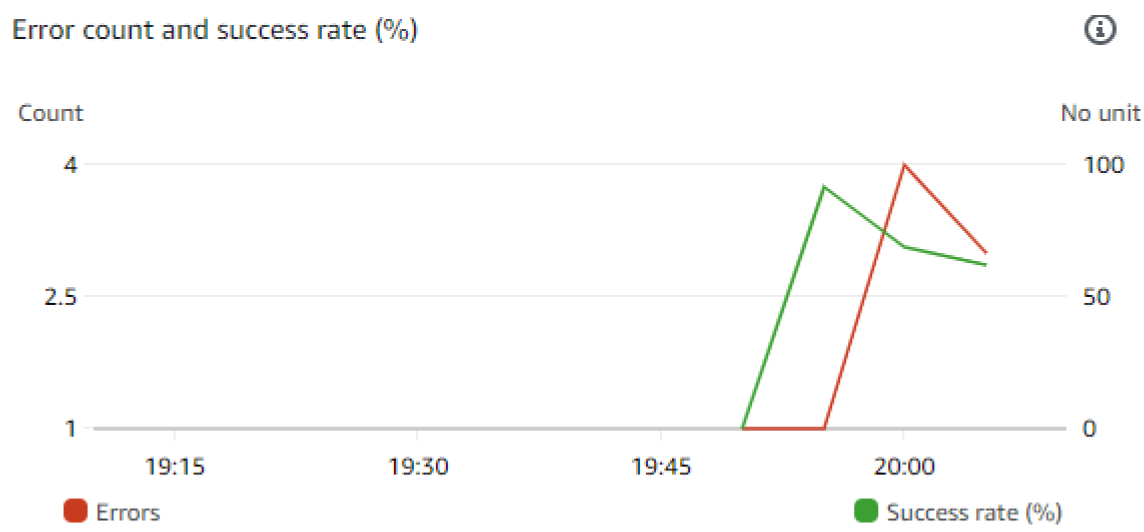

Figure 27 Cloud Watch metric with small data load.

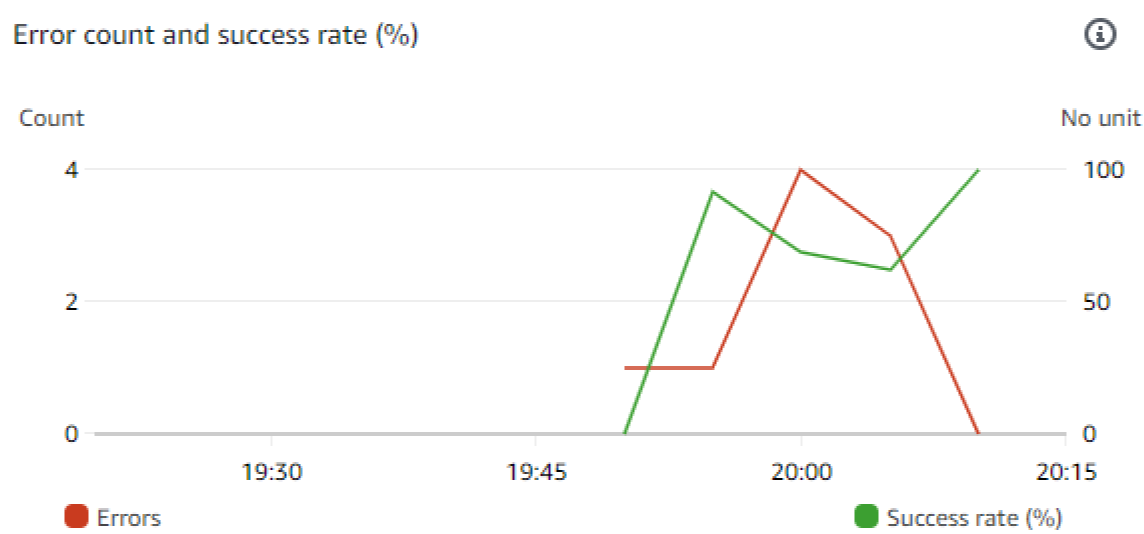

Figure 28 Cloud Watch metric with large data load.

The developed model predicts the heart rate considering various parameters including animal activity, temperature, breathing rate etc. Figure 29 shows the predicted and actual values of the HR using Sage Maker.

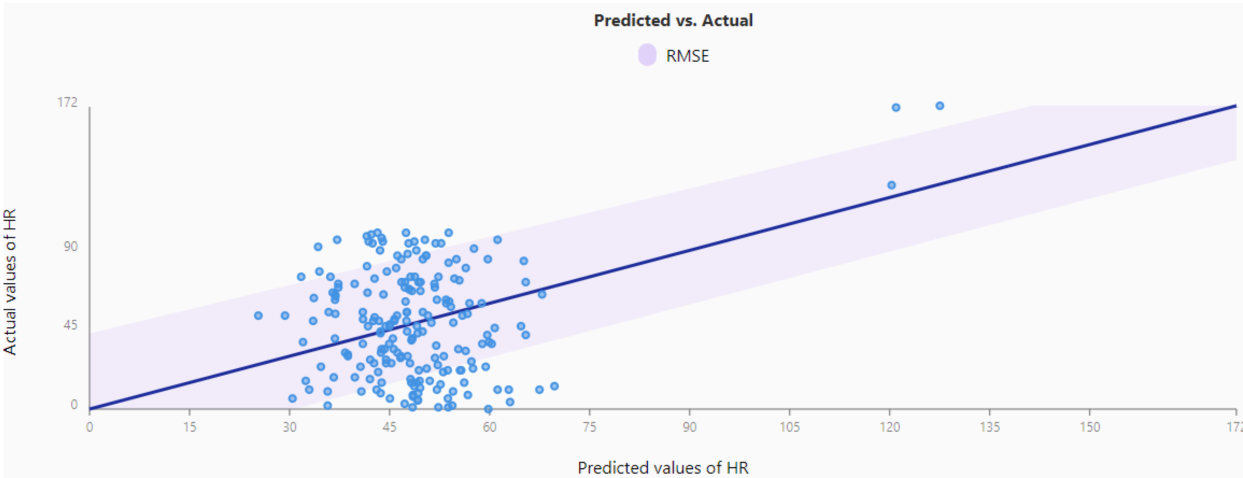

Figure 29 Graph displaying RMSE of predicted and actual values of HR.

Among all the features available to predict HR, the significant contributors are Breathing Waveform Figure 30 and Activity Figure 31.

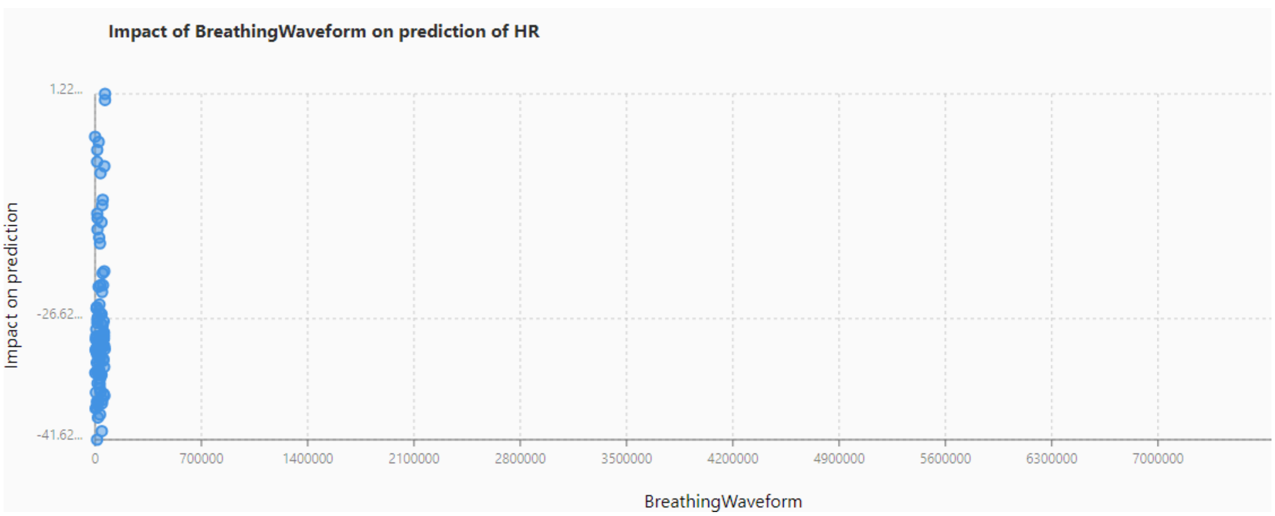

Figure 30 The plotted graph shows the Breathing Waveform in the x-axis and its impact on prediction on the y-axis in forecasting HR value.

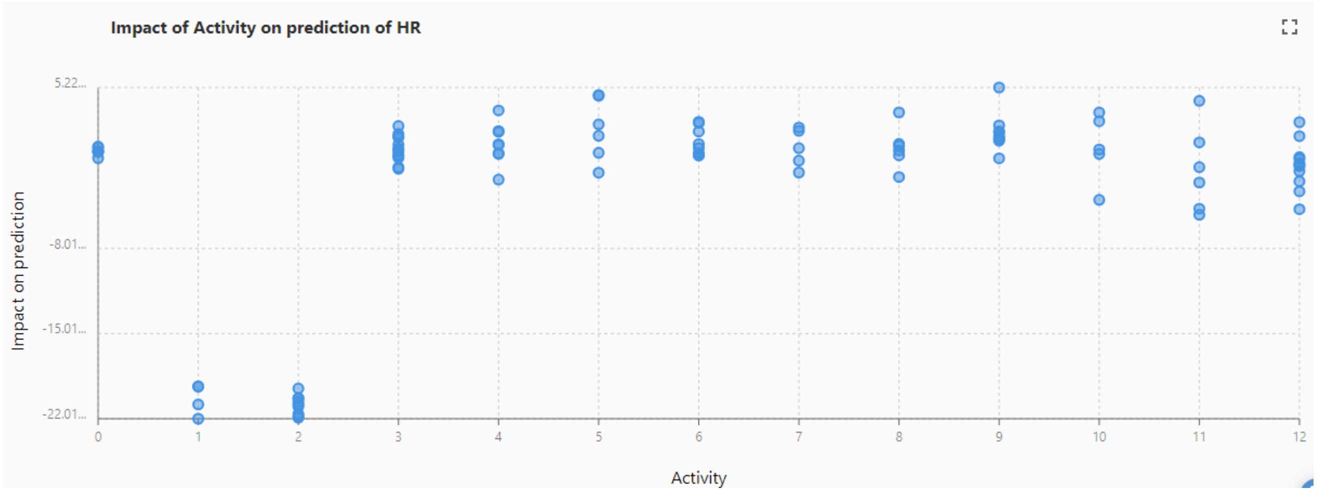

Figure 31 The graph displays the Activity of the animal against the impact of prediction to predict the values of HR.

4.2.3 Scenario Based Testing

Scenario-based testing is a critical component of the software development and validation process, especially for complex systems like IoT applications using AWS and NB-IoT. It allows to test the use case in a realistic environment that mimics the actual usage conditions. Some scenarios that comprehensively covers the most common use cases are discussed as follows.

4.2.3.1 Handling Robustness

The developed model ensures the ability to cope with errors while execution and effectively handle unexpected or invalid inputs. The redundancy and continuity of the system is handled by AWS Lambda, that scales in response to incoming requests, ensuring robustness. The comprehensive error handling and logging mechanism is monitored by the AWS CloudWatch that watches the application's performance, logs, and metrics, allowing for rapid detection and resolution of issues. The ELB distributes incoming application traffic across multiple targets, improving fault tolerance. Resilience testing can be performed using AWS FIS that helps run experiments on AWS resources to simulate failures such as instance terminations, CPU throttling, and network blackholes. Additionally, to automate resilience testing to periodically assess and improve system robustness, AWS provides AWS Code Pipeline and AWS Step Functions where the former automates build, test, and deploy function and the latter orchestrates resilience testing workflows.

4.2.3.2 Data Throughput Changes

The amount of data that can be processed by the system in each time frame is referred to as Data Throughput. Various testing scenarios including load testing, scalability, caching can be performed to ensure system's capacity.

$$T = I/F$$

where T stands for Throughput, I stand for (the number of units in the production process) and F stands for the time the inventory units spend in production from start to finish. In the study performed, AWS Scaling, automatically scales to adjust the computing capacity to maintain consistency and performance.

Scalability, within the context of this project, refers to the system's capacity to efficiently manage increasing amounts of work, data, or users without experiencing a significant decline in performance. Scalability is a critical consideration, particularly for the livestock health monitoring system developed in this research, which may need to handle a growing number of IoT devices, more extensive datasets, and increasingly complex computational tasks as the system is scaled to larger farms or deployed across multiple locations.

- **System Scalability**

From a system perspective, scalability implies the infrastructure's ability to accommodate an increasing load through efficient resource management. This can be achieved through:

Horizontal Scaling: It involves the addition of more instances of services to distribute the workload across multiple resources. This means instead of relying on a single Lambda function to process the large concurrency of data (>1000 instances) being uploaded, multiple such instances can be set up to handle the incoming data. Another instance when the system detects anomalies, it could trigger multiple Lambda functions to send alerts to different groups of farmers simultaneously. The default time taken is 3 minutes and maximum is 15 minutes. If the data volume is enormous then inclusion of a second instance is crucial. This ensures that the alerts are sent quickly and efficiently, even when the number of anomalies increases. Thus, the system remains responsive and scalable as the data load increases, rather than relying on a single source that might become a bottleneck. Such an approach helps maintain performance and reliability, especially in dynamic environments where demand can fluctuate.

Vertical Scaling: Vertical scaling focuses on boosting the capabilities of existing resources to meet higher demands, rather than adding more instances like in horizontal scaling. For instance, considering the data load of 516 MB running on small EC2 instance t2.small. If the data load increases enormously, then EC2 instance of size m5.large or more is required for the complex calculations to be performed. In such cases, vertical scaling can be done by upgrading to large instance with more CPU cores, memory and storage that allows the existing application to handle the increased demand without changing the underlying architecture. Although this incurs high cost, it is useful when more power is essential for a specific task without the complexity of managing multiple resources.

The scalability of the system was measured by simulating various data loads categorized as low (86.3 MB), medium (256 MB), and high (516 MB) and evaluating the system's performance in terms of processing speed, latency, and overall efficiency. The use of AWS services, including S3 and Lambda, was integral to this process, as these services inherently support automatic scaling to manage varying workloads, thereby ensuring consistent performance even as demands increase.

- **ML Model Scalability**

From the perspective of the ML model, scalability refers to the model's ability to handle larger datasets, an increased number of features, or more complex data structures without a loss in predictive accuracy or a substantial increase in computational time. While the primary focus of this project was not on developing a new ML model but rather on applying existing models to the data collected, ensuring the scalability of the data pipeline was crucial. This validates that as the volume of data increases (from 86.3 MB to 516 MB in our use case), the model can still be trained, validated, and tested efficiently, a process facilitated by tools such as Amazon Sage Maker.

The distinction between system scalability and ML model scalability is critical. System scalability refers to the infrastructure's capacity to scale with growing demands, whereas ML model scalability pertains to the model's ability to process larger or more complex datasets. While the scalability of the ML model was an important consideration, the primary emphasis was on ensuring that the entire system including data handling, processing, and analysis from various IoT devices—remained robust and efficient as the scale of operations increased. Further, Kinesis is deployed to process and analyze real-time streaming data at scale. Lastly, Amazon S3 offers scalable storage capacity for any amount of data and handling varying data throughputs seamlessly.

4.2.3.3 Environmental Conditions

The varying environmental conditions such as temperature, humidity, etc., can hinder the performance and reliability of the system. This is administered by AWS IoTCore, that connects IoT devices to AWS Services enabling data collection. Additionally, edge computing feature allows the devices to work on the local data at edge level even when not connected to the internet. Condition Simulation using AWS CloudFormation allows user to define environment as a code template. This helps setting up different environmental conditions such as varying traffic, different instance types, or geographic regions. AWS Snowball provides edge computing, data storage, and transfer solutions to environments with limited connectivity that can also be extended in the existing model.

4.2.3.3 Network Latency and Bandwidth Variability

The system functions well in environment with varying network speeds and bandwidth. The AWS Global Accelerator improves the availability and performance of the model to global users. AWS IoT Core with NB-IoT is designed for low-bandwidth, high-latency networks, and AWS IoT Core can manage devices and data even under these conditions.

4.2.3.4 Power Supply Interruptions

Another major concern of deploying IoT over Cloud is the power outrage. When. The system experiences unexpected abrupt power cuts, fluctuations, or variations in power supply, adding AWS Outposts can be installed that ensure continuity even during power disruptions. It extends the AWS infrastructure, services to the on-premises location thereby providing a consistent hybrid experience. To simulate such conditions to the model, AWS FIS can be utilized to simulate instances failures and power interruptions.

4.2.3.5 Hardware Failures

In situation where hardware such as sensors fails to communicate to the system, the AWS Device Management manages and monitors connected devices, helping detect and address hardware issues. This hardware failure can be simulated and tested using AWS FIS.

Chapter 5 Future Works

The realm of IoT systems is characterized by a diverse range of sensors and communication protocols, laying the groundwork for efficient ecosystems. The system is designed to be flexible with regard to the types of sensors that can be integrated. While certain sensors are essential for monitoring specific health indicators like body temperature, heart rate, and movement patterns, the system is not limited to any specific brand or model of sensors. This flexibility allows for the integration of various sensor types, depending on the specific requirements of the livestock being monitored or the farm's existing infrastructure. Sensors including environmental sensor that measure temperature, humidity, air quality that are crucial for optimizing the living conditions of livestock . Additionally, the system can work with both wearable sensors attached to the animals and embedded sensors within the farm environment, offering flexibility in how data is collected.

The ability to integrate different sensors allows the system to scale more easily, both in terms of the number of sensors deployed and the types of data collected. Farms can start with basic monitoring and expand as needed without technical barriers. Depending on the size of the farm and its diversity, the system can be adapted to meet specific requirements without compromising performance.

Incorporating this architecture to assess the health of other livestock like dairy cow would necessitate modifications to accommodate the physiological, behavioral, and environmental differences. Dairy cows have different health indicators compared to pigs, meaning that the algorithms used for data interpretation will need to be adapted. For instance, detecting signs of mastitis (a common condition in dairy cows) would require specific indicators not typically monitored in pigs, such as milk yield and composition.

Dairy farms operate on different economic models than pig farms, often focusing on milk production efficiency. The cost-benefit analysis for implementing such a system would need to consider the potential return on investment in terms of improved milk yield, reduced veterinary costs, and enhanced overall herd health. Hence, by addressing these challenges, the system could provide significant benefits in monitoring and managing the health of dairy cows, ultimately improving productivity and animal welfare on dairy farms.

Within this complexity lies the realm of digital twin technology, aimed at replicating physical systems for extensive analysis and optimization. Viewing through the lens of digital twin technology, the exploration of LoRaWAN and NB-IoT provides insights into their uniqueness, advantages, and integration nature. LoRaWAN, focusing on Low-power Wide Area Networks, excels in facilitating long-range communication with minimal energy usage. As foundational technologies for digital twin technology, LoRaWAN enables monitoring of devices across vast landscapes with minimal energy requirements, making it crucial in energy-constrained scenarios. On the other hand, while NB-IoT deployment may incur higher costs and complexity compared to LoRaWAN, its efficiency in coverage and power usage outweighs these drawbacks. In the realm of digital twins, extensive data is required to accurately mirror complex systems like those found in manufacturing industries or intelligent infrastructures. Supported by major telecommunication networks, NB-IoT offers high asset fidelity and facilitates consistent data development from various sensors, enabling real-time analysis and predictive maintenance. The claim that the proposed application reduces costs is based on a detailed examination of the system's architecture and the use of cloud-based resources. However, while the assertion is made that the model is cost-effective, it is essential to note that no direct cost comparisons with alternative models were conducted as part of this research. The cost-efficiency of the system was inferred from several key factors inherent to the architecture and technologies employed.

The specific cost metrics analyzed include:

1. **Infrastructure Costs**: The use of AWS services, such as Amazon S3 for data storage and AWS Lambda for serverless computing, was evaluated in terms of their pay-as-you-go pricing model. This pricing strategy allows for significant cost savings, especially when compared to traditional, on-premises infrastructure that requires upfront capital investment and ongoing maintenance.
2. **Operational Costs**: The scalability of the system reduces operational costs by automatically adjusting resources based on demand. For instance, AWS Lambda functions only incur charges when they are executed, which minimizes unnecessary spending during periods of low activity. Additionally, the automation of data processing tasks reduces the need for manual intervention, further lowering operational costs.
3. **Sensor and IoT Device Costs**: The choice of sensors and IoT devices was influenced by their affordability and reliability. By selecting cost-effective hardware that meets the required performance standards, the overall system cost

was kept within reasonable limits. Furthermore, the integration of LPWAN technologies like Nb-IoT and LoRaWAN (as proposed) can further reduce communication costs due to their low power consumption and extensive coverage, minimizing the need for expensive infrastructure.

4. **Maintenance Costs**: The use of cloud-based services and the modular design of the system contribute to lower maintenance costs. Cloud services often include maintenance and updates as part of their service offerings, reducing the burden on the end-user. The modular design allows for easy updates and replacements of individual components without disrupting the entire system.

Comparison with Alternative Models

While a direct cost comparison with alternative models was not conducted, the architecture of this system is designed to be inherently cost-efficient compared to traditional, non-cloud-based systems. Traditional systems often involve higher upfront costs, ongoing maintenance expenses, and less flexibility in scaling resources according to demand. In future work, it would be beneficial to conduct a comprehensive cost comparison with other existing models to quantify the cost savings more precisely. This could involve analyzing both the initial setup costs and the long-term operational expenses, considering different scales of deployment and usage scenarios.

Looking ahead, IoT and digital twin technologies hold the potential to not only replicate but also predict future states. Integration with advanced AI and neural machine learning could enable real-time decision-making, ushering in a new era of self-optimizing systems capable of predicting and adapting to changing conditions without human intervention. The landscape of Internet of Things (IoT) systems is marked by a rich array of sensors and communication protocols, which collectively form the backbone of highly efficient ecosystems. Central to this technological frontier is the concept of digital twin technology, designed to create virtual replicas of physical systems for in-depth analysis and optimization. This approach provides a profound opportunity to enhance system monitoring and management across various sectors, including agriculture. Focusing on specific technologies, LoRaWAN and NB-IoT stand out for their unique capabilities and integration potential. LoRaWAN is particularly adept at enabling long-range communication with minimal power consumption, making it ideal for monitoring devices across extensive areas such as agricultural fields, where energy efficiency is paramount.

This technology forms a foundational element of digital twin architectures, facilitating the remote observation and management of devices in energy-limited scenarios. Conversely, while NB-IoT may present higher initial costs and complexity than LoRaWAN, its superior coverage and energy efficiency provide significant benefits. In the context of digital twins, the extensive data required to accurately reflect complex systems necessitates robust and reliable communication technologies. NB-IoT, supported by major telecommunication networks, offers high fidelity in asset monitoring, and enables consistent data collection from a diverse array of sensors. This capability is critical for real-time analysis and the effective implementation of predictive maintenance strategies. Ensuring the optimization of the architecture when excessive data load reaches the model is unanswered. This shall ensure performance optimization and effective cost-cutting. Looking to the future, the convergence of IoT with digital twin technology holds the promise of transforming predictive capabilities in numerous domains. By integrating with advanced artificial intelligence (AI) and machine learning algorithms, these technologies could foster the development of self-optimizing systems. Such systems would not only replicate current conditions but also anticipate and adapt to future.

Additionally, if the livestock health monitoring system were to be applied in a new country with different breeds of pigs and varying housing conditions, several adaptations would be necessary to ensure the system's effectiveness and accuracy. The performance of the system could be influenced by these new variables, and careful consideration would be required to tailor the system to the local context. Although core functionalities of the system such as data collection, processing, and analysis should generally remain robust when applied to different contexts. However, the system's performance may be affected by factors such as the specific breed of pigs, local environmental conditions, and the nature of housing facilities. These factors could influence the baseline health indicators and behavior patterns that the system monitors, potentially requiring recalibration of the sensors and adjustments in the data analysis algorithms. It is essential to understand that different breeds of pigs may have varying physiological parameters, such as body temperature, heart rate, and activity levels. To ensure accurate data collection, it may be necessary to recalibrate the sensors or select sensors specifically suited to the new breed's characteristics.

Furthermore, the thresholds for detecting anomalies in health indicators might need to be adjusted to account for local variations. What constitutes a normal heart rate or activity level in one breed or environment might differ in another. By addressing these factors, the system can be effectively deployed in diverse environments, maintaining its accuracy and reliability in monitoring livestock health. In developing the livestock health monitoring system, the primary vision was to create a solution that could provide real-time monitoring of critical health indicators, allowing farmers to respond immediately to potential issues. Additionally, the system was designed with scalability in mind, ensuring that it could seamlessly manage data from a growing number of animals, regardless of farm size. These goals reflect an idealistic vision of a technologically advanced, responsive, and adaptable system capable of enhancing livestock management on a large scale. However, achieving these idealistic goals in practice presented several challenges. While the system was designed for real-time monitoring, the reliability of data transmission was dependent on network availability, which could be inconsistent in rural farming environments. Additionally, maintaining the accuracy of real-time data processing required robust computational resources, which might not be readily available in all settings.

Given these challenges, it became necessary to set realistic expectations regarding the system's capabilities. The definition of 'real-time' monitoring was refined to acknowledge potential delays in data processing and transmission, particularly in environments with limited network connectivity. Hence, we propose the use of Nb-IoT in place of the LoRaWAN technology for effective and efficient transmission of data in remote areas.

This ensured that the system's capabilities were grounded in practical realities, balancing the initial idealistic vision with the operational challenges identified during testing."

In comparing the idealistic vision with the practical outcomes, it is evident that while the system successfully demonstrated the potential for real-time monitoring and scalability, certain limitations emerged that must be addressed in future work. The practical constraints identified during testing provide valuable insights for refining the system, ensuring that future iterations can more closely align with the original goals while remaining grounded in the realities of agricultural environments. This approach ensures that the system not only meets technological aspirations but also delivers tangible benefits in the complex and variable conditions of modern agriculture.

In the development and deployment of any data-driven system, ethical considerations are paramount, particularly in fields like agriculture where both animal welfare and data privacy are concerned. A key ethical aspect of this research involves ensuring data anonymity. In the context of livestock health monitoring, data related to individual animals must be handled with care to prevent any potential misuse or breach of privacy. Although the data primarily pertains to animals, which do not have personal identity concerns like humans, the anonymity of data can still be significant in maintaining the integrity of research and protecting farm operations from potential exploitation or unfair scrutiny.

Another critical ethical consideration is the potential harm to animals. This system, designed to monitor the health of livestock, inherently carries the responsibility of ensuring that the data collection methods do not cause stress, discomfort, or harm to the animals being monitored. The use of non-invasive sensors and careful monitoring protocols are essential to minimize any negative impact on animal welfare. Bias in predictive analysis is also a significant concern. Predictive models, if not carefully designed and tested, can lead to biased outcomes that might favor certain breeds, conditions, or management practices over others, potentially leading to unequal treatment of animals or incorrect health interventions. Ensuring that the predictive algorithms are trained on diverse and representative datasets is crucial to avoid such biases. Furthermore, the continuous evaluation and adjustment of these models are necessary to ensure fair and accurate predictions across different farming contexts.

Chapter 6 Conclusions

In the realm of agricultural technology, automated smart livestock monitoring systems represent a frontier yet to be fully conquered. While substantial technological advancements have been achieved, the seamless integration of these systems into daily farm operations with minimal human oversight remains a challenging endeavor. This study has taken significant strides toward overcoming these challenges by developing and refining an intelligent livestock monitoring architecture. Our extensive testing of the system's most critical aspects from sensor accuracy to network resilience—has confirmed its robust functionality and reliability. These positive outcomes demonstrate the system's readiness for broader adoption in livestock farms. The core of our contribution through this paper is the presentation of a novel IoT architecture that stands out due to its independence from the IoT device layer. This design is not only innovative but highly adaptable, supporting a wide variety of data formats, enhancing feature extensibility, and accommodating diverse communication protocols. One of the key strengths of this architecture is its ability to adapt to future technological changes. By decoupling the IoT layer from the cloud, we have created a system that can easily integrate new devices or update communication protocols without disrupting existing operations. This flexibility is crucial for maintaining the longevity and relevance of the system as technological standards evolve. Additionally, the use of Narrowband IoT (Nb-IoT) technology is a pivotal aspect of our system design. Nb-IoT enhances the system by minimizing power consumption, which is crucial for long-term, sustainable operations in remote or difficult-to-access areas. This technology also extends the coverage area well beyond that of traditional monitoring systems, reaching deep indoor environments where conventional signals might falter. Moreover, the inherent simplicity of the Nb-IoT devices ensures that the system remains manageable and scalable, even as farm operations grow or as the technology landscape shifts. These enhancements made possible by Nb-IoT not only meet but exceed the current requirements for modern livestock management, offering unprecedented levels of operational efficiency, data reliability, and system scalability. This robust validation of the architecture marks a significant milestone in the journey towards automated, smart livestock management systems and sets a new benchmark for the industry, promising enhanced predictive analytics, and operational efficiencies. The practical implications of these advancements are profound, signaling a shift towards more proactive and precision-based farming practices that could redefine livestock management in the years to come.

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