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Research paper

COGNIHERD: Livestock Health Monitoring Using Artificial Intelligence (AI) and Internet of Things (IoT)

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KEYWORDS

CogniHerd
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Artificial Intelligence
Internet of Things
Anomaly Detection
Predictive Modeling
ESP8266
Arduino Uno
Sustainable Agriculture
XAI

ABSTRACT

The amalgamation of Artificial Intelligence (AI) and Internet of Things (IoT) technologies is revolutionising livestock health monitoring, offering novel ways to improve animal welfare and productivity. This document introduces the CogniHerd system. "CogniHerd amalgamates two root words: "Cogni," derived from the Latin "cognitio," signifying knowledge or awareness, which embodies the AI-driven intelligence and data analysis within the system, and "Herd," originating from the Old English "heord," denoting a collective of domesticated animals. CogniHerd represents the astute management and surveillance of livestock with AI and IoT technologies to enhance health and welfare, employing an ESP8266, Arduino Uno, audio sensors, temperature sensors, and video sensors for real-time health monitoring of animals. The system gathers essential measurements, encompassing physiological factors and behavioural data. CogniHerd employs advanced AI methodologies, including anomaly detection and predictive modelling, to facilitate the early diagnosis of health issues, hence enhancing informed decision-making. A case study of a participating farm illustrates the system's efficacy in identifying health anomalies and enhancing livestock management, attaining an accuracy of 0.9. The study also examines issues with data privacy, infrastructure demands, and interoperability. The findings underscore the CogniHerd system's capacity to augment conventional cattle management approaches, facilitating sustainable agriculture via enhanced health monitoring and proactive interventions.

1. Introduction

1.1 "CogniHerd " Term Origin & Definition

"COGNI" = Latin "cognitio" (knowledge/awareness), **"HERD"** = Classical English "heord" (domesticated animals).
"CogniHerd, a term introduced by Gurjant Singh as a principal title for his project, amalgamates two root words: 'Cogni,' derived from the Latin 'cognitio,' signifying knowledge or awareness, which embodies the AI-driven intelligence and data analysis within the system, and 'Herd,' originating from the Old English 'heord,' denoting a collective of domesticated animals."

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In unison,
"CogniHerd denotes the astute administration and surveillance of livestock through AI and IoT technologies to enhance health and welfare."
CogniHerd is a comprehensive system developed to oversee animal health through the integration of Artificial Intelligence (AI) and Internet of Things (IoT) technology. It utilises IoT devices, including sensors (e.g., audio, temperature, camera), and AI algorithms (e.g., anomaly detection, predictive modelling) to gather and analyse real-time physiological, behavioural, and environmental data from livestock. The technology facilitates early disease identification, behavioural observation, and proactive health administration, assisting farmers in optimising herd management, enhancing animal welfare, and increasing farm productivity.

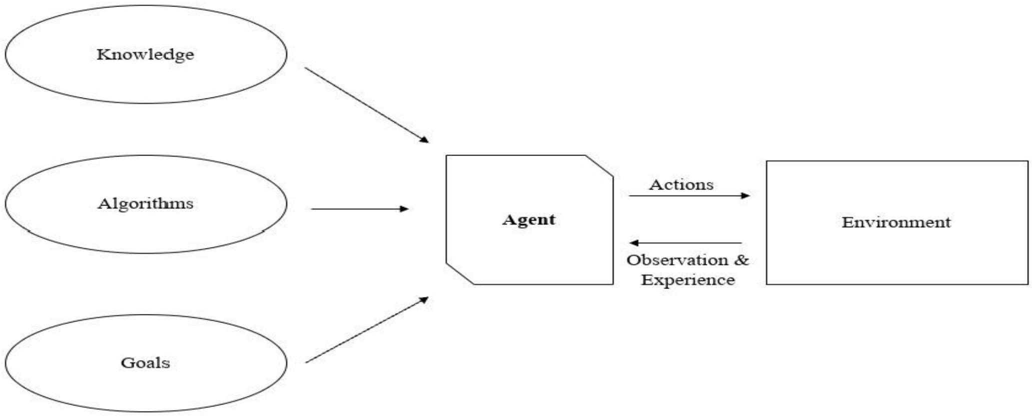

Fig. 1 Schematic Illustration Of A Typical Block Diagram Of An AI (Artificial Intelligence) System

1.2 Overview of Livestock Health Challenges

Livestock health management is fundamental to agricultural production and sustainability, profoundly influencing food security and economic results. Conventional approaches to monitoring cattle health predominantly depend on visual assessments, manual documentation, and delayed reactions to health concerns, frequently leading to less than ideal results. Health issues including mastitis in dairy cattle and respiratory infections in poultry sometimes go unnoticed until they escalate, resulting in diminished output, heightened veterinary expenses, and possible animal fatalities (Abubakar, M. et al., 2020).

The expanding magnitude of contemporary agriculture exacerbates these difficulties. In extensive operations involving thousands of animals, it is virtually unfeasible for farmers to manually monitor and assess the health of each individual animal efficiently. This leads to the recurrent late identification of infections, intensifying the dissemination of illnesses throughout the herd or flock (Rasu, Eeswaran. Et al., 2022). Furthermore, rural regions frequently encounter a deficiency of veterinary practitioners, complicating early diagnosis and treatment (Villarroel, Aurora et al., 2010).

Moreover, due to increasing consumer and regulatory emphasis on animal welfare, producers face pressure to adhere to rigorous animal health and welfare requirements. Effective monitoring is essential for safeguarding animal welfare and sustaining the economic viability of agricultural enterprises (Sardar, Muhammad et al., 2023). Conventional approaches also fail to consider external elements, such as climatic conditions (e.g., temperature or humidity), which can significantly impact livestock health if not regularly monitored (Habeeb, AA. et al., 2023).

1.3 Role of Emerging Technologies

Innovative technologies like Artificial Intelligence (AI) and the Internet of Things (IoT) are revolutionising cattle health monitoring by providing a more automated and data-centric methodology. The Internet of Things (IoT) encompasses the utilisation of interconnected devices such as sensors, wearable trackers, and cameras to collect real-time data on diverse health metrics, including temperature, heart rate, mobility, and feeding behaviours. These devices produce continuous data streams that can be analysed with AI algorithms, which are proficient at detecting patterns and abnormalities that may signify early health issues (Chaudhry, Abdul. Et al., 2020).

The amalgamation of AI and IoT empowers farmers to transition from reactive to proactive health management. AI-powered systems can identify subtle behavioural or physiological changes that occur before to the manifestation of clinical symptoms, rather than waiting for overt evidence of sickness (Wei-Hsun Wang & Wen-Shin Hsu, 2023). Minor alterations in locomotion, dietary behaviours, or physiological indicators may indicate the preliminary stages of illness. AI-driven predictive analytics can anticipate health hazards, enabling farmers to take preventive measures before diseases proliferate or inflict substantial damage (Sk Injamamul Islam et al., 2024). CogniHerd exemplifies an AI-IoT system that delivers a holistic strategy for animal health, offering real-time information and automatic notifications for prompt intervention.

AI and IoT technology extend beyond disease detection. They serve a vital role in enhancing breeding procedures, controlling nutrition, and assuring compliance with animal welfare requirements. AI algorithms can track reproductive cycles and forecast optimal breeding periods, enhancing animal productivity (Wassie, Awoke. Et al., 2024). Likewise, IoT-enabled sensors can monitor animals' feed consumption and weight increase, assisting farmers in optimising nutrition management (Muhammad Osama Akbar et al., 2020). These technologies jointly enhance a comprehensive approach to animal health and welfare.

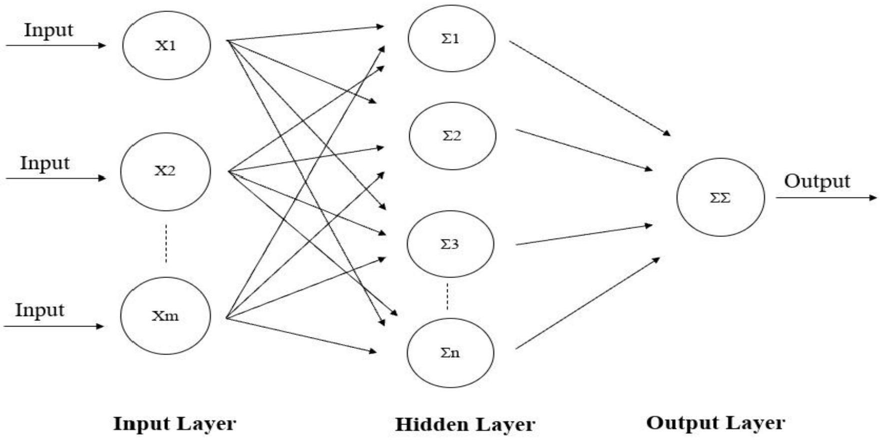

Fig. 2 Artificial Neural Network System (ANNs), Building Blocks of AI

1.4 Purpose and Scope of the Paper

This study examines the progress in AI and IoT technologies, emphasising its implementation in animal health monitoring within the CogniHerd framework. The objective is to examine the present condition of AI-IoT integration in agriculture, evaluating its advantages for real-time disease diagnosis, predictive health management, and animal welfare. The evaluation will also address the constraints of large-scale implementation of these technologies, including data privacy issues, substantial initial expenditures, and the necessity for dependable internet connectivity in remote regions (Abreu, C. & van Deventer, Jacobus. 2022).

This review aims to emphasise successful case studies, demonstrate how AI and IoT are improving cattle health outcomes, and offer insights into the future possibilities of smart agricultural technology. This initiative is to enhance the existing knowledge on precision agriculture and provide practical guidance for farmers, researchers, and policymakers focused on improving livestock health management through technological innovation (Curti, PF. 2023).

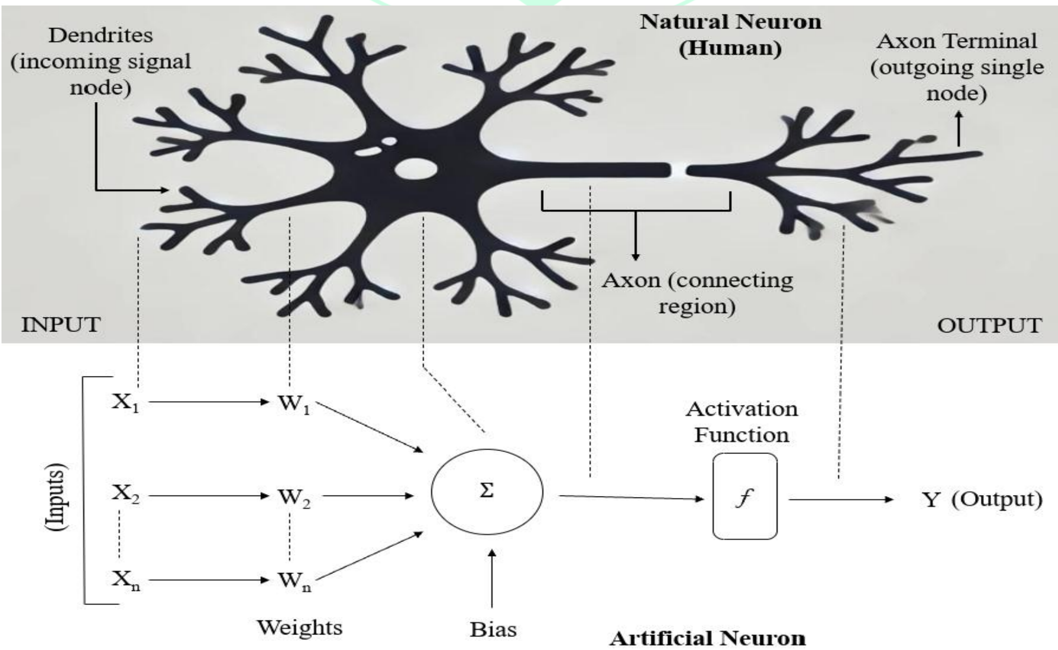

Fig. 3 Homology & Analogy of Natural Neuron (Human Neuron) vs Artificial Neuron (Machine Neuron)

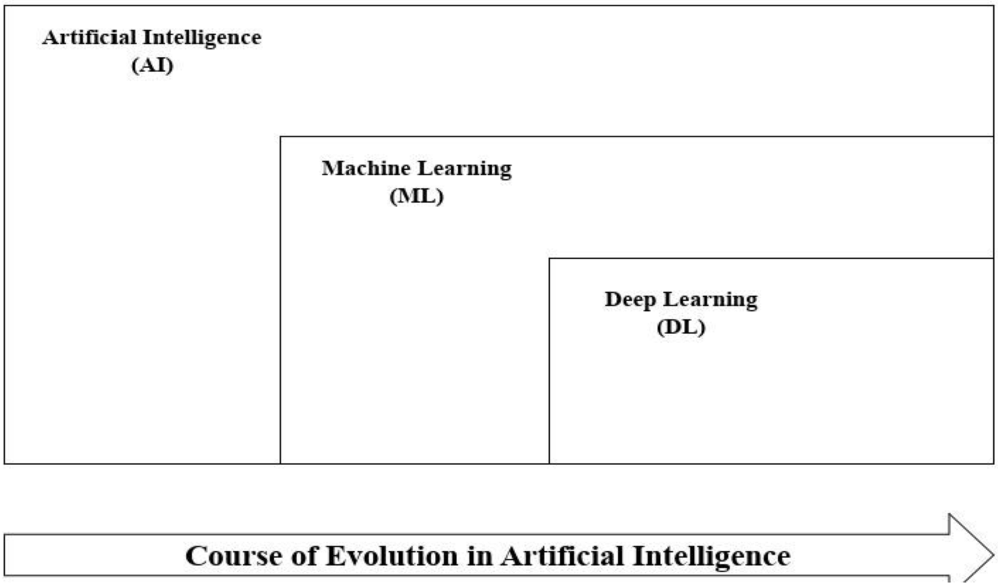

Fig. 4 Evolution of Artificial Intelligence (AI)

2. Literature Review

The emergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has transformed multiple sectors, including agriculture. This literature review examines the present research and uses of AI and IoT technologies in animal health monitoring, emphasising significant findings, improvements, and problems.

2.1 AI Applications in Livestock Health Monitoring

Artificial intelligence has gained prominence in agriculture, especially in the monitoring of animal health. Machine learning algorithms, particularly those employing deep learning, have proved essential in analysing intricate datasets produced by IoT devices. Researchers have effectively utilised convolutional neural networks (CNNs) to analyse images captured by cameras observing animal behaviour. These systems can identify minor alterations in animal posture or movement, signifying possible health concerns (AlZubi Ali Ahmad, Al-Zu'bi Maha. 2023). These applications illustrate the effectiveness of AI in improving disease identification and facilitating prompt interventions.

Predictive analytics, a domain of AI application, facilitates the predicting of health-related occurrences utilising past data. Through the analysis of trends in animal behaviour and environmental variables, AI systems can forecast disease outbreaks, facilitating preventive interventions. A study by Wassie, Awoke, et al. (2024) underscored the efficacy of AI in forecasting health outcomes, accentuating the capacity of these technologies to improve comprehensive herd management.

2.2 IoT Innovations in Livestock Monitoring

The significance of IoT in monitoring animal health is substantial. IoT technologies, encompassing sensors and wearable devices, provide real-time data acquisition on diverse health parameters, including heart rate, temperature, and activity levels. These technologies furnish farmers with instantaneous insights into their livestock's health, facilitating swift responses to arising issues (R., Balamurugan & Alagarsamy, Manjunathan. 2023).

An important benefit of IoT devices is their capacity to provide detailed health profiles for individual animals. By gathering continuous data over time, farmers can monitor trends and recognise variations from standard behaviour, facilitating early identification of potential health issues. Unold, O. et al. (2020) discovered that the incorporation of IoT technology in cattle management markedly enhanced the precision of health monitoring and diminished the response time to health concerns.

2.3 Synergy of AI and IoT

The integration of AI and IoT technology provides significant advantages for monitoring animal health. Artificial Intelligence can evaluate the extensive data produced by Internet of Things devices, yielding actionable insights that enhance decision-making. This collaboration improves real-time monitoring, predictive diagnoses, and autonomous interventions, resulting in a more efficient livestock management system (Ding, Mike & Mahadasa, Ravikiran, 2019).

AI systems can analyse data from wearable sensors to detect trends that signify health problems, such as alterations in food behaviour or diminished activity levels. By integrating these insights with environmental data, including temperature and humidity, farmers may make informed decisions regarding necessary treatments to sustain animal health. Neethirajan, S. (2024) demonstrates that this integration enhances disease management and overall herd productivity.

2.4 Case Studies and Real-World Implementations

Numerous case studies demonstrate the effective application of AI-IoT systems in monitoring livestock health. A prominent instance is the FarmWizard platform, which amalgamates IoT sensors and AI analytics to assess cattle health. This system has shown considerable advancements in disease identification and herd management, offering farmers real-time data and predictive insights (Darvesh, Karthika, et al., 2023).

Nonetheless, obstacles persist in the implementation of AI-IoT systems in agricultural settings. Economic obstacles, like the elevated expenses of technology and infrastructure, can impede adoption, especially among small-scale farmers. Furthermore, technical obstacles, such as data integration and interoperability across diverse devices, must be resolved to guarantee flawless functionality (Hussein, Abbas, et al., 2024).

2.5 Benefits and Ethical Considerations

The advantages of incorporating AI and IoT in animal health monitoring are extensive. These technologies augment disease prevention, refine decision-making, and diminish labour expenses. Through the automation of data gathering and analysis, farmers can concentrate on strategic decision-making and enhance overall agricultural productivity (Kushagra Sharma & Shiv Kumar Shivandu, 2024).

Nevertheless, ethical considerations must also be considered. Concerns over data privacy and the likelihood of diminished human engagement with livestock pose significant enquiries concerning the ramifications of automation in agriculture. Prioritising animal welfare is crucial as the agricultural industry increasingly depends on technology for livestock management (Coghlan, S., & Quinn, T. 2024).

2.6 Future Directions and Innovations

Anticipating the future, numerous advancements and improvements are projected to influence the domain of animal health monitoring. Advanced AI methodologies, like swarm intelligence and explainable AI, offer potential for augmenting system functionalities. Swarm intelligence facilitates decentralised decision-making by emulating the behaviours of social creatures, whereas explainable AI enhances transparency and confidence in AI systems (Li, Zhang, et al., 2023).

Furthermore, the advancement of IoT technologies and the deployment of 5G networks will significantly improve real-time data transmission and processing capacities. The integration of modern sensors and high-speed communication will provide increasingly complex applications, including remote monitoring and automated interventions (Dixit, Sheetal et al., 2024).

The amalgamation of AI and IoT technology in animal health monitoring signifies a revolutionary change in agricultural methodologies. Despite notable progress, issues concerning cost, scalability, and ethical implications require resolution. Ongoing research and innovation are crucial for realising the complete potential of these technologies, resulting in healthier cattle and more sustainable agricultural operations.

3. Materials and Methodologies

This section delineates the materials and methodology employed in the development and deployment of AI and IoT technologies for cattle health monitoring, emphasising the design and application of the CogniHerd system. The approaches include data collecting, system architecture, artificial intelligence algorithms, and evaluation metrics.

3.1 System Architecture

The CogniHerd system features a modular architecture that incorporates IoT devices, AI algorithms, and cloud computing services. The architecture comprises the following essential components:

Internet of Things (IoT) Devices: This encompasses many sensors and wearable gadgets utilised on animals for ongoing surveillance. The sensors gather essential health parameters including temperature, heart rate, activity level, and environmental variables.

Frequently utilised devices comprise:

Biometric sensors: These devices assess physiological characteristics such as heart rate and body temperature.

GPS Trackers (Accelerometer): Employed to monitor the movement patterns and locations of cattle. Environmental Sensors: Quantify temperature, humidity, and more environmental variables influencing animal health.

Data Processing Layer: This layer comprises edge computing devices that preprocess data from IoT sensors to minimise latency and bandwidth consumption. Edge devices preprocess and consolidate data prior to transmitting it to the cloud for additional analysis.

Cloud Computing Services: The cloud platform facilitates the storage of substantial data quantities and the execution of intricate AI algorithms. This architecture permits scalable data analytics and supports the implementation of machine learning models.

3.2 Data Collection

Data gathering has two principal phases: real-time monitoring and historical data aggregation.

Continuous Data Collection: Information is gathered incessantly from the IoT devices. Data streams are conveyed to edge computing devices via wireless communication protocols like LoRaWAN or NB-IoT. The data include physiological indicators, such as body temperature and heart rate. Behavioural data (e.g., activity levels, feeding behaviours) Environmental metrics (e.g., temperature, humidity, and air quality).

Historical Data Accumulation: Data amassed over time is retained in the cloud database. This historical data underpins the training of AI models and the advancement of predictive analytics capabilities.

3.3 AI Algorithms

The AI element of the CogniHerd system utilises various machine learning methodologies to examine the gathered data and extract meaningful insights. Principal algorithms comprise:

Anomaly Detection: Algorithms like Isolation Forest and One-Class SVM are employed to detect atypical patterns in animal behaviour that may signify health problems. This method facilitates early disease identification.

Predictive Modelling: Methods such as regression analysis and time-series forecasting are employed to anticipate health outcomes utilising past data. Models can predict probable disease outbreaks by examining patterns in physiological and environmental variables.

Deep Learning: Convolutional neural networks (CNNs) are utilised for image analysis in the observation of livestock behaviour. Cameras positioned in barns may photograph livestock, while convolutional neural networks can categorise behaviours or detect health issues through visual indicators.

3.4 Evaluation Metrics

To evaluate the efficacy of the CogniHerd system, various assessment measures are utilised:

Accuracy and Precision: These measures assess the efficacy of predictive algorithms in accurately diagnosing health conditions. Accuracy is the ratio of properly predicted observations to the total number of observations, whereas precision quantifies the ratio of true positives to the aggregate of true positives and false positives.

Response Time: The duration required for the system to identify a health abnormality and notify the farmer Is crucial. Reduced reaction times signify a more effective monitoring system.

User Satisfaction: Surveys and comments from farmers are administered to assess the system’s usability and efficacy. Metrics of user satisfaction assist in pinpointing areas requiring enhancement.

3.5 Case Study Implementation

To validate the effectiveness of the CogniHerd system, a case study was conducted on a participating farm. The implementation involved:

Deployment of IoT Devices: A selection of biometric sensors, GPS trackers, and environmental sensors was installed on the livestock.

Training of AI Models: Historical data was utilized to train the predictive models. The models were iteratively refined based on feedback and additional data collected during the monitoring phase.

Monitoring and Data Analysis: The system was monitored for several months to collect real-time data and assess the performance of AI algorithms in detecting health issues.

A case study was done on a participating farm to assess the efficacy of the CogniHerd technology. The execution encompassed:

Implementation of IoT Devices: A variety of biometric sensors, GPS trackers, and environmental sensors were mounted on the cattle.

AI Model Training: Historical data was employed to train the predictive models. The models were progressively enhanced using feedback and supplementary data gathered throughout the monitoring period.

Surveillance and Data Evaluation: The system underwent monitoring for several months to gather real-time data and evaluate the efficacy of AI algorithms in identifying health concerns.

3.6 Limitations

During the implementation of the CogniHerd system, certain constraints were recognised:

Concerns Regarding Data Privacy: The accumulation and retention of sensitive data have elicited apprehensions about data privacy and security. Comprehensive encryption and access controls were established to alleviate these issues.

Infrastructure Specifications: The system's effectiveness depended on reliable internet connectivity and the presence of essential infrastructure, which might be problematic in remote regions.

Challenges of Integration: The interoperability of various IoT devices and platforms presents hurdles, highlighting the need for standardisation in future advancements.

This section details the resources and procedures that establish a thorough foundation for designing and implementing the CogniHerd system for monitoring livestock health. The system seeks to optimise animal health monitoring, increase production, and promote sustainable agricultural practices through the use of IoT devices and sophisticated AI algorithms. Future endeavours will concentrate on rectifying the highlighted shortcomings and augmenting the system's capabilities to facilitate wider applications in animal health monitoring.

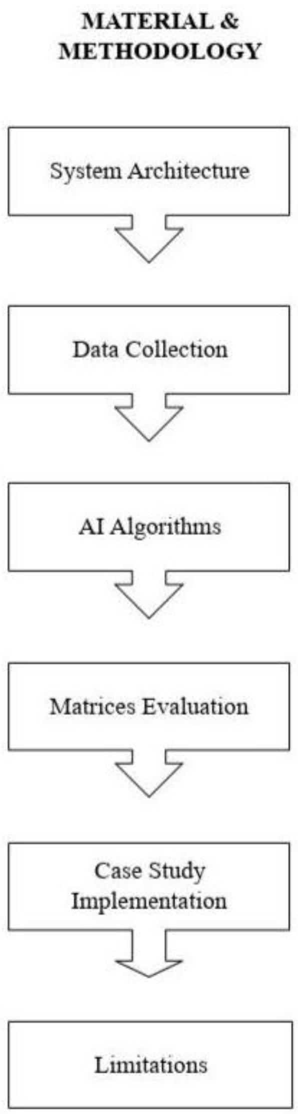

Fig. 5 Material & Methodology of CogniHerd System

4. Existing System of Livestock Health Management

Historically, dairy farms depended on manual observation methods to identify health-related problems in cattle, necessitating constant or daily surveillance by farmworkers. These conventional approaches were arduous and susceptible to inaccuracies, especially when symptoms were not overtly evident. Agriculturists frequently required visual evaluations of sickness indicators, such alterations in behaviour, food habits, or physical condition; nevertheless, these methods were not consistently dependable and could result in erroneous judgements. Misdiagnosis or delayed disease detection presents considerable dangers to cattle health, frequently resulting in exacerbated conditions or heightened mortality (Aleluia, Vitor et al., 2022).

Furthermore, conventional methods were insufficient in detecting early-stage diseases that do not exhibit obvious exterior symptoms, resulting in a reactive rather than a preventive strategy in animal healthcare. The lack of early detection methods resulted in frequent treatment delays, adversely affecting overall animal welfare and productivity (Pengguang, He. et al., 2022). Moreover, ongoing manual oversight required substantial labour, particularly for extensive herds, thus leading to economic inefficiencies for farmers.

In response to these issues, researchers have suggested automated solutions that incorporate AI and IoT technology to enhance cattle health monitoring. These systems incessantly monitor essential health metrics, including temperature, mobility, and heart rate, utilising wearable sensors and IoT devices. AI algorithms subsequently examine the gathered data to deliver real-time insights and facilitate the early identification of any health concerns, enabling prompt action and treatment (Shajari S. et al., 2023). This method decreases labour demands while simultaneously enhancing accuracy and expediting illness identification, hence greatly improving animal health and operating efficiency on farms (Dayoub, Moammar et al., 2024).

The necessity for automated health monitoring systems is clear, as they provide more accurate and rapid disease diagnosis than conventional methods, facilitating early intervention and diminishing the total risk to cattle health (Neethirajan, Suresh. Et al., 2017).

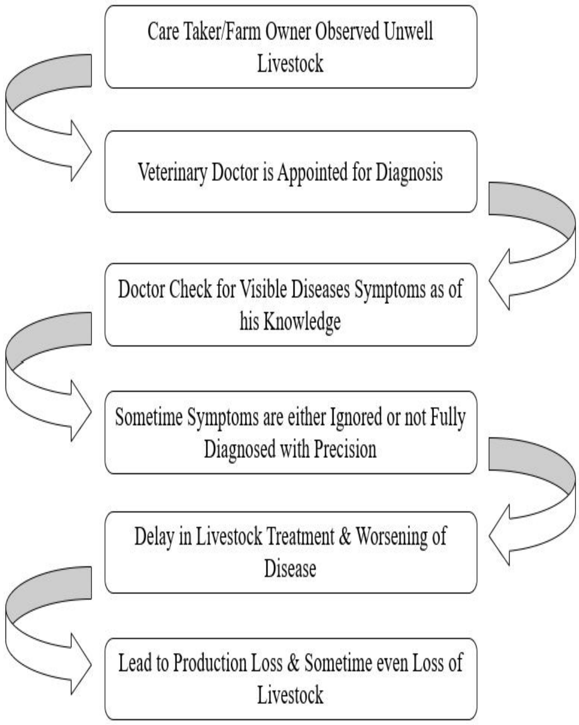

Fig. 6 Flow Diagram of Existing System Of Livestock Health Monitoring

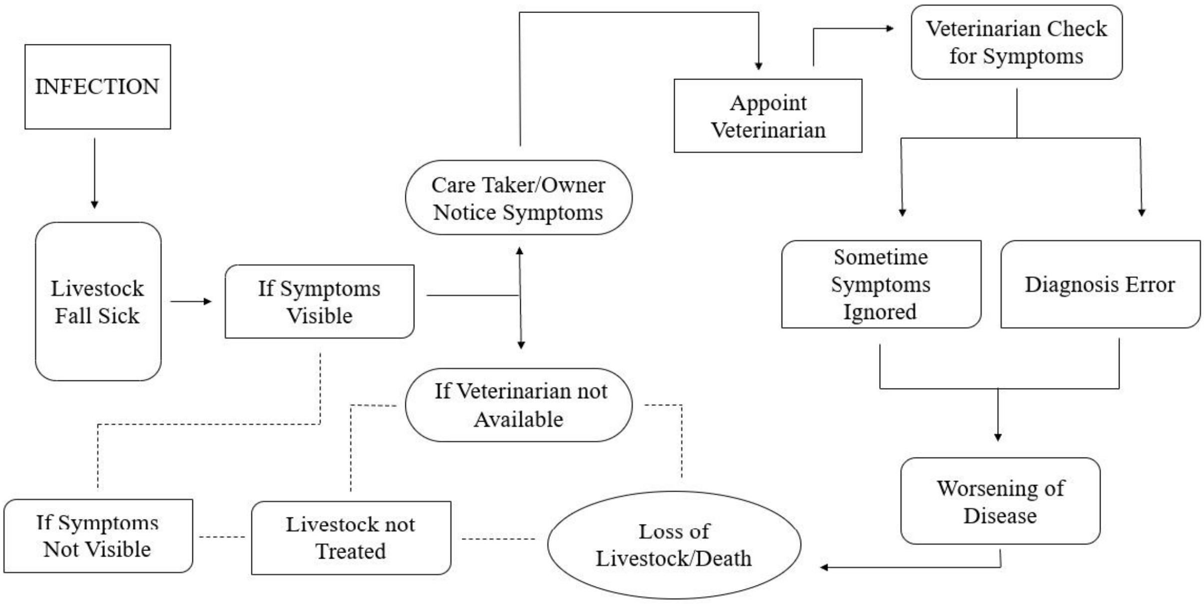

Fig. 7 Schematic Representation of Existing System For Livestock Health Monitoring

5. Gaps in Existing System of Livestock Health Management

The current animal health monitoring systems include significant shortcomings that impede their efficacy, especially as farms expand and new health issues arise.

5.1 Manual Monitoring is Time-Consuming and Prone to Errors

Conventional health monitoring techniques predominantly depend on visual assessment and human evaluation. These procedures are both laborious and susceptible to inaccuracies, particularly in identifying nuanced alterations in animal behaviour or health condition. As agricultural operations expand, it becomes progressively challenging for employees to consistently observe individual animals, frequently resulting in the oversight of early-stage disease symptoms (Linas, Saikevičius, et al., 2024). The assessment of animal health is significantly compromised by human error, diminishing the efficacy of early illness detection methods.

5.2 Limited Data Analysis Misses Crucial Indicators

Manual systems generally lack comprehensive data analytics, resulting in the potential oversight of crucial markers such minor fluctuations in temperature, heart rate, or movement patterns that may indicate the onset of illness. In the absence of continuous data collection and analysis, farmers frequently depend on observable symptoms that typically manifest only after a disease has advanced considerably (K. Darvesh et al., 2023). This constraint hinders timely responses that could mitigate animal suffering and economic losses.

5.3 Subjectivity Leads to Variations in Diagnosis

Health assessments reliant on human observation are intrinsically subjective, resulting in diagnostic variations among various farmworkers or even across different farms. Two personnel may evaluate the same animal differently based on their experience and subjective judgement, resulting in inconsistencies in treatment decisions (Vourc'h, G. et al., 2006). This variability contributes to the ambiguity of animal health status and undermines the precision of disease management measures.

5.4 Challenges in Real-Time Monitoring and Scalability

Conventional livestock health monitoring systems face challenges in real-time, large-scale surveillance, particularly on commercial farms housing hundreds or thousands of animals. Daily monitoring of such a substantial number of animals is impracticable using manual methods. Moreover, these systems lack real-time updates, hindering rapid responses to emergent health issues (Papakonstantinou, Georgios I. et al., 2024). The gathering and analysis of real-time data are essential for swift measures that can avert disease transmission.

5.5 Lack of Predictive Analytics and Data Integration

Predictive analytics, essential for preempting health risks, is lacking in the majority of conventional monitoring techniques. These systems predominantly depend on reactive measures, responding solely to observable indications of sickness. Moreover, they lack data integration skills, resulting in the failure to amalgamate information regarding an animal's health history, environmental circumstances, and other pertinent data points for educated forecasts or judgements (Papst, Franz et al., 2019). In the absence of integrated data, farmers possess disjointed information that constrains their capacity to proactively oversee animal health.

5.6 Higher Costs and Inefficiencies in Traditional Methods

Manual monitoring involves considerable labour and frequently results in inefficiencies, including postponed diagnosis and treatment. The labour expenses linked to ongoing manual inspections can be substantial, particularly in extensive agricultural enterprises. Furthermore, the imprecision of these procedures frequently leads to superfluous veterinary interventions or the oversight of early-stage disorders, hence escalating overall expenses (Aleluia, Vitor. et al., 2022). This inefficiency constitutes a significant obstacle to enhancing agricultural productivity and preserving animal health.

The deficiencies of current systems underscore the pressing necessity for the implementation of more sophisticated, automated health monitoring technologies, such as artificial intelligence and the Internet of Things, which can address numerous difficulties by delivering real-time, data-driven insights and diminishing dependence on manual labour.

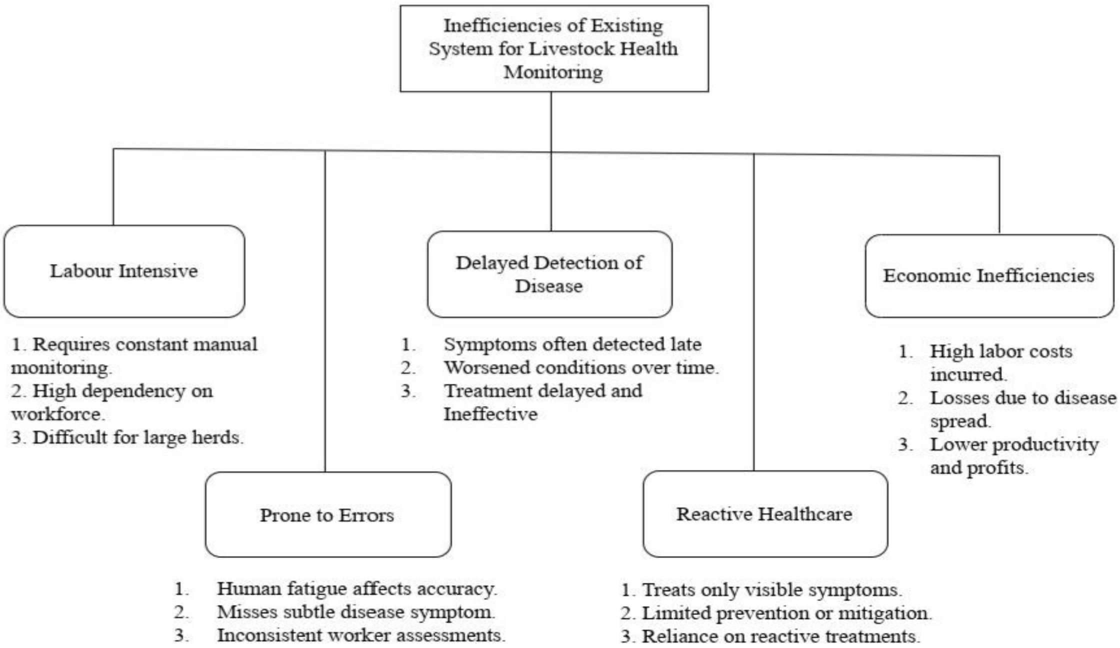

Fig. 8 Inefficiencies of Existing System For Livestock Health Monitoring

6. Proposed System of Livestock Health Management

Recently, the utilisation of machine learning (ML) methodologies has markedly increased in veterinary medicine, especially in forecasting disease occurrences in cattle (Guitian, J. et al., 2023). This suggested method intends to utilise powerful machine learning techniques to accurately detect several diseases common in cattle within disease-prone communities.

The primary aim of this system is to employ past cow health data gathered from real-world situations to develop and evaluate predictive models. Utilising modified estimating methods, the system can deliver actionable insights into cow health management, facilitating prompt interventions and perhaps mitigating disease outbreaks (Swain, Satyaprakash. 2024).

A major obstacle in predictive modelling is the problem of inadequate data, which can result from variables such as inconsistent record-keeping or unreported health occurrences (Gorelick, MH., 2006). The suggested system employs a latent factor methodology to recreate absent data points, hence enhancing the dataset's comprehensiveness for analysis. This technique facilitates the estimation of absent values by leveraging the associations present in the available data, hence augmenting the robustness of prediction models (R. Thiyagarajan et al., 2024).

Machine learning, a branch of artificial intelligence, enables the prediction of future events by analysing patterns in historical data. In the realm of cattle health, although machine learning methods are acknowledged for their effectiveness in disease prediction and risk factor identification, there is a significant lack of literature that comprehensively examines these techniques in veterinary science (Swain, Satyaprakashet. Et al., 2024).

The amalgamation of many machine learning methodologies facilitates the examination of varied data kinds, including visual manifestations of diseases, hence enhancing predicted precision (A. A. Chaudhry et al., 2020). The integration of various algorithms seeks to establish a comprehensive method for predicting cow health, resulting in enhanced accuracy and dependability in illness forecasting (García, Rodrigo. Et al., 2020).

We firmly assert that the implementation of this system will enable stakeholders in the agriculture sector to gain superior disease prediction capabilities, resulting in greater herd management and improved animal welfare.

7. Objectives

The main goal of this project is to improve cattle management by utilising artificial intelligence (AI) technologies. The explicit aims are as follows:

1. ***Early Detection of Health Issues:*** The system seeks to enable the swift detection of possible health issues in animals. The AI-driven methodology, through the analysis of diverse data sources, can identify atypical patterns or anomalies that may signify the emergence of diseases, facilitating timely

interventions and mitigating the danger of significant outbreaks (Bohr, A. et al., 2020; AlZubi Ali Ahmad, 2023).

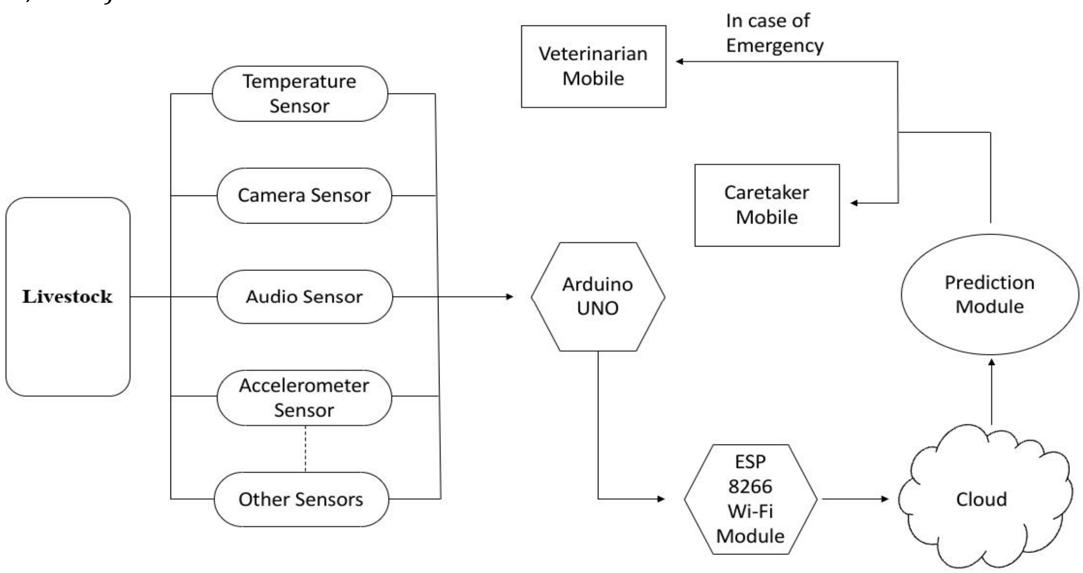

Fig. 9 Flow Diagram Represents The Proposed System (CogniHerd) For Livestock Health Monitoring

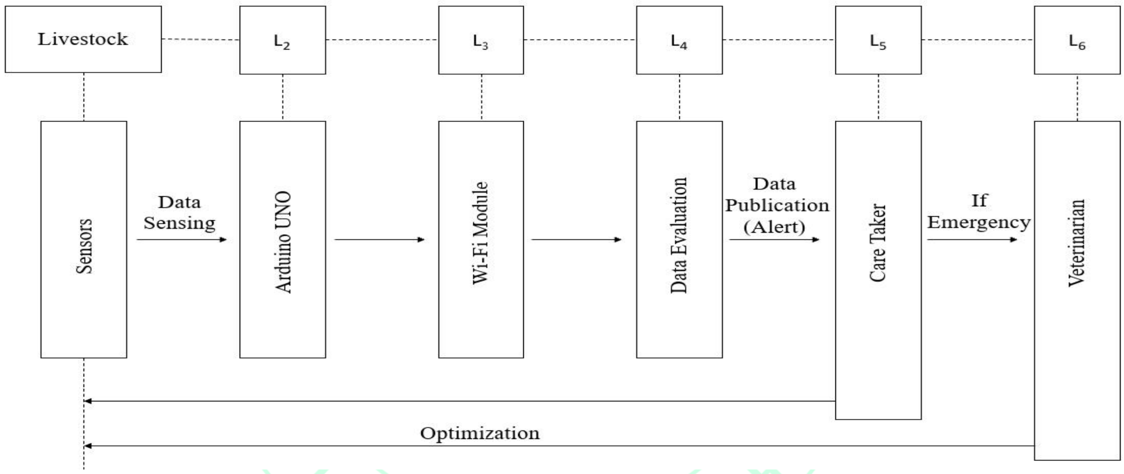

Fig. 10 Block Diagram Showing the Flow of Information through Various Layered System in CogniHerd: A Proposed Livestock Health Monitoring System

2. ***Continuous Real-Time Monitoring of Vital Parameters:*** The manuscript will integrate sensors and data acquisition instruments to perpetually assess critical health metrics, including temperature, heart rate, and activity levels. This real-time data stream offers prompt insights into the animals' welfare, facilitating rapid responses to any alterations in their health condition (Neethirajan, S. 2024; Abdulmalek, S. et al., 2022). The primary diseases addressed in our project case study, covered in the following parts, include faecal identification, voice recognition, bovine mastitis, and temperature monitoring utilising AI and IoT technologies.

3. ***Predictive Analytics for Risk Assessment:*** Utilising predictive analytics, the system will evaluate the probability of health complications based on historical and real-time data. This capability facilitates the identification of risk factors linked to certain diseases, assisting in the formulation of proactive management measures that can alleviate prospective health problems (Alotaibi, Eid. 2023).

4. ***Data-Driven Decision Support:*** The use of AI will facilitate data-driven decision-making processes in cattle management. Stakeholders can utilise insights obtained from the analysed data to make informed decisions about breeding, feeding, and general herd management, hence enhancing productivity and health outcomes (Tantalaki, Nicole a. et al., 2019; Awoke, Melak. Et al., 2024).

5. ***Automation of Monitoring Tasks:*** The research aims to automate conventional, labour-intensive monitoring duties. Employing AI technologies, including machine learning and computer vision, enables the system to optimise data gathering and analysis, thereby reallocating resources for more strategic endeavours in cattle management (AlZubi Ali Ahmad, Al-Zu'bi Maha. 2023).

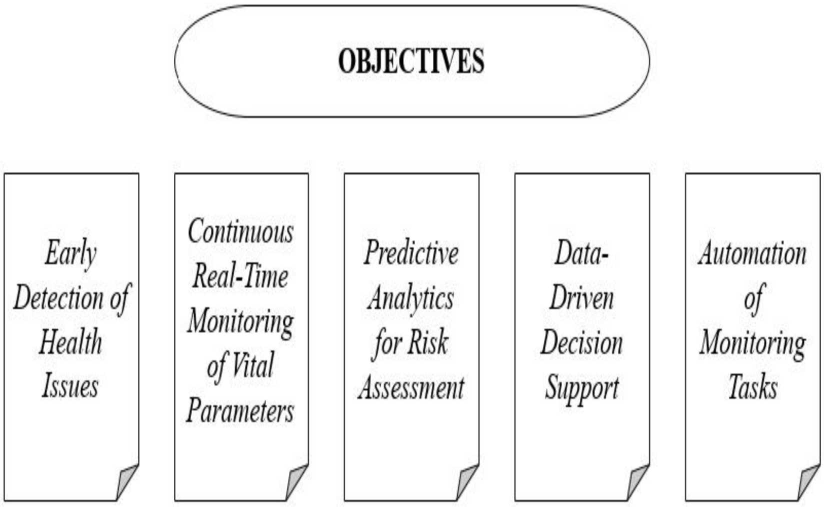

Fig. 11 Key Objectives Of Proposed Livestock Health Monitoring Using Artificial Intelligence (AI) And Internet Of Things (IoT) (CogniHerd System)

8. Fundamentals of AI AND IoT in Livestock Health

8.1 Artificial Intelligence in Agriculture

Artificial Intelligence (AI) has swiftly emerged as a revolutionary influence in agriculture, particularly in the area of animal health monitoring. Artificial intelligence utilises sophisticated computational models, including machine learning and deep learning, to discern patterns in extensive datasets, rendering it especially beneficial for the analysis of intricate biological and environmental factors in agriculture. A key application of AI in livestock health is pattern recognition. By examining previous data regarding an animal's locomotion, dietary behaviours, or physiological indicators, AI systems can detect anomalies from typical patterns that may indicate the first stages of illness (Das, Parinita & Saha, Kaushik. 2022).

Furthermore, AI-driven predictive analytics enables farmers to anticipate potential health problems prior to the manifestation of visible symptoms. Predictive models can evaluate variables such as meteorological conditions, feed intake, and behavioural alterations to anticipate disease outbreaks or nutritional deficits in livestock (Delfani, P., Thuraga, V., Banerjee, B. et al. 2024). This skill allows farmers to implement preventive actions, thereby diminishing the economic and health repercussions of diseases. AI algorithms are proficient at identifying nuances that may be undetectable to the human eye, such as minor alterations in an animal's posture or stride, which can signify injury or disease (Hashem, Tareq & Joudeh, Jamal & Ahmad Zamil, Ahmad. 2024).

Machine learning models can be perpetually taught and enhanced as new data is acquired, hence enhancing their accuracy over time. This iterative learning technique is very beneficial for monitoring the health of individual animals in extensive herds. AI technologies personalise health assessments to guarantee that each animal receives care tailored to its specific biological and environmental circumstances. This is essential for enhancing livestock productivity and safeguarding wellbeing. Zhang, Li, et al. (2023).

8.2 Internet of Things (IoT) in Farming

The Internet of Things (IoT) is essential in contemporary animal health management through facilitating real-time data acquisition and remote surveillance. The Internet of Things (IoT) denotes a network of networked devices, such as sensors, cameras, and wearables, that continuously collect and transmit data. In cattle husbandry, IoT devices are commonly affixed to animals as wearables, such biometric collars, ear tags, or leg bands. These devices can assess many health metrics, including heart rate, temperature, activity levels, and reproductive status (Al-Kahtani MS, Khan F, Taekeun W. 2022).

The data gathered by these IoT devices is transmitted to centralised systems for real-time analysis. This allows farmers to oversee the well-being of their cattle remotely, facilitating prompt responses upon the detection of anomalies. IoT sensors can identify an increase in body temperature that may signify fever or observe irregularities in an animal's movement that could indicate damage or distress. The Internet of Things (IoT) enhances continuous monitoring, so diminishing the likelihood of overlooked health concerns and lessening dependence on manual evaluations (Liang, Chen & Shah, Tufail. 2023).

The Internet of Things (IoT) technology transcends the monitoring of individual animal health. Environmental sensors deployed across the farm can monitor temperature, humidity, air quality, and feed levels, all of which influence animal health. This comprehensive strategy allows farmers to enhance animal welfare and agricultural productivity by modifying environmental controls to sustain ideal living circumstances (Suresh, Neethirajan. 2020).

8.3 Synergy of AI and IoT

The integration of AI and IoT presents exceptional opportunities for transforming animal health management. Although IoT devices deliver a constant flow of real-time data, AI algorithms are crucial for interpreting that data. This collaboration facilitates instantaneous decision-making and anticipatory diagnosis. AI can analyse IoT-generated data to identify trends that signal disease or stress prior to their escalation (Aunindita, Rudaba. Et al., 2022). This allows farmers to use proactive measures, diminishing the necessity for reactive interventions and decreasing the overall healthcare expenses.

Furthermore, AI may independently evaluate data gathered from IoT devices and provide recommendations or implement solutions. For instance, if IoT sensors identify early signals of distress in an animal, AI algorithms can autonomously modify the animal's environment—such as enhancing ventilation or altering feed—without necessitating human intervention. This autonomous intervention capability is especially beneficial for extensive operations, when individualised attention to each animal is difficult (Bao, Jun & Xie, Qiuju. 2022).

The amalgamation of AI and IoT not only augments animal health results but also optimises overall farm efficiency by decreasing labour expenses, reducing antibiotic usage through preventive measures, and assuring adherence to regulatory norms. The ongoing evolution of these technologies is expected to enhance the sustainability, scalability, and animal welfare of farming practices (Karthik, Darvesh. Et al., 2021).

Table 1 Overview of AI, IoT, and Their Synergistic Applications in Modern Livestock Health Management and Farming Practices

Category	Key Applications	Technology Used	Outcomes/Benefits	References
Artificial Intelligence in Agriculture	Detects anomalies in animal behavior and physiological indicators through pattern recognition. Predicts potential health problems using predictive analytics. Identifies subtle signs of illness or injury undetectable to the human eye.	Machine learning and deep learning models. Predictive analytics leveraging environmental and behavioral data.	Early disease detection and prevention. Personalised health assessments for individual animals. Improved livestock productivity and wellbeing.	Das, Parinita & Saha, Kaushik, 2022; Delfani, P., Thuraga, V., Banerjee, B. et al., 2024; Hashem, Tareq & Joudeh, Jamal & Ahmad Zamil, Ahmad, 2024; Zhang, Li, et al., 2023
Internet of Things (IoT) in Farming	Real-time monitoring of health metrics (heart rate, temperature, activity, etc.). Remote surveillance and data acquisition. Monitoring environmental factors like temperature, humidity, and air quality.	IoT wearables (biometric collars, ear tags, leg bands). Environmental sensors for farm-wide monitoring.	Enables prompt responses to anomalies. Reduces manual evaluations and overlooked health issues. Enhances animal welfare through optimized living conditions.	Al-Kahtani MS, Khan F, Taekeun W., 2022; Liang, Chen & Shah, Tufail, 2023; Suresh, Neethirajan, 2020
Synergy of AI and IoT	Real-time interpretation of IoT-generated data using AI. Proactive measures for disease and stress prevention. Autonomous environmental	Integration of IoT data streams with AI algorithms. Autonomous systems for	Reduced healthcare expenses and labour costs. Minimised antibiotic usage through	Aunindita, Rudaba et al., 2022; Bao, Jun & Xie, Qiuju, 2022; Karthik, Darvesh et al., 2021

	adjustments based on sensor data.	intervention and recommendations.	preventive measures. Enhanced sustainability and scalability in farming practices.

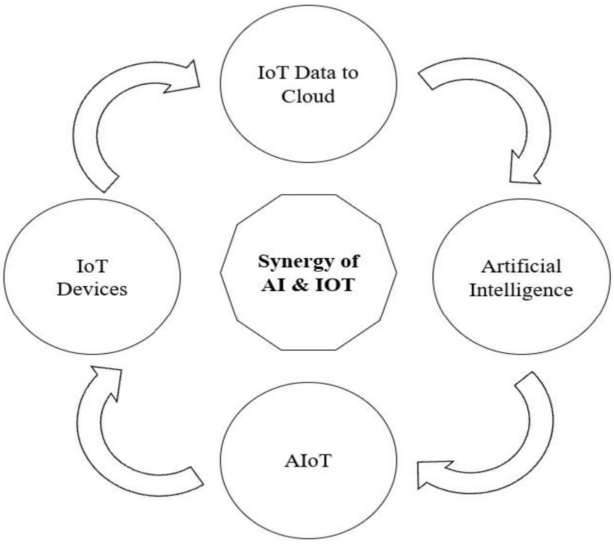

Fig. 12 Integration of Artificial Intelligence (AI) & Internet of Things (IoT) In CogniHerd System

9. Components of the Cogniherd System

9.1 Smart Sensors and Wearable

The foundation of the CogniHerd system is comprised of intelligent sensors and wearable devices that gather real-time data from animals. These IoT-enabled devices provide several features for ongoing health monitoring. Commonly used sensors encompass biometric sensors, GPS trackers, and environmental sensors, each fulfilling a distinct role in preserving animal health and welfare (Suresh Neethirajan, et al., 2017).

Biometric sensors are commonly affixed to animals via collars, ear tags, or leg bands. These sensors track essential physiological parameters including heart rate, body temperature, and respiratory rate. Ongoing surveillance of these markers facilitates the early identification of health issues, including fever, stress, or infection (Bhisham Sharma & Deepika Koundal, 2018). An increased body temperature may suggest a viral infection, whereas irregular heart rhythms could indicate discomfort or metabolic disorders. Biometric sensors monitor reproductive health by tracking hormonal variations and forecasting optimal breeding periods, hence enhancing fertility rates and herd productivity (Awasthi, Amruta et al., 2020).

GPS trackers provide real-time location monitoring, which is especially advantageous for expansive agricultural enterprises as cattle traverse vast territories. These devices can identify variations from typical behaviour by tracking animal movement patterns, which may signify injury, illness, or theft. A cow that remains immobile for extended durations may sustain injuries or become ill. The integration of GPS data with additional biometric information offers a comprehensive perspective on an animal's physical health and activity levels (Schieltz, J.M. et al., 2017; Gaur, Mahesh. Et al., 2013).

Environmental sensors installed across the farm assess parameters like temperature, humidity, air quality, and noise levels. These characteristics are essential for sustaining good living circumstances for animals. Elevated temperatures or subpar air quality can aggravate respiratory conditions or induce heat stress, both of which adversely impact animal health. The system may continuously gather environmental data to notify farmers of potential problems and provide corrective measures, such as altering ventilation or revising feeding schedules (Lee M, & Seo S. 2021).

9.2 AI Algorithms and Models

The AI element of the CogniHerd system is tasked with analysing the extensive data produced by IoT devices. AI algorithms utilise machine learning, deep learning, and reinforcement learning methodologies to identify patterns, forecast health outcomes, and propose remedies (Fuentes, S. et al., 2022).

A key application of AI within the system is anomaly detection. Through the ongoing comparison of real-time data with historical baselines, AI models can identify anomalies that may signify early indicators of illness or discomfort. A gradual yet persistent decline in an animal's activity, accompanied by an increase in body temperature, may indicate the development of an infection (Rajawat, Anand. Et al., 2022). This skill facilitates preventive measures, hence diminishing the necessity for expensive treatments.

Deep learning models are utilised to analyse intricate datasets, such as photos captured by cameras or video feeds employed to observe animal behaviour. These models can identify nuanced alterations in posture, movement, or feeding behaviour that may signify injury or disease. With increased data exposure, deep learning models enhance their accuracy, hence improving the system's efficiency in recognising health concerns (Cheng, Man. Et al., 2022).

Reinforcement learning is an essential AI methodology employed in CogniHerd . It entails instructing AI systems to make decisions by incentivising favourable outcomes and sanctioning unfavourable ones. Reinforcement learning algorithms can optimise feeding schedules, ambient conditions, and treatment plans in livestock management by utilising continuous input from sensor data (Xinyu, Tian. Et al., 2024).

9.3 Edge and Cloud Computing

The CogniHerd system's innovative feature is its utilisation of edge and cloud computing to handle and manage the vast quantities of data produced by IoT devices.

Edge computing pertains to the local processing of data at or near the point of data collection (e.g., on the farm). This method reduces latency, facilitating real-time analysis and decision-making. If a biometric sensor identifies a substantial increase in an animal's temperature, the system can promptly alert the farmer or initiate an automated response, such as modifying the ventilation system to alleviate heat stress. Edge computing facilitates prompt decision-making, which is crucial in extensive operations where delays may lead to overlooked health concerns (Ricardo S. Alonso et al., 2020).

Conversely, cloud computing is employed for comprehensive data processing and prolonged storage. Data gathered from IoT devices is transmitted to cloud platforms, where sophisticated AI algorithms analyse extensive datasets to identify trends and create prediction models. Historical health data from several animals can be analysed to forecast disease outbreaks or determine optimal breeding periods. Cloud computing allows farmers to remotely access their livestock data from any device, offering flexibility and maintaining the constant availability of essential information (Harini, Shree Bhaskaran. Et al., 2024).

CogniHerd integrates the rapidity and efficacy of edge computing with the scalability of cloud platforms, providing real-time insights and facilitating long-term strategic planning, so optimising livestock health management and augmenting farm output.

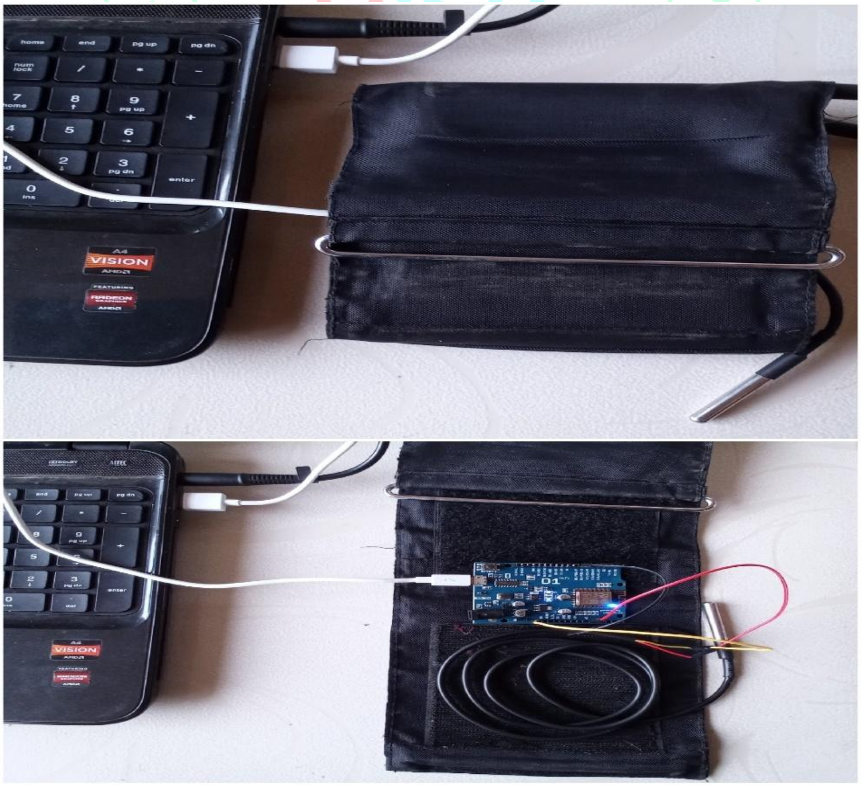

Fig. 13 CogniHerd Wearable Devices

10. Breif Overview of Working Principle of IoT in Livestock Health Monitoring

The Internet of Things (IoT) denotes a network of interlinked devices that exchange and transmit data via the internet. This interconnection allows devices to gather, share, and respond to information autonomously, rendering it a potent instrument for applications like cattle health monitoring (Isaac, Justin. 2021). The operational principle of IoT can be comprehended through several fundamental layers:

1. ***Perception Layer:*** This is the fundamental layer of the IoT architecture, where sensors and actuators collect data from the physical environment. In livestock health monitoring, numerous sensors, such as temperature, heart rate, and movement sensors, are utilised to continuously assess the health and behaviour of the animals. These sensors gather essential parameters that offer insights into the animals' welfare, facilitating the early identification of potential health concerns (Krishnan, Saravanan & S., Saraniya. 2017).

2. ***Network Layer:*** This layer enables communication between devices and centralised servers through various protocols, including Wi-Fi, Bluetooth, and cellular networks. Data gathered by sensors in the perception layer is relayed to a central system for processing and analysis. The network layer guarantees secure and efficient data transfer, facilitating real-time monitoring and prompt responses to identified anomalies (Bello, Oladayo, et al., 2016).

3. ***Application Layer:*** The application layer processes and analyses data gathered from sensors, frequently employing cloud-based services and data analytics platforms. This layer utilises advanced analytical approaches in cattle health monitoring to extract meaningful insights from data, including trend identification, risk assessment, and data-driven management decision-making. Implementing machine learning algorithms at this level can improve predictive analytics, facilitating more precise evaluations of animal health (Gordon, Miriam et al., 2024).

4. ***Edge Computing Layer (Optional):*** This supplementary layer conducts data processing nearer to the source, therefore substantially diminishing latency and bandwidth consumption. By processing data at the edge instead of transmitting all information to a centralised server, the system may deliver real-time insights and prompt actions depending on the data gathered from the sensors. This is especially advantageous in situations when prompt reactions are essential, such as in the management of acute health concerns in livestock (Tri Nguyen et al., 2024).

The IoT framework boosts livestock health monitoring systems by utilising these layers, allowing for continuous, real-time surveillance of animal health and fostering proactive management tactics.

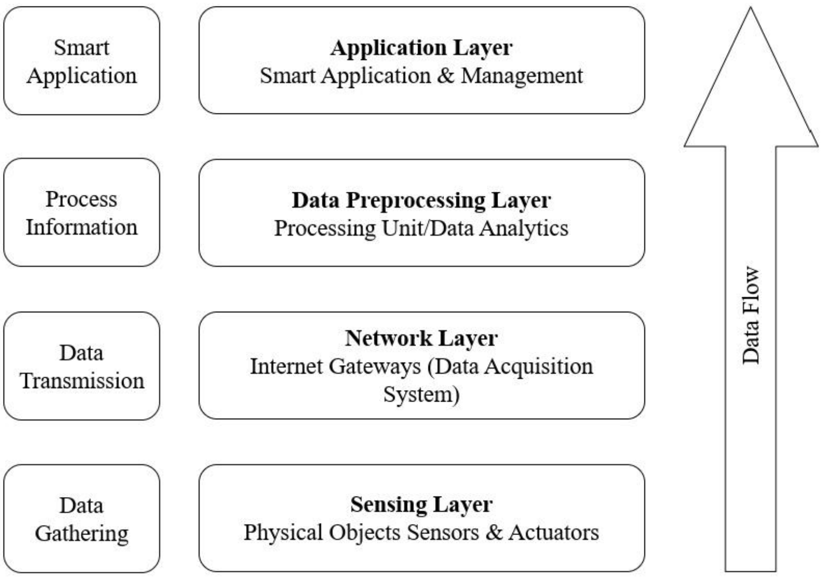

Fig. 14 Architecture in Internet of Things (IoT)

11. Key Applications of AI and IoT in Livestock Health Monitoring

11.1 Disease Detection and Early Warning Systems

A fundamental application of AI and IoT in cattle health is disease detection. Conventional techniques frequently depend on visual assessments, which may be imprecise or tardy, leading to delayed identification of conditions such as mastitis, respiratory ailments, or gastrointestinal disorders. AI-IoT systems provide a solution by persistently monitoring health metrics, including body temperature, heart rate, and mobility, detecting minor alterations that may precede observable symptoms (Unold, O. et al., 2020).

Wearable IoT devices, such as biometric collars or ear tags, gather data in real-time and transmit it to AI models intended for anomaly detection. These algorithms juxtapose current data with established baselines to detect preliminary indicators of sickness. A rise in temperature coupled with decreased mobility may signify the development of mastitis in dairy cattle. Upon detection, the system can notify farmers using cellphones or farm management platforms, facilitating prompt intervention (Majumder, S. et al., 2017). This early warning system mitigates disease severity, reduces treatment expenses, and curtails the transmission of infectious diseases within the herd (AlZubi, Ali Ahmad. 2023).

In sophisticated configurations, AI systems can forecast disease outbreaks by analysing environmental variables such as temperature and humidity, which affect the likelihood of respiratory diseases. By connecting sensor data with meteorological patterns, these technologies assist farmers in implementing preventive actions such as modifying ventilation systems or altering feeding methods to mitigate disease risk (Hammad, Shahab et al., 2024).

11.2 Behavioral and Environmental Monitoring

Artificial Intelligence and Internet of Things technologies facilitate behavioural and environmental monitoring, crucial for ensuring the overall welfare of livestock. Behavioural alterations—such as diminished mobility, modified dietary habits, or extended periods of rest—may signify health concerns. IoT devices, like motion sensors and GPS trackers, gather data about animal behaviour and movement patterns. AI algorithms subsequently examine this data to identify anomalies in typical behaviour. For instance, if a cow that usually grazes energetically exhibits less mobility, the system may identify this as a potential health issue (Halachmi, Ilan. Et al., 2019).

Behavioural monitoring is crucial for detecting problems that may lack immediate physical manifestations, such as lameness or stress. AI models can identify patterns of reduced mobility or abnormal gait, which frequently serve as preliminary signs of lameness. Timely identification facilitates expedited treatment, enhancing animal comfort and mitigating economic costs linked to diminished output (Santosh Pandey et al., 2021).

Alongside behavioural monitoring, environmental sensors measure variables such as temperature, humidity, and air quality, which can profoundly affect livestock health. In chicken farms, elevated humidity levels heighten the risk of respiratory diseases. AI models can offer appropriate modifications to ventilation systems or feeding schedules by integrating environmental data with behavioural data, hence preventing stress or disease induced by environmental circumstances (Pereira, Wariston, et al., 2020).

11.3 Reproductive Health and Breeding Optimization

AI and IoT are significantly contributing to the management of reproductive health. Monitoring oestrus cycles is essential for optimising breeding periods; however, conventional methods of oestrus identification, like as eye inspection, are labour-intensive and frequently imprecise. AI-IoT systems provide automatic oestrus identification by continuously monitoring physiological and behavioural alterations, such heightened activity or variations in body temperature (Cho, Youngjoon & Kim, Jongwon. 2023).

IoT devices such as leg bands or collars can detect movement patterns that generally intensify during oestrus, while biometric sensors assess hormonal fluctuations. AI models use this data to precisely forecast the commencement of oestrus, enabling farmers to time breeding optimally, thus enhancing conception rates and minimising calving intervals (Lee, Meonghun. 2018). Furthermore, AI-driven predictive algorithms can ascertain optimal breeding couples utilising genetic data, hence enhancing herd productivity and progeny quality.

11.4 Nutritional and Wellness Management

Optimal nutrition is crucial for sustaining cattle health and productivity, with AI-IoT systems significantly contributing to nutritional and wellness management. IoT-enabled feeding systems oversee feed consumption, while weight sensors monitor variations in body mass. Artificial intelligence programs evaluate this data to guarantee that animals are ingesting adequate feed quantities and achieving optimal weight gain rates (Tak, Pooja. & Kumawat, Ajay. 2024).

For instance, if an animal's feed consumption abruptly declines or it has insufficient weight gain, the system might notify the farmer of a possible health concern, such as digestive issues or starvation. These systems can recommend modifications to feeding schedules or rations tailored to the individual needs of each animal, so optimising growth and ensuring nutritional requirements are fulfilled (Sonea, Cosmin. 2023).

The integration of AI and IoT facilitates the creation of personalised wellness plans, utilising each animal's health data to customise interventions. Sensors that monitor vital signs, such as pulse rate and body temperature, can identify early indicators of stress or disease, prompting AI systems to suggest modifications in food or medication. This tailored method enhances overall animal wellbeing and diminishes the necessity for antibiotics or alternative treatments (Thilakarathne, Navod. Et al., 2021).

Table 2 Applications of AI and IoT in Livestock Health Monitoring and Management with Associated Benefits

Category	Key Applications	Technology Used	Outcomes/Benefits	Reference
Disease Detection and Early Warning Systems	Continuous monitoring of health metrics like temperature, heart rate, and mobility. Detects early signs of diseases (e.g., mastitis, respiratory ailments).	Wearable IoT devices (biometric collars, ear tags). AI-based anomaly detection algorithms.	Enables early disease detection and timely intervention. Reduces treatment costs and disease severity. Prevents disease spread within the herd.	Unold, O. et al., 2020; Majumder, S. et al., 2017; AlZubi, Ali Ahmad, 2023; Hammad, Shahab et al., 2024
Behavioral and Environmental Monitoring	Tracks changes in movement, feeding, and resting behavior to detect health concerns. Monitors environmental factors like temperature, humidity, and air quality.	IoT devices (motion sensors, GPS trackers, environmental sensors). AI algorithms analyze behavioral and environmental data.	Detects stress or health issues (e.g., lameness, respiratory diseases). Improves animal welfare and comfort.	Halachmi, Ilan et al., 2019; Santosh Pandey et al., 2021; Pereira, Wariston, et al., 2020
Reproductive Health and Breeding Optimization	Automates oestrus detection via activity and temperature monitoring. Identifies optimal breeding pairs using genetic data.	IoT devices (leg bands, biometric collars). AI predictive algorithms for genetic analysis and oestrus detection.	Increases conception rates and reduces calving intervals. Enhances herd productivity and progeny quality.	Cho, Youngjoon & Kim, Jongwon, 2023; Lee, Meonghun, 2018
Nutritional and Wellness Management	Oversees feed intake and weight changes. Identifies health concerns based on nutritional patterns. Creates personalized wellness plans.	IoT-enabled feeding systems and weight sensors. AI models analyze vital signs and feeding data.	Ensures optimal nutrition and growth. Detects early signs of digestive issues or malnutrition.	Tak, Pooja & Kumawat, Ajay, 2024; Sonea, Cosmin, 2023; Thilakarathne, Navod et al., 2021

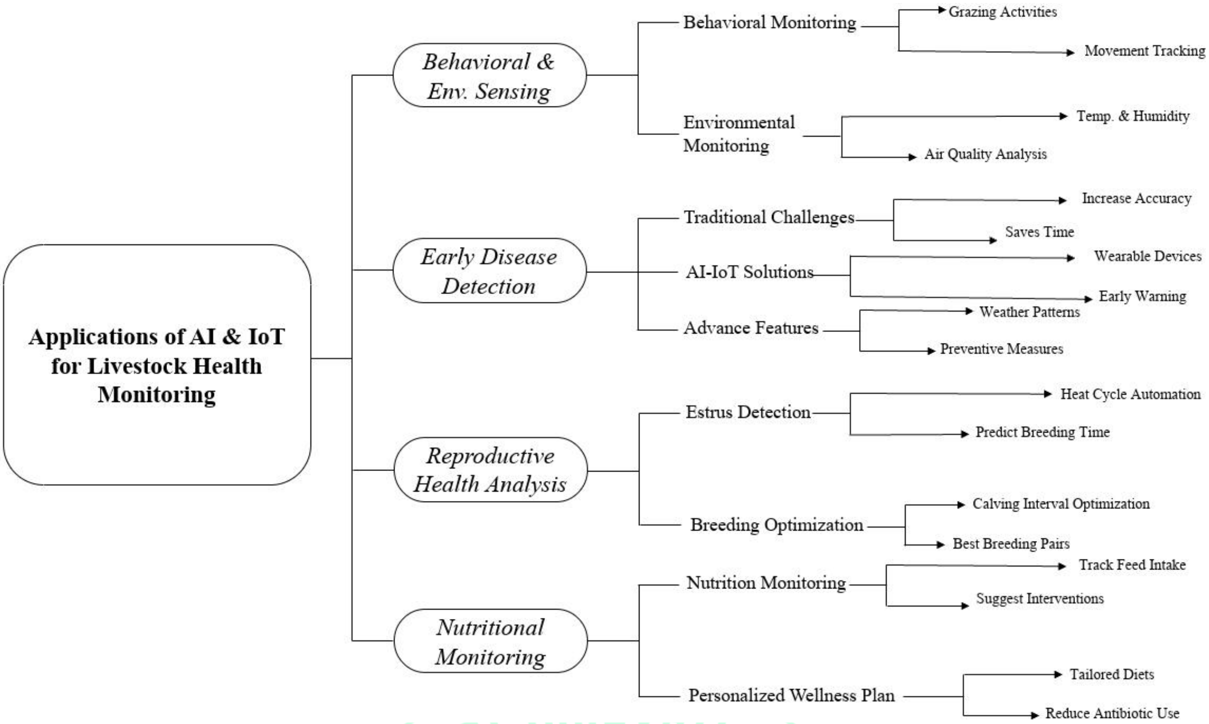

Fig. 15 Applications Of AI & Iot For Livestock Health Monitoring (CogniHerd System)

12. Case Studies and Real-World Implementations

12.1 Successful Case Studies

1. **CowMonitor System, Poland:** This IoT-based system, implemented on a dairy farm, utilised sensor data to monitor the health of dairy cows, specifically targeting the detection of oestrus and mastitis. Over a six-month interval, the method identified 90% of mastitis cases prior to the manifestation of physical signs through the analysis of rumination patterns. This facilitated real-time oversight of therapeutic advancement, leading to prompt veterinarian interventions. Unold, O. et al. (2020).

2. **Dairy Farm in Mehsana, India:** A novel cattle health monitoring system named My Herd was created utilising Internet of Things (IoT), Thing Speak, and a smartphone application. My Herd consistently assesses the health status of cattle by gathering and analysing physiological metrics, including body temperature, heart rate, and activity level. The data is subsequently communicated to the ThingSpeak cloud platform via IoT nodes, where it is analysed utilising MATLAB algorithms. A mobile application has been developed to offer farmers real-time monitoring and warnings regarding any abnormalities in cattle health. The suggested method was evaluated on a cohort of cattle, revealing its capability to reliably identify and diagnose multiple health problems. My Herd offers farmers a cost-effective and efficient option for monitoring cattle health, thereby enhancing production and profitability in the livestock sector. Bhatla, Ayushi et al., 2023.

3. **Smart Cattle, Mumbai, India:** Our findings indicate that general health monitoring may serve as a viable solution to the body temperature problem. The Mlx90614 sensor yields erroneous body temperature measurements due to the thick skin of cattle. After completing an experiment, we determined that we could obtain precise measurements of upper skin temperature; so, we choose to convert body temperature to skin temperature to assess heat stress in cattle. Heat stress results from a confluence of environmental elements, including relative humidity, sun radiation, air movement, and precipitation. Combinations of ambient temperature and relative humidity that result in mild heat stress (THI 72 to 79), moderate heat stress (THI 79 to 89), and severe heat stress (THI > 89). Our findings indicate that pulse rate (BPM) and activity status can be utilised to assess sleep status. (Darvesh, Karthik, et al., 2023).

4. **Animal Production and Reproduction, Brazil:** The utilization of sensors and other data collection techniques, such as CV, serves as a viable alternative to obtain quantitative information from animals while reducing data collection costs, as they enable data acquisition over an extended period, offer the potential for automating processes on the farm and the possibility of making data-based informed

decisions. In the reviews addressed in our work, it is clear that PLF methods are currently under development to assess various challenges existing in the animal production and reproduction fields, and there is a future trend towards an expansion of the usage of such techniques. However, its adoption by end-users still is not at its full potential. In order to address this issue and optimize the practical implementation of new PLF projects, this work targeted important aspects to be taken into consideration during the different steps involved in the creation of a full cycle project: data collection, transferring, storage, analysis and delivery of results. (Curti, P. F. et al., 2023).

5. **Lumpy Skin Disease, Pakistan:** The suggested IoT-enabled cow health monitoring system, utilising a collar equipped with intelligent sensors, exhibited notable enhancements in the early identification of Lumpy Skin Disease (LSD) through the continuous and remote surveillance of key data, including body temperature, heart rate, and tri-axial movements. This sophisticated system offers a cost-efficient and complete solution for real-time health monitoring and management of cattle, featuring an open-source cloud computing platform and distinctive mobile application support. The incorporation of contemporary technology, including cloud computing and the Internet of Things (IoT), ensures enhanced precision and timely notifications, hence augmenting the ability to detect cattle health irregularities promptly and facilitating swift remote intervention. This innovative method is distinguished by its capacity to identify LSD symptoms and its significant role in enhancing livestock health management and productivity. (Shahab, H. et al., 2024).

These case studies underscore the capability of AI-IoT systems in tackling significant difficulties in cattle management, including disease identification and reproductive enhancement. The findings indicate concrete advantages, such as enhanced animal health, heightened output, and cost reductions, rendering AI-IoT solutions appealing for farms of all scales.

12.2 Challenges in Deployment

The advantages of AI and IoT in animal health management are evident; nevertheless, the implementation of these systems presents problems. Technical constraints pose a considerable obstacle, especially in rural regions where several farms are situated. Dependable internet access is essential for IoT devices to relay data in real-time, and inadequate connectivity might impede system performance. The substantial expense of modern AI and IoT technology can be a barrier for small-scale farmers, complicating wider adoption (Elijah, Olakunle. Et al., 2018).

Table 3 Examples of IoT-Based Livestock Health Monitoring Systems

System/Location	Key Features	Applications	Outcomes/Benefits	References
CowMonitor System, Poland	Sensor-based IoT system to monitor rumination patterns.	Detects oestrus and mastitis in dairy cows.	Identified 90% of mastitis cases before visible symptoms; enabled real-time therapeutic monitoring.	Unold, O. et al., 2020
My Herd, Mehsana, India	IoT nodes with physiological sensors, ThingSpeak cloud platform, MATLAB algorithms, and mobile app.	Monitors cattle health (body temperature, heart rate).	Reliable health diagnostics; cost-effective solution improving production and profitability.	Bhatla, Ayushi et al., 2023
Smart Cattle, Mumbai, India	MLX90614 sensor for body and skin temperature conversion; monitors pulse rate and activity status.	Heat stress evaluation and sleep status monitoring.	Enhanced temperature accuracy; effective assessment of stress and sleep status.	Darvesh, Karthik et al., 2023
Animal Production, Brazil	Sensors and CV techniques for automated, long-term data acquisition.	Assesses challenges in animal production and reproduction.	Quantitative data collection; reduced costs; supports informed decision-making.	Curti, P. F. et al., 2023
Lumpy Skin Disease, Pakistan	IoT collar with sensors for monitoring temperature, heart rate, and movements; cloud computing support.	Early detection and management of Lumpy Skin Disease.	Precise detection; cost-efficient solution with real-time alerts for swift interventions.	Shahab, H. et al., 2024

Furthermore, the effective execution of AI systems is contingent upon the quality of data. Agricultural operations devoid of previous health data or exhibiting discrepancies in data collection may encounter challenges in efficiently training AI models. This may lead to erroneous projections and diminished system reliability, fostering scepticism among farmers who anticipate prompt outcomes from such investments (Khan, B. et al., 2023).

Operational difficulties emerge, especially with the integration of AI-IoT systems with current farm management methodologies. Agriculturalists must receive training in the utilisation of these technology, which may necessitate considerable time and resources. Resistance to change, particularly among older generations of farmers, constitutes another obstacle, as they may prefer to depend on conventional livestock management practices. Moreover, AI systems necessitate frequent upgrades and maintenance, which might increase the operational strain on farms (Dawn, Nabarun. Et al., 2023).

12.3 Future Prospects

Notwithstanding these limitations, the prospects for AI and IoT in animal health management are encouraging. Advancements in IoT technologies and AI models are anticipated to render systems like CogniHerd more accessible, economical, and efficient. An area of advancement is the creation of more sophisticated AI algorithms that can handle more datasets and yield increasingly precise predictions. AI algorithms may ultimately forecast not just sickness probability but also the most effective treatment alternatives based on specific animal data and environmental factors (Issa, Ali. Et al., 2024).

Another prospective development is the global deployment of these technology to other farms, especially in underdeveloped nations. With the decreasing cost of IoT devices and advancements in internet connectivity, even small-scale farmers in distant regions may gain advantages from AI-IoT systems. Governments and agricultural organisations could facilitate the adoption of these technologies by providing subsidies or technical assistance (Prem, Rajak et al., 2023).

Moreover, advancements in edge computing would facilitate real-time data processing on farms, diminishing the reliance on constant internet connectivity. This may assist in surmounting the technological obstacles now encountered in rural regions. As sustainability and animal welfare gain prominence, AI-IoT systems are expected to integrate environmental impact monitoring, enabling farms to diminish their carbon footprint while enhancing cattle health (Preetha Evangeline David et al., 2024).

In summary, the integration of AI and IoT has demonstrated significant advantages in cattle health management, and its future potential is extensive. With ongoing technological advancements and declining costs, systems such as CogniHerd have the potential to transform global livestock farming, enhancing animal welfare, boosting productivity, and promoting sustainable agricultural methods.

13. Our Project Case Study: Integrating AI and IoT For Livestock Health Monitoring Using Esp8266 and Arduino Uno

This project case study was executed at Guru Nanak Dev University, Amritsar, Punjab, under the guidance of Dr. Amandeep Singh, as a component of the partial fulfilment for the Post Graduate (PG) Diploma in AI in Agriculture. The project aimed to integrate AI and IoT technologies for monitoring cattle health, utilising hardware components including ESP8266, Arduino Uno, and different sensors. The technology sought to gather real-time health data from cattle and analyse it with AI algorithms to identify any health issues promptly. This research demonstrates the actual use of advanced technology in agriculture, along with the academic program's emphasis on utilising AI to address contemporary agricultural issues.

13.1 CogniHerd System Setup & Requirements

The cattle health monitoring system we established utilises ESP8266 and Arduino Uno microcontrollers as the primary processors for collecting and transferring data from various sensors. The ESP8266, an economical Wi-Fi module, facilitated the wireless connectivity required for real-time data transmission. The Arduino Uno, a multifunctional microcontroller, managed the sensors and facilitated data acquisition.

To assess animal health, the subsequent sensors were incorporated:

Audio sensor (KY-038): Employed to identify vocalisations or atypical sounds from animals, potentially signalling stress, discomfort, or sickness.

Temperature sensor (DS18B20): Assessed body temperature to identify fever or hypothermia.

Accelerometer Sensor (ADXL345): Detects the movement of the cattle's neck, crucial for identifying aberrant patterns like decreased activity or stress.

Camera sensor (OV7670): Acquired visual data, encompassing movement patterns or observable indications of sickness, and might facilitate remote investigation.

The hardware components collaborated to create an IoT-based system that gathered and sent real-time data regarding the animals' health state. Jumper wires and patch cords were utilised to link the sensors to the microcontrollers. Data was processed and saved in a MySQL Server, facilitating subsequent analysis and monitoring.

A mobile phone was employed for remote monitoring and control of the system, while a laptop enabled system development and data visualisation. A hotspot internet connection was essential for sustaining real-time communication among the sensors, ESP8266, and the cloud database.

13.1.1 Purpose

The main objective of incorporating these IoT devices was to facilitate real-time health monitoring of cattle. By persistently monitoring characteristics like as temperature, sound, and movement, the device could identify anomalies that may signify early health concerns. The early diagnosis would aid in preventing sickness progression and reducing the necessity for manual intervention, hence improving animal welfare and operational efficiency.

13.1.2 Hardware Requirements:

Arduino Uno: Serves as the primary microcontroller to control the sensors.

ESP8266: Provides Wi-Fi connectivity for real-time data transmission.

Internet connection: A hotspot is required for communication between the sensors and the database.

Sensors: Includes audio (KY-038), temperature (DS18B20), accelerometer sensor (ADXL345), and camera sensors (OV7670) for monitoring health parameters.

Jump Wires and Patch Chords: Used for physical connections between sensors and microcontrollers.

USB Data Cable: Used to power the WiFi module.

Laptop: For system development, coding, and data analysis.

Mobile phone: For real-time monitoring and remote control.

13.1.3 Software Requirements:

MySQL Server: Database software used for storing and managing sensor data.

Software Development IDE: Integrated Development Environment, such as Arduino IDE, used for coding the microcontroller.

ASP.NET: A framework for building web applications to display and manage data.

Visual Studio: A development tool used to build the front-end interface for monitoring livestock health data.

In combination, these hardware and software components formed a robust system that could reliably monitor livestock health in real-time and support decision-making through data analytics.

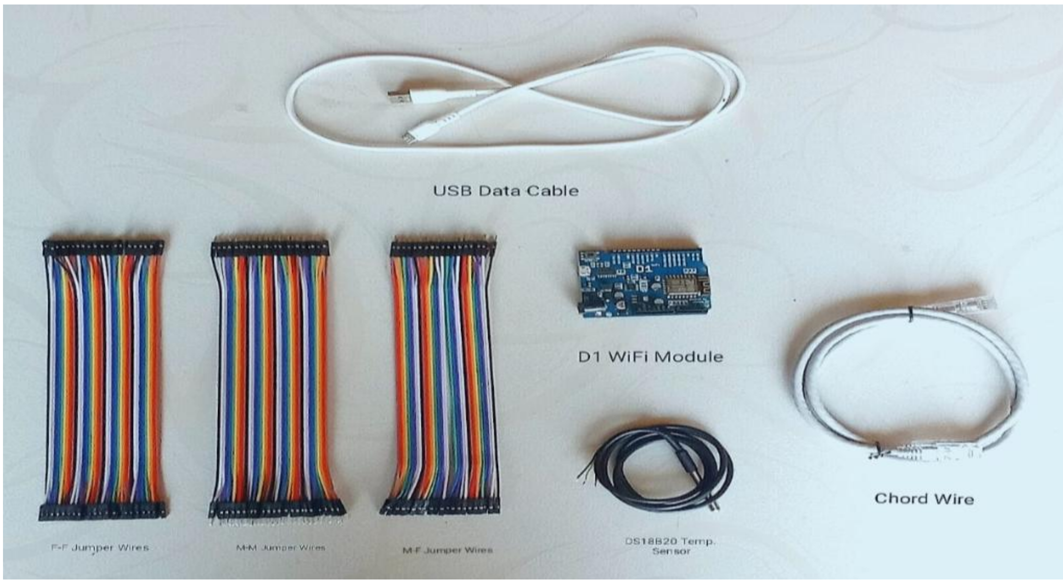

Fig. 16 Material Requirements For CogniHerd System

13.2 Methodology

This section explains how the cattle health monitoring system works, highlighting the AI-IoT integration and how data is collected and analyzed.

13.2.1 Hardware and Sensors

The system comprises four primary sensors connected to an ESP8266 Wi-Fi module and controlled by an Arduino Uno microcontroller:

Temperature Sensor (DS18B20): Monitors the cattle's body temperature to detect fever or abnormal fluctuations.

Accelerometer Sensor (ADXL345): Senses the movement of the cattle's neck, which is essential for detecting abnormal patterns such as reduced activity or stress.

Camera Sensor (OV7670): Captures visual data of the cattle's behavior, helping identify changes in posture or visible signs of illness.

Microphone Sensor (KY-038): Detects the intensity and pattern of sounds, which may indicate distress, pain, or illness.

Each sensor serves a crucial role in providing real-time data about the cattle's health status, ensuring early detection of potential issues.

13.2.2 Data Collection

The sensors continuously collect data on temperature, movement, sound, and visual cues from the livestock. This information is transmitted through the ESP8266 Wi-Fi module to a cloud platform where the data is stored and analyzed.

The data flow diagram of the cattle health monitoring system outlines the process:

1. The temperature, accelerometer, camera, and microphone sensors collect real-time data from the cattle.
2. Data is transmitted wirelessly via the ESP8266 to the cloud.
3. In the cloud, the collected data is processed and analyzed using advanced machine learning models.
4. If abnormal patterns are detected, such as a sudden change in temperature or movement, the system sends a notification to the caretaker and veterinary doctor for intervention.

13.2.3 Finding Datasets for our Model Training

We have compiled information from various trustworthy platforms to train AI models for forecasting bovine health across multiple diseases. These datasets furnish essential information that augments the precision and comprehensiveness of my predictive models:

1. ***Bovine Milk Datasets (From Mendeley):*** To detect bovine mastitis, a prevalent and expensive affliction in dairy cattle, we employed milk datasets accessible on Mendeley. These databases provide comprehensive milk composition and somatic cell count information, which are critical indications for the early identification of mastitis. The models provide the evaluation of alterations in milk quality associated with infection, hence enhancing the precision and timeliness of forecasts (K. ANKITHA., et al., 2020).

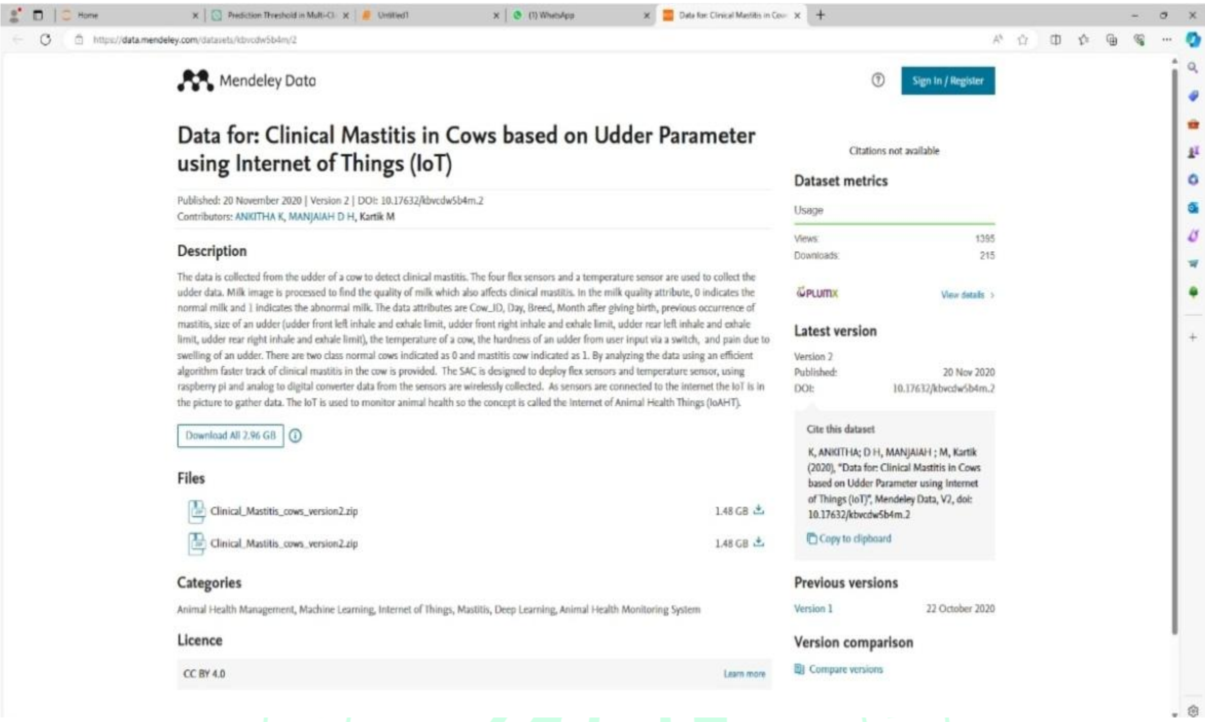

Fig. 17 Bovine Milk Datasets From Mendeley For Bovine Mastitis Detection

2. ***Bovine Talk Dataset (From GitLab):*** We obtained audio recordings from GitLab to examine vocalisation trends in cattle. Cattle frequently display alterations in vocalisation when experiencing stress or pain. We intend to forecast health complications associated with stress, illness, or injury by training our models on vocalisation data. This dataset offers unprocessed audio signals, allowing the model to identify nuanced variations in frequency and patterns (Annazam, I. S. 2023).

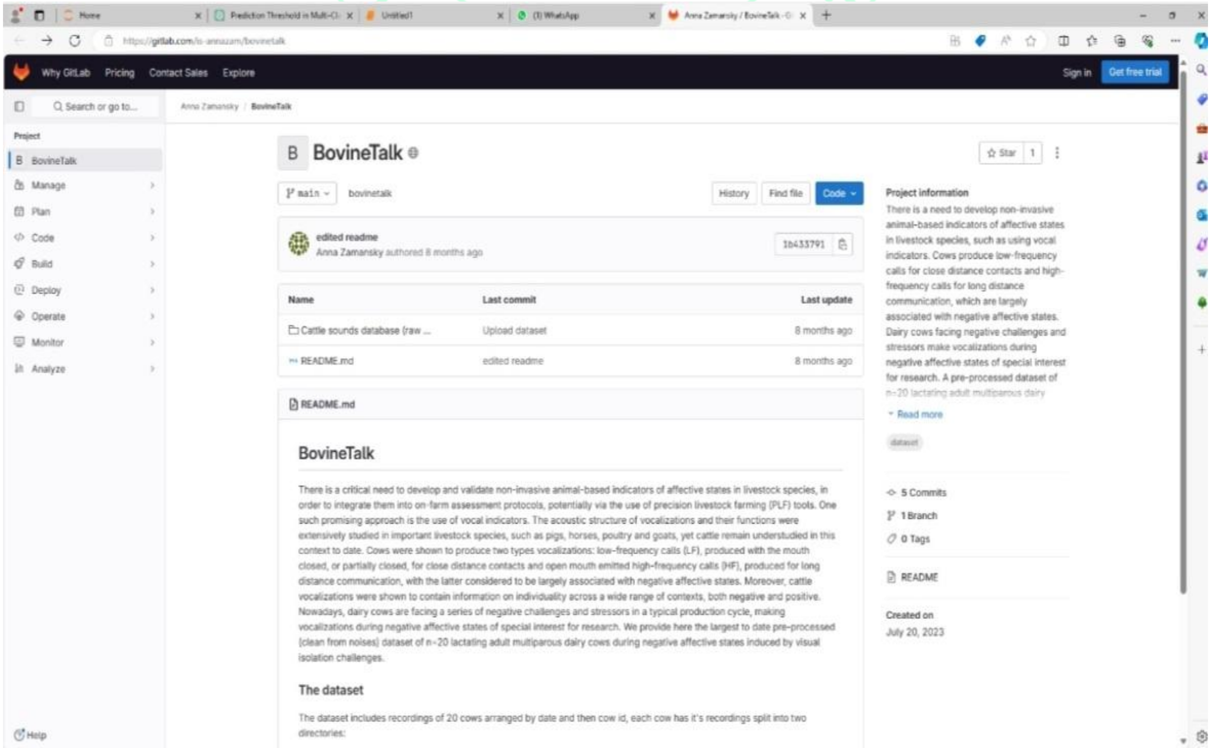

Fig. 18 Bovinetalk Dataset from GitLab For Vocalization Analysis

3. ***Bovine Faecal Matter Dataset (From Roboflow):*** Digestive health is a vital aspect of cattle management. The faecal matter dataset from Roboflow comprises photos and annotations that facilitate the identification of digestive diseases via faeces analysis. The program utilises this data to identify anomalies in faecal matter, including alterations in colour and texture, which may indicate underlying health concerns such as infections or malnutrition (University of Illinois Urbana-Champaign, 2022).

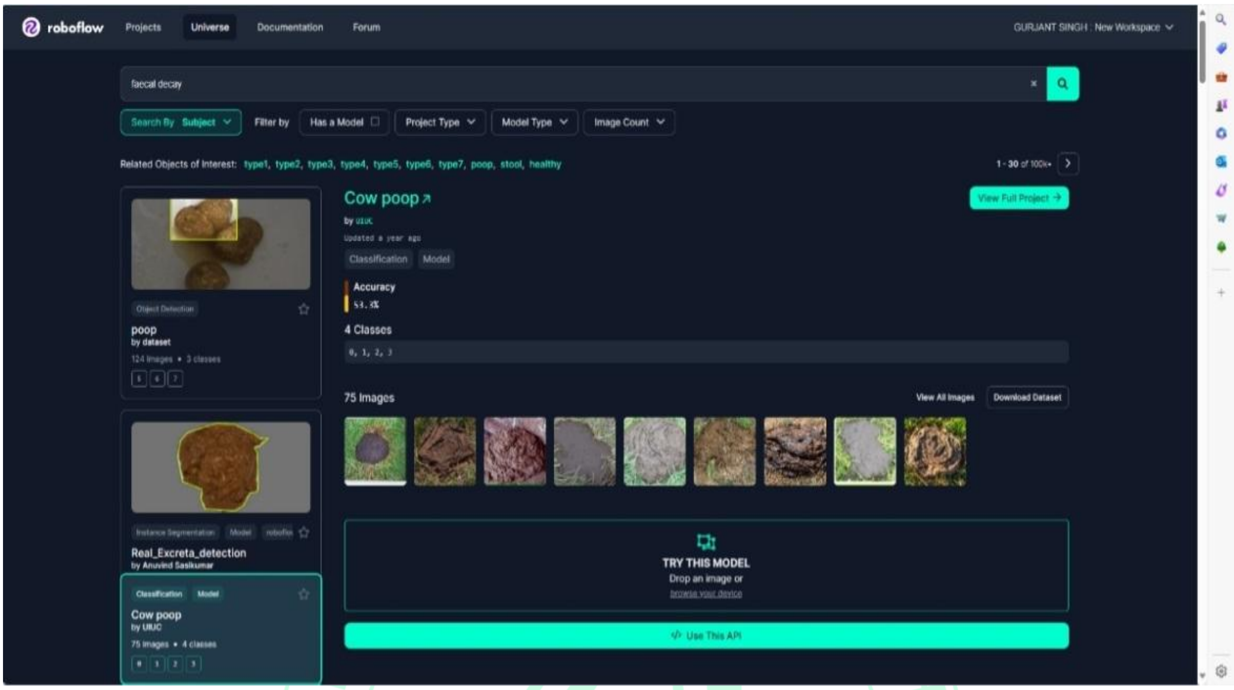

Fig. 19 Bovine Faecal Matter Dataset From Roboflow For Digestive Health Monitoring

4. ***Mixed Bovine Disease Prediction Datasets (From Kaggle):*** To adopt a more complete technique, we utilised Kaggle's assortment of mixed datasets pertaining to distinct bovine ailments. These databases amalgamate many health markers, including body temperature, movement patterns, and milk production statistics. This allows the model to conduct comprehensive assessments and forecast many ailments, enhancing its overall efficacy in health monitoring systems (Padhyay, K. 2022).

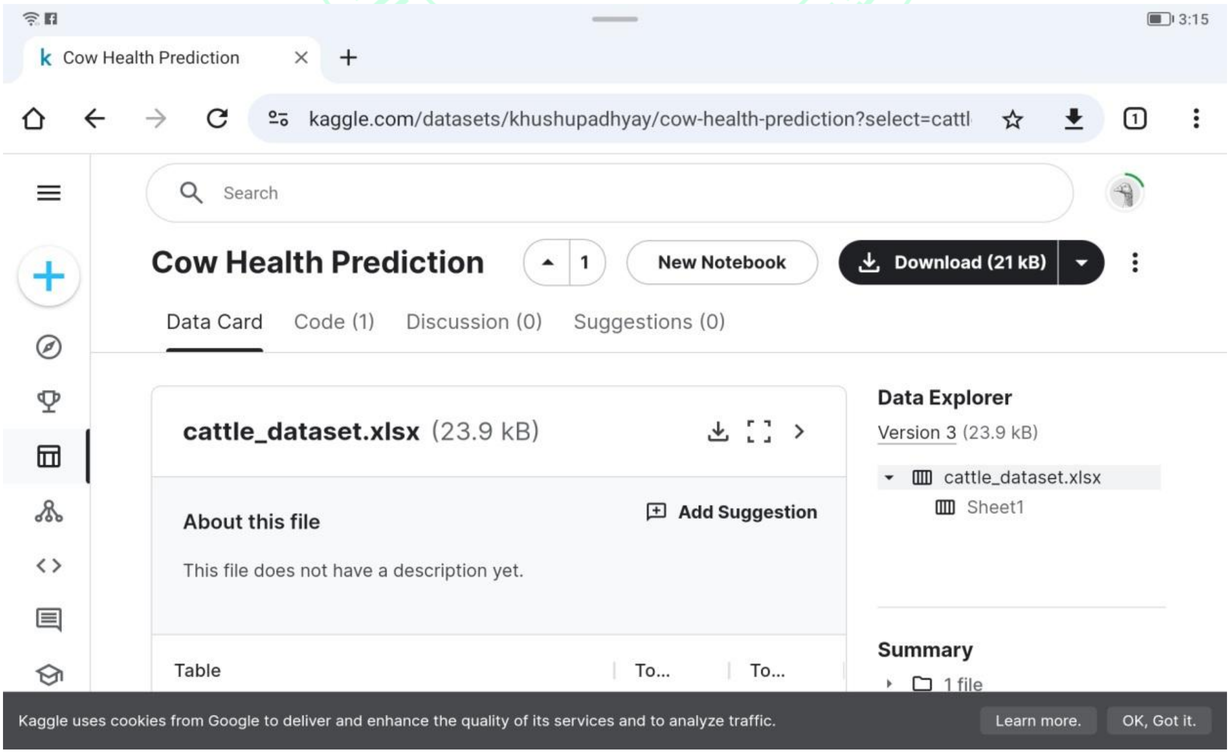

Fig. 20 Mixed Multiple Datasets For Cow Health Prediction From Kaggle

Utilising datasets from numerous platforms, the model is trained on a varied array of data, hence boosting its robustness and accuracy in forecasting bovine health across multiple diseases.

13.2.4 AI Integration

The AI integration involves applying various machine learning algorithms to analyze the sensor data and predict health issues:

Naïve Bayes: Used for temperature monitoring, identifying fever or abnormal temperature trends.

Convolutional Neural Network (CNN): Applied to faecal identification using images captured by the camera sensor to detect digestive disorders.

Support Vector Machine (SVM): Analyzes sound data from the microphone sensor to recognize abnormal vocalizations that could indicate distress or illness.

ResNet152V2: A deep learning model used to predict bovine mastitis by analyzing multiple data streams, including temperature, sound, and movement, for early detection.

These algorithms execute pattern recognition and anomaly detection to discern alterations in cow behaviour or physical states that may indicate sickness. A rise in body temperature, along with alterations in movement and auditory responses, may signify an infection. The system employs predictive models to notify the caretaker, facilitating prompt intervention and treatment.

This methodology integrates real-time data acquisition from IoT sensors with AI-based analysis to deliver a thorough health monitoring solution for livestock. The system utilises AI models such as CNN, SVM, and ResNet152V2 to forecast cattle health problems promptly and facilitate timely alerts for remedial measures. The use of IoT facilitates ongoing surveillance, markedly diminishing dependence on manual labour and enhancing overall animal wellbeing.

A concise summary of the methodology that has been used for this livestock health monitoring project using AI includes the following:

1. *Data Collection and Preprocessing:* Gather sensor data from livestock, cleaned, and normalized. For training dataset sites like Mendely, Kaggal, GitLab, and Roboflow were used.

2. *Model Selection:* AI models for Prediction used CNN, SVM, ResNet152V2.

3. *Training and Validation:* Training of models, validation with testing data using metrics like accuracy and F1-score.

4. *Integration and Deployment:* Integration of models into the monitoring system, deploy for real-time use.

5. *Feedback and Improvement:* Collect feedback, retrain models periodically for better performance.

13.3 Integration of IoT Device

In the cattle health monitoring system, a Data Flow Diagram explains how data is collected, transmitted, and analyzed using various sensors and machine learning algorithms. Here is a detailed breakdown of the process:

1. ***Sensor Data Collection:***

Temperature Sensor (e.g., DS18B20): This sensor monitors the cattle's body temperature. Temperature anomalies can indicate potential health issues such as fever or infection.

Accelerometer Sensor: This sensor detects the neck movement of the cattle. Unusual movements or changes in activity patterns can signal distress or illness.

Microphone Sensor: The microphone detects sound intensity and vocalization patterns from the cattle. Distress calls or unusual vocalization may point to pain or discomfort.

Camera Sensor: The camera captures real-time images or videos to monitor behavioral changes, such as lethargy or abnormal posture, which can indicate health issues.

2. ***Transmission to Cloud*:**

Data from all the sensors is collected and processed through an ESP8266 Wi-Fi module. This module serves as the communication bridge, transmitting the data to a cloud server where further analysis takes place.

3. ***Cloud-Based Data Processing:***

Once the data reaches the cloud, it is analyzed using machine learning algorithms like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and ResNet152V2. These models are trained to detect anomalies in the collected data.
CNN may be used for image-based predictions (from camera data) or pattern recognition.
SVM could be employed to analyze audio data for identifying distress signals.
ResNet152V2, a deep learning model, is particularly effective for identifying specific conditions, such as bovine mastitis.

4. ***Analysis and Prediction:***

The models analyse sensor data to execute pattern recognition and anomaly detection for predicting potential health problems. A abrupt increase in temperature accompanied by atypical vocalisations may signify an infection.

5. ***Alerts and Notifications*:**

Upon detection of any health fluctuations or anomalies, the system promptly transmits notifications to the caretaker and veterinary physician via mobile applications or other communication channels. This early identification facilitates timely intervention and treatment, mitigating the risk of serious health complications.

6. ***Action and Response:***

According on the forecasts and notifications, the carer or veterinarian can undertake suitable measures, such as providing treatment or doing further diagnosis in person.

This procedure facilitates real-time surveillance and effective illness forecasting, reducing manual effort while guaranteeing swift reactions to possible health threats. This solution markedly improves farm management, boosts animal comfort, and decreases operational expenses through the integration of IoT devices and AI models.

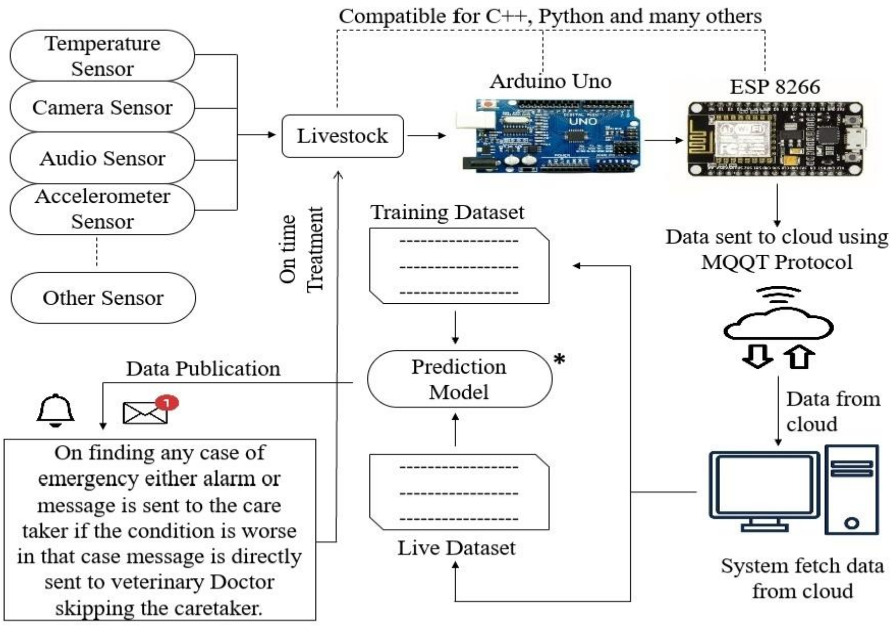

Fig. 21 Integration & Working of CogniHerd System for Real Time Continuous Livestock Health Monitoring

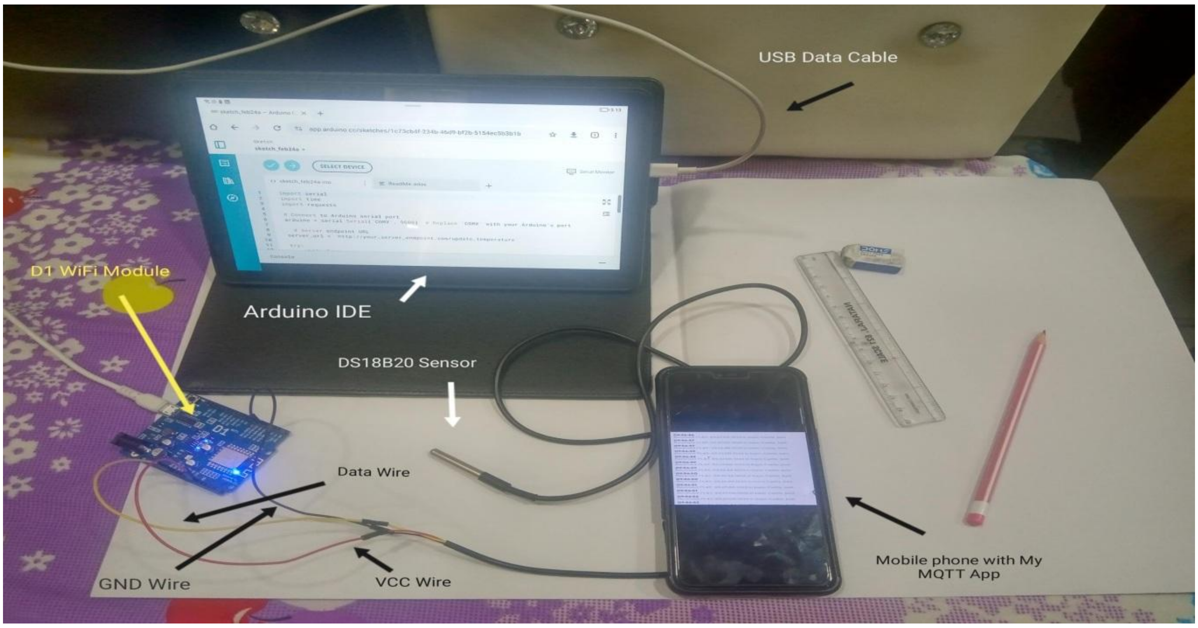

Fig. 22 Working on Sensors and Code Implementation

13.4 Code Implementation

This livestock health monitoring initiative seeks to identify several diseases in cattle through a methodical process comprising several essential stages. Every phase is structured to guarantee efficient data management, model training, and real-time illness forecasting, resulting in improved livestock administration.

1. ***Collect and Preprocess Sensor Data:*** The initial phase entails acquiring data from several sensors installed in the animal habitat. These sensors may encompass temperature monitors, heart rate sensors, accelerometers, and additional health indicators. The gathered data frequently necessitates preprocessing to purify and standardise it for analysis. This may entail eliminating noise, addressing missing values, and transforming raw sensor readings into a functional format, so guaranteeing that the data accurately represents the health state of the cattle.

2. ***Choose and Train AI Models:*** Select and Train AI Models: Following data preprocessing, the subsequent stage is to identify suitable artificial intelligence models for training. Diverse models can be employed, including convolutional neural networks (CNNs) for image data processing (e.g., identifying visual illness signs), support vector machines (SVMs) for classification tasks, and deep learning architectures such as ResNet152V2 for intricate pattern identification. Training these models entails providing them with preprocessed data, enabling them to learn from historical patterns and predict cattle health.

3. ***Validation and Evaluation of Model Performance:*** Following the training of the models, it is crucial to validate and assess their performance utilising a distinct dataset. This phase evaluates the models' ability to generalise to novel data, employing criteria including accuracy, precision, recall, and F1-score. Cross-validation methods can be utilised to verify that the models are resilient and not overfitting to the training dataset. This assessment phase is essential for identifying the model or combination of models that yields optimal prediction performance.

4. ***Implementation of Real-Time Monitoring and Notification:*** Following the validation of models, the project advances to the execution phase, wherein real-time monitoring of livestock health is conducted. This entails the integration of trained models with sensor data streams, facilitating ongoing analysis and the identification of abnormalities that may signify health concerns. Upon identification of a potential issue, the system can initiate notifications to farmers or caretakers, facilitating timely intervention.

5. ***Integrate with Cloud Services for Scalability:*** Integration with cloud services is essential to augment the system's capabilities and facilitate scalable operations. This phase entails employing cloud computing resources for data storage, processing, and model rollout. Utilising cloud architecture, the

project can handle substantial data quantities and offer access to analytical tools, guaranteeing that the system may expand in response to the rising demands of livestock management.

6. ***Develop a User-Friendly Interface, Like GUI:*** An intuitive interface is essential for enabling interaction between users (e.g., farmers, veterinarians) and the monitoring system. Creating a graphical user interface (GUI) enables users to effectively visualise data, obtain real-time monitoring results, and receive notifications. The interface must be user-friendly and informative, equipping users with essential tools for effective animal health management.

7. ***Continuously Update and Improve Models:*** The final step entails the perpetual update and enhancement of the AI models. With the accumulation and analysis of additional data, the models can be refined to improve their precision and forecasting skills. This iterative approach guarantees the system's efficacy in illness detection and adaptation to emerging health trends, hence enhancing livestock management and welfare.

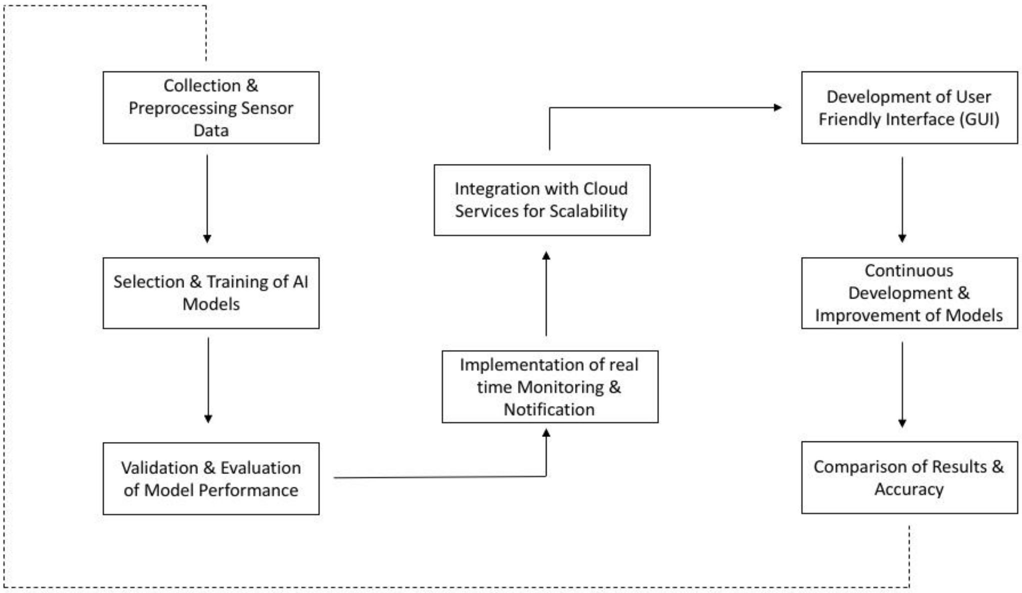

Fig. 23 Methodology Employed in Code Implementation for CogniHerd System

13.4.1 C++ code for Real-Time Livestock Temperature Monitoring

A temperature monitoring system is employed to observe and regulate temperature variations in real-time, frequently utilised in contexts such as cattle health, medical storage, or industrial activities. It entails the utilisation of sensors, such as the DS18B20, to precisely monitor temperature. Sensor data is generally handled by a microcontroller or module such as the D1 WiFi (ESP8266) or Arduino, which communicates with the sensors and manages communication. Data transmission occurs via protocols such as MQTT, facilitating real-time monitoring through a central server or cloud. A Naïve Bayes classifier is utilised to classify temperature data, including the identification of anomalous states in cattle, such as fever or hypothermia. This system guarantees regular updates, notifications, and possible interventions in the event of temperature anomalies.
To efficiently monitor cattle temperature utilising the D1 WiFi module, DS18B20 sensor, and MQTT protocol, the subsequent processes have been implemented for real-time data gathering and analysis:

1. *Hardware Connection*

Connection of the DS18B20 temperature sensor to the D1 WiFi module (ESP8266). Proper wiring with the sensor's VCC, GND, and Data pins connected to the respective pins on the D1 Module was ensured.

Voltage Common Collector (VCC): This pin supplies power to the sensor. VCC pin of the DS18B20 to the 3.3V pin on the D1 Module was connected.

Ground pins (GND): This is the ground pin. GND pin of the DS18B20 to the GND pin on the D1 Module was connected.

Data: This pin transmits the temperature data. Data pin of the DS18B20 to GPIO pin D4 (pin number can vary, but D4 is commonly used) on the D1 Module was connected.

D1 WiFi module was powered using computer for training and to battery for experimentation as fit in wearable device.

2. *Programming the D1 Module using Arduino:*

Installation of Arduino IDE and include the necessary libraries: MQTT, OneWire, and DallasTemperature (for the DS18B20 sensor).
Setting up the code to interface with the DS18B20 sensor and include MQTT functionalities.

```
#include <ESP8266WiFi.h>
#include <PubSubClient.h>
#include <OneWire.h>
#include <DallasTemperature.h>

// WiFi credentials
Const char* ssid = “YOUR_SSID”;
Const char* password = “YOUR_PASSWORD”;

// MQTT broker settings
Const char* mqtt_server = “MQTT_BROKER_IP”;
Const char* mqtt_topic = “livestock/temperature”;

// Setup for DS18B20 temperature sensor
#define ONE_WIRE_BUS D2 // Data pin connected to the DS18B20
OneWire oneWire(ONE_WIRE_BUS);
DallasTemperature sensors(&oneWire);

WiFiClient espClient;
PubSubClient client(espClient);

// Function for classifying livestock health using Naïve Bayes
String classifyLivestockHealth(float temp) {
 If (temp < 37.5) {
  Return “Low Temperature (Hypothermia)”;
 } else if (temp >= 37.5 && temp <= 39.5) {
  Return “Normal Temperature (Healthy)”;
 } else {
  Return “High Temperature (Fever)”;
 }
}

Void setup() {
 Serial.begin(115200);

 // Setup WiFi
 Setup_wifi();

 // Setup MQTT
 Client.setServer(mqtt_server, 1883);

 // Setup DS18B20
 Sensors.begin();
```

```
}

Void loop() {
 // Reconnect to MQTT if disconnected
 If (!client.connected()) {
  Reconnect();
 }
 Client.loop();

 // Request temperature
 Sensors.requestTemperatures();
 Float temperature = sensors.getTempCByIndex(0); // Get temperature from the first sensor

 // Publish temperature reading
 If (temperature != DEVICE_DISCONNECTED_C) {
  Char tempString[8];
  Dtostrf(temperature, 1, 2, tempString); // Convert float to string
  Client.publish(mqtt_topic, tempString);
  Serial.print("Temperature: ");
  Serial.println(tempString);

  // Classify health status using Naïve Bayes
  String healthStatus = classifyLivestockHealth(temperature);
  Serial.print("Health Status: ");
  Serial.println(healthStatus);
  Client.publish("livestock/health_status", healthStatus.c_str());
 } else {
  Serial.println("Failed to read from DS18B20");
 }

 // Delay before the next reading
 Delay(5000); // Adjust delay as necessary
}

Void setup_wifi() {
 Delay(10);
 Serial.println();
 Serial.print("Connecting to ");
 Serial.println(ssid);

 WiFi.begin(ssid, password);

 While (WiFi.status() != WL_CONNECTED) {
  Delay(500);
  Serial.print(".");
 }

 Serial.println("");
 Serial.println("WiFi connected");
}

Void reconnect() {
 // Loop until we're reconnected
 While (!client.connected()) {
  Serial.print("Attempting MQTT connection…");
  // Attempt to connect
  If (client.connect("D1Client")) {
   Serial.println("connected");
```

```
  } else {
    Serial.print("failed, rc=");
    Serial.print(client.state());
    Serial.println(" try again in 5 seconds");
    Delay(5000);
  }
 }
}
```

3. *MQTT Broker Setup:*

Setting up with an MQTT broker, the publishing services that we have used in our case study (you can use cloud-based brokers like Mosquitto, Adafruit IO, or HiveMQ).
Obtaining the necessary credentials, we have used our private credentials (you should use your appropriate broker address, port, username, password)

4. *Coding the D1 for Data Publishing using MQTT and Node MCU:*

Following is the simple explanation of code using Naive Bayes that we have employed to:
It Reads the temperature data from the DS18B20 sensor.
It connects the D1 module to the WiFi network.
Publishes the sensor data to the MQTT broker at regular intervals (e.g., every 5 seconds).

```
#include <ESP8266WiFi.h>
#include <PubSubClient.h>
#include <OneWire.h>
#include <DallasTemperature.h>

// WiFi credentials
Const char* ssid = "YOUR_SSID"; // Replace with your WiFi SSID
Const char* password = "YOUR_PASSWORD"; // Replace with your WiFi password

// MQTT broker settings
Const char* mqtt_server = "MQTT_BROKER_IP"; // Replace with your MQTT broker IP
Const char* mqtt_topic = "temperature"; // MQTT topic for publishing

// Setup for DS18B20
#define ONE_WIRE_BUS D2 // Data pin connected to the DS18B20
OneWire oneWire(ONE_WIRE_BUS);
DallasTemperature sensors(&oneWire);

WiFiClient espClient;
PubSubClient client(espClient);

Void setup() {
 Serial.begin(115200);

 // Setup WiFi
 Setup_wifi();

 // Setup MQTT
 Client.setServer(mqtt_server, 1883);

 // Setup DS18B20
 Sensors.begin();
}

Void loop() {
```

```
  // Ensure MQTT connection
  If (!client.connected()) {
    Reconnect();
  }
  Client.loop();

  // Request temperature
  Sensors.requestTemperatures();
  Float temperature = sensors.getTempCByIndex(0); // Get temperature from the first sensor

  // Publish temperature reading
  If (temperature != DEVICE_DISCONNECTED_C) {
    Char tempString[8];
    Dtostrf(temperature, 1, 2, tempString); // Convert float to string
    Client.publish(mqtt_topic, tempString);
    Serial.print("Temperature: ");
    Serial.println(tempString);

    // Classify temperature using Naïve Bayes
    String classification = classifyTemperature(temperature);
    Serial.print("Classification: ");
    Serial.println(classification);
    Client.publish("temperature/classification", classification.c_str());

  } else {
    Serial.println("Failed to read from DS18B20");
  }

  // Delay before the next reading
  Delay(5000); // Publish every 5 seconds
}

Void setup_wifi() {
  Delay(10);
  Serial.println();
  Serial.print("Connecting to ");
  Serial.println(ssid);

  WiFi.begin(ssid, password);

  While (WiFi.status() != WL_CONNECTED) {
    Delay(500);
    Serial.print(".");
  }

  Serial.println("");
  Serial.println("WiFi connected");
}

Void reconnect() {
  // Loop until we're reconnected
  While (!client.connected()) {
    Serial.print("Attempting MQTT connection…");
    // Attempt to connect
    If (client.connect("D1Client")) {
      Serial.println("connected");
    } else {
      Serial.print("failed, rc=");
```

```
      Serial.print(client.state());
      Serial.println(" try again in 5 seconds");
      Delay(5000);
    }
  }
}

// Naïve Bayes classification function for temperature
String classifyTemperature(float temp) {
  If (temp < 10) {
    Return "Low";
  } else if (temp >= 10 && temp <= 30) {
    Return "Normal";
  } else {
    Return "High";
  }
```

5. *Testing the Setup*:

Monitoring the MQTT topic where the temperature data is being published using an MQTT client which has been used for our project (e.g., MQTT Explorer or Mosquitto).
Data is accurately reflecting the temperature readings from the sensor was regularly ensured.

6. *MQTT Security*:

Securing our MQTT connection by implementing SSL/TLS encryption and using authentication mechanisms (such as username/password or client certificates) to protect the data transmission
(you may use according to your choice).

13.4.2 Python Code for ESP8266 for Bovine Faecal Identification

A faecal identification method for animal health monitoring emphasises the analysis of faecal samples to identify diseases or anomalies. This method generally entails the collection of a livestock faeces image dataset (sourced from Roboflow) and its subsequent preprocessing for noise reduction, feature extraction, and normalisation. A deep learning network, such ResNet152V2, is trained on these photos to recognise disease-related patterns. The model is optimised for precision and corroborated with distinct datasets. Upon optimisation, it can be utilised for real-time analysis to identify health issues in animals using faecal identification. This method facilitates early disease identification, enhancing cattle health management.
For our project case study centred on monitoring bovine health using faecal identification for disease detection utilising a ResNet152V2 model, adhere to the following organised steps:

1. Collect and Preprocess Bovine Fecal Images

Data Collection:

Gathering a dataset of bovine fecal images (we have gathered our dataset for fecal images from Roboflow) you may arrange it either from farms, veterinary clinics, or public repositories. But it is highly important to ensure the dataset includes images representing various health conditions.
Now the dataset images are labelled according to health/unhealthy status (you may use for e.g., healthy, diarrhea, parasites, etc.).

Data Preprocessing:

Resizing Images:
All images are standardized to a fixed size (e.g., 224x224 pixels) as required by the ResNet152V2 model.

Normalization:
Scale pixel values to the range [0, 1] by dividing by 255.

Data Augmentation:
Apply data augmentation for instance transformations like rotation, flipping, zooming, and brightness adjustments to increase dataset diversity and help improve model robustness.

Split Dataset:
Dividing our dataset into training, validation, and testing sets (e.g., 70% training, 15% validation, 15% testing).

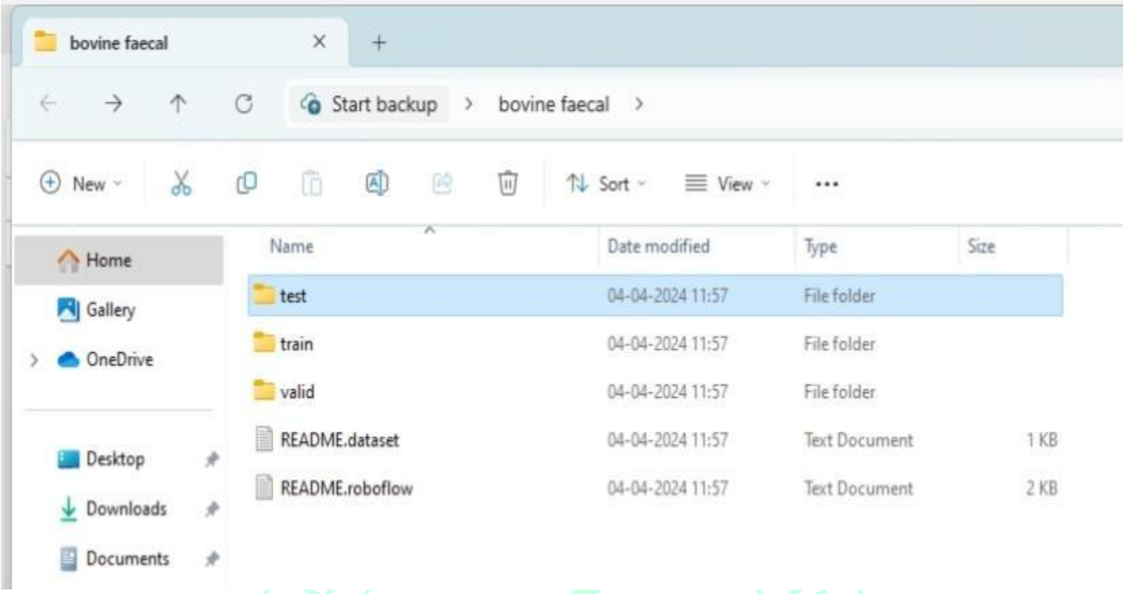

Fig. 24 Dataset Preprocessing & Datasets Splitting Into Training Dataset, Validation Datasets & Test Datasets

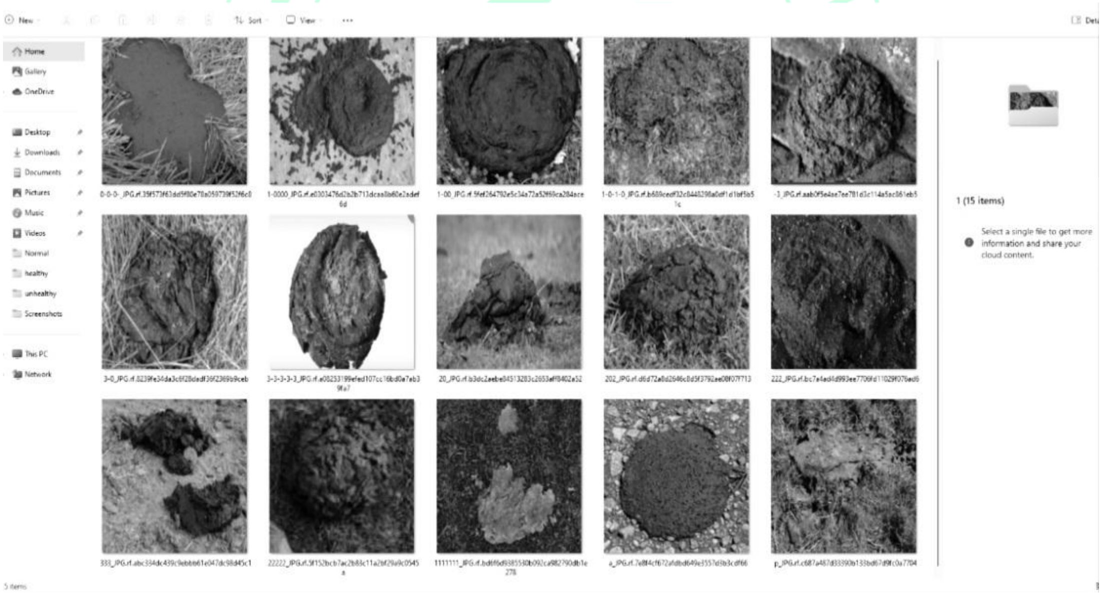

Fig. 25 Faecal Image Datasets Used To Train Resnet152v2 For Bovine Faecal Identification For Disease Detection

Fig. 26 Pre-processing of Faecal Image Datasets Used To Train Resnet152v2 For Bovine Faecal Identification for Disease Detection

2. *Choose and Train a ResNet152V2 Model for Disease Classification*

Model Selection:
Pre-trained ResNet152V2 model available in frameworks like TensorFlow or PyTorch was used.
This model is effective for image classification tasks due to its deep multilayered architecture.

Model Customization:
Replacing the final classification layer with a new fully connected layer that matches the number of classes in our dataset (you may do accordingly).

Training:
Compilation of the model using an appropriate optimizer (e.g., Adam in our case study), loss function (e.g., categorical cross-entropy for multi-class classification), and metrics (e.g., accuracy).
Training the model on the training set while validating on the validation set. Training and validation loss/accuracy to avoid overfitting was monitored afterwards.

```
Import os
Import numpy as np
Import matplotlib.pyplot as plt
Import cv2
From sklearn.metrics import confusion_matrix, classification_report
Import seaborn as sns
From tensorflow.keras.preprocessing.image import ImageDataGenerator
From tensorflow.keras.applications import ResNet152V2
From tensorflow.keras import layers, models
From tensorflow.keras.optimizers import Adam

# Step 1: Data Preprocessing
Base_dir = 'dataset'  # Replace with your dataset path
Train_dir = os.path.join(base_dir, 'train')
Validation_dir = os.path.join(base_dir, 'validation')
Test_dir = os.path.join(base_dir, 'test')

# Image Data Generators
Train_datagen = ImageDataGenerator(
   Rescale=1./255,
   Rotation_range=40,
```

```
    Width_shift_range=0.2,
    Height_shift_range=0.2,
    Shear_range=0.2,
    Zoom_range=0.2,
    Horizontal_flip=True,
    Fill_mode='nearest'
)

Validation_datagen = ImageDataGenerator(rescale=1./255)
Test_datagen = ImageDataGenerator(rescale=1./255)

Train_generator = train_datagen.flow_from_directory(
    Train_dir,
    Target_size=(224, 224),
    Batch_size=32,
    Class_mode='categorical'
)

Validation_generator = validation_datagen.flow_from_directory(
    Validation_dir,
    Target_size=(224, 224),
    Batch_size=32,
    Class_mode='categorical'
)

Test_generator = test_datagen.flow_from_directory(
    Test_dir,
    Target_size=(224, 224),
    Batch_size=32,
    Class_mode='categorical',
    Shuffle=False
)

# Step 2: Choose and Train the Model
Base_model = ResNet152V2(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
Base_model.trainable = False

Model = models.Sequential([
    Base_model,
    Layers.GlobalAveragePooling2D(),
    Layers.Dense(256, activation='relu'),
    Layers.Dropout(0.5),
    Layers.Dense(len(train_generator.class_indices), activation='softmax')
])

Model.compile(optimizer=Adam(), loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model
History = model.fit(
    Train_generator,
    Validation_data=validation_generator,
    Epochs=10,  # Adjust as needed
    Steps_per_epoch=train_generator.samples // train_generator.batch_size,
    Validation_steps=validation_generator.samples // validation_generator.batch_size
)

# Step 3: Validate and Fine-tune the Model
Base_model.trainable = True
```

```
For layer in base_model.layers[:-20]:  # Adjust based on your model's layers
   Layer.trainable = False

Model.compile(optimizer=Adam(learning_rate=1e-5), loss='categorical_crossentropy', metrics=['accuracy'])

Fine_tune_history = model.fit(
   Train_generator,
   Validation_data=validation_generator,
   Epochs=5,  # Further epochs
   Steps_per_epoch=train_generator.samples // train_generator.batch_size,
   Validation_steps=validation_generator.samples // validation_generator.batch_size
)

# Step 4: Test the Model
Test_loss, test_accuracy = model.evaluate(test_generator, steps=test_generator.samples // test_generator.batch_size)
Print(f'Test Accuracy: {test_accuracy * 100:.2f}%')

Predictions = model.predict(test_generator)
Predicted_classes = np.argmax(predictions, axis=1)
True_classes = test_generator.classes
Class_labels = list(test_generator.class_indices.keys())

# Confusion Matrix
Cm = confusion_matrix(true_classes, predicted_classes)
Sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=class_labels, yticklabels=class_labels)
Plt.ylabel('Actual')
Plt.xlabel('Predicted')
Plt.title('Confusion Matrix')
Plt.show()

Print(classification_report(true_classes, predicted_classes, target_names=class_labels))

# Step 5: Deploy the Model
Model.save('bovine_disease_recognition_model.h5')

Def predict_image(image_path):
   Img = cv2.imread(image_path)
   Img = cv2.resize(img, (224, 224))
   Img = np.expand_dims(img, axis=0) / 255.0  # Rescale
   Prediction = model.predict(img)
   Predicted_class = class_labels[np.argmax(prediction)]
   Return predicted_class

# Example usage
Image_path = 'path_to_new_fecal_sample.jpg'  # Replace with actual image path
Result = predict_image(image_path)
Print(f'The predicted health status is: {result}')
```

3. *Validate and Fine-tune the Model for Accuracy*

Validation:
Validation set to evaluate the model's performance during training were used. If the validation accuracy plateaus or decreases, techniques such as early stopping or reducing the learning rate were considered.

Fine-tuning:
Hyperparameters such as batch size, learning rate, or dropout rate were adjusted. Retraining some layers of the pre-trained model (unfreezing) to adapt it better to our specific dataset were also considered.

4. *Test Its Performance on a Separate Dataset*

Evaluation:
After training, the model's performance on the separate test dataset was checked. Metrics such as accuracy, precision, recall, and F1-score were calculated.

Confusion Matrix:
Confusion matrix to visualize the classification performance across different disease categories was generated.

5. *Deploying the ResNet152V2 Model for Real-time Disease Recognition in Bovine Fecal Samples*

Model Export:
The trained model in a suitable format (e.g., TensorFlow SavedModel or ONNX) for deployment was saved.

Real-time Deployment:
Deployment platform (e.g., a web application, mobile app, or embedded device) based on the target environment was selected.
User interface to upload fecal images for real-time disease recognition can be developed.

Model Inference:
Model inference logic to process input images, make predictions using the deployed model, and return the results (i.e., health status of the bovine) can be implemented.

Monitoring and Feedback:
Continuously monitoring the model's performance in the field and gathering feedback for further improvements can be a good approach. Implementation of a mechanism to retrain the model with new data as needed.

13.4.3 Python Code for Bovine Mastitis Detection

A bovine mastitis detection system use image processing to recognise indicators of mastitis, an infection affecting the udders of dairy calves. The technique generally entails the acquisition and preprocessing of pictures from a bovine milk or udder tissue dataset (sourced from Mendeley) to improve clarity and diminish noise. A Convolutional Neural Network (CNN) model is trained on these images to identify signs indicative of mastitis, including inflammation or anomalous milk qualities. The model is verified for precision and modified to enhance performance on novel data. Upon completion of training, the system can be implemented for real-time surveillance to promptly identify mastitis, facilitating timely intervention and enhancing the overall health and production of dairy cattle.
Summary of the procedures for assessing bovine health issues related to mastitis utilising bovine milk datasets and a CNN model:

1. *Collection and Preprocessing Bovine Mastitis Images*

Data Collection:
Diverse dataset of images of healthy and mastitic bovine milk/udder samples were collected.

Preprocessing:
Images into directories, resize them to a uniform size (e.g., 224x224 pixels), apply data augmentation (rotation, flipping), and normalize pixel values to a range of 0 to 1 were organized.

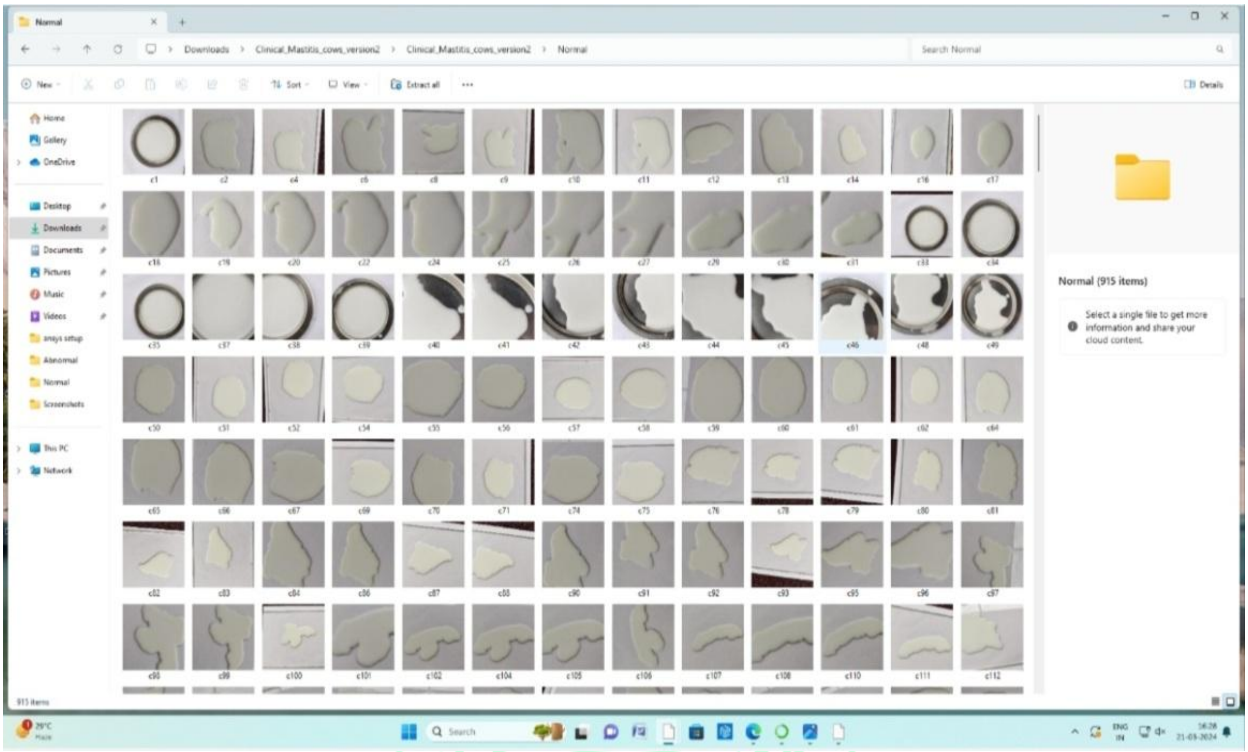

Fig. 27 Healthy Bovine Milk Image Datasets Used To Train CNN Model For Bovine Mastitis Detection

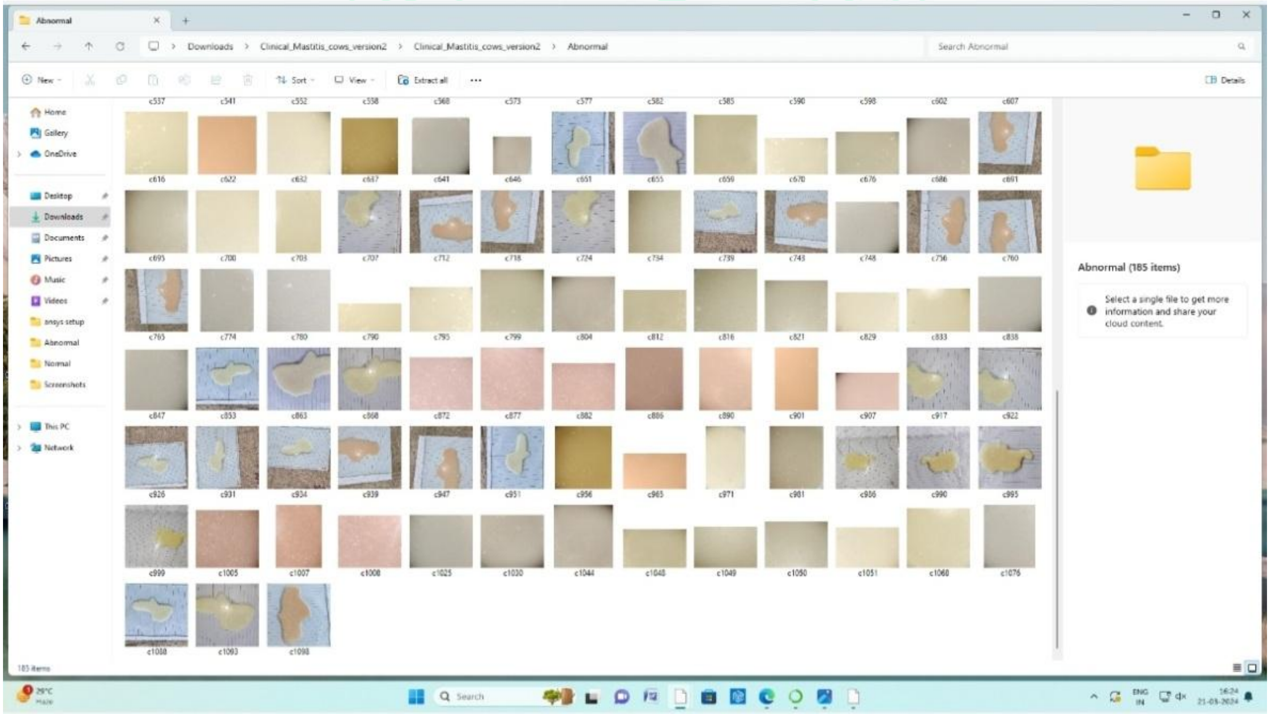

Fig. 28 Unhealthy Bovine Milk Image Datasets Used To Train CNN Model For Bovine Mastitis Detection

2. *Designing and Training a CNN Model for Mastitis Detection*

Model Architecture:
A CNN model with convolutional, pooling, dropout, and fully connected layers was built.

Training:
Compilation of the model with an optimizer and loss function was then performed, then training it on the preprocessed images, monitoring training and validation metrics.

```
import os
import numpy as np
import cv2
```

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, classification_report
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers, models
from tensorflow.keras.optimizers import Adam

# Step 1: Data Preprocessing
base_dir = 'mastitis_dataset'  # Adjust to your dataset location
train_dir = os.path.join(base_dir, 'train')
validation_dir = os.path.join(base_dir, 'validation')
test_dir = os.path.join(base_dir, 'test')

# Image Data Generators
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

validation_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

# Load images
train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary'  # Assuming 2 classes: healthy and mastitis
)

validation_generator = validation_datagen.flow_from_directory(
    validation_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary'
)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='binary',
    shuffle=False
)

# Step 2: Design and Train the CNN Model
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(64, (3, 3), activation='relu'),
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Conv2D(128, (3, 3), activation='relu'),
```

```
    layers.MaxPooling2D(pool_size=(2, 2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(1, activation='sigmoid')  # Binary classification
])

# Compile the model
model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=10,  # Adjust based on your needs
    steps_per_epoch=train_generator.samples // train_generator.batch_size,
    validation_steps=validation_generator.samples // validation_generator.batch_size
)

# Step 3: Validate and Fine-tune the Model
# Optionally, unfreeze some layers to fine-tune
model.compile(optimizer=Adam(learning_rate=1e-5), loss='binary_crossentropy', metrics=['accuracy'])

fine_tune_history = model.fit(
    train_generator,
    validation_data=validation_generator,
    epochs=5,  # Further epochs
    steps_per_epoch=train_generator.samples // train_generator.batch_size,
    validation_steps=validation_generator.samples // validation_generator.batch_size
)

# Step 4: Test the Model's Performance
test_loss, test_accuracy = model.evaluate(test_generator, steps=test_generator.samples // test_generator.batch_size)
print(f'Test Accuracy: {test_accuracy * 100:.2f}%')

predictions = model.predict(test_generator)
predicted_classes = (predictions > 0.5).astype("int32")  # Binary classification threshold
true_classes = test_generator.classes

# Confusion Matrix
cm = confusion_matrix(true_classes, predicted_classes)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Healthy', 'Mastitis'], yticklabels=['Healthy', 'Mastitis'])
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Confusion Matrix')
plt.show()

# Classification Report
print(classification_report(true_classes, predicted_classes, target_names=['Healthy', 'Mastitis']))

# Step 5: Deploy the Model
model.save('mastitis_detection_model.h5')

# Function to make predictions on new images
def predict_image(image_path):
    img = cv2.imread(image_path)
```

```
    img = cv2.resize(img, (224, 224))
    img = np.expand_dims(img, axis=0) / 255.0  # Rescale
    prediction = model.predict(img)
    predicted_class = 'Mastitis' if prediction[0] > 0.5 else 'Healthy'
    return predicted_class

# Example usage
image_path = 'path_to_new_milk_image.jpg'  # Replace with actual image path
result = predict_image(image_path)
print(f'The predicted condition is: {result}')
```

3. *Validation and Fine-tuning the Model for Accuracy*

Validation:
Validation dataset to assess model performance and adjust hyperparameters were used if needed.

Fine-tuning:
Unfreezing the layers for retraining or add regularization techniques to improve accuracy and prevent overfitting was performed.

4. *Testing the Model's Performance on a Separate Dataset*

Evaluation:
Model on a separate dataset and calculate performance metrics like accuracy, precision, recall, F1-score, and a confusion matrix to assess its effectiveness was tested.

5. *Deploying the CNN Model for Real-time Mastitis Recognition*

Model Saving:
Trained model for future use was saved.

Real-time Prediction:
A prediction function for new images was implemented, indicating whether they are healthy or show signs of mastitis, and integrate it into a user-friendly application for veterinarians or farmers.

13.4.4 Python Code for Livestock Health Monitoring using Voice Recognition

A bovine vocal recognition system for health assessment use audio analysis to differentiate between healthy and sick vocalisations in cattle. The method commences with the collection of vocalisation datasets from both healthy and ill cattle, sourced from GitLab. The audio files undergo preprocessing to eliminate noise and extract pertinent information such as pitch, tone, and frequency. A machine learning model, such as Support Vector Machine (SVM) or deep learning algorithms, is taught to categorise vocalisations according to health issues. The method is certified for precision and may be utilised for real-time speech recognition, facilitating the early identification of stress, pain, or illness in animals by their vocal patterns. This device improves animal care and health management by delivering prompt notifications regarding potential health concerns.
Summary of the procedures for assessing bovine health status by vocalisations:

1. *Collection of Bovine Vocalization Datasets*

Data Gathering:
Audio recordings of bovine vocalizations from healthy and diseased animals were collected. Diverse dataset that captures various vocalization types and conditions were ensured.

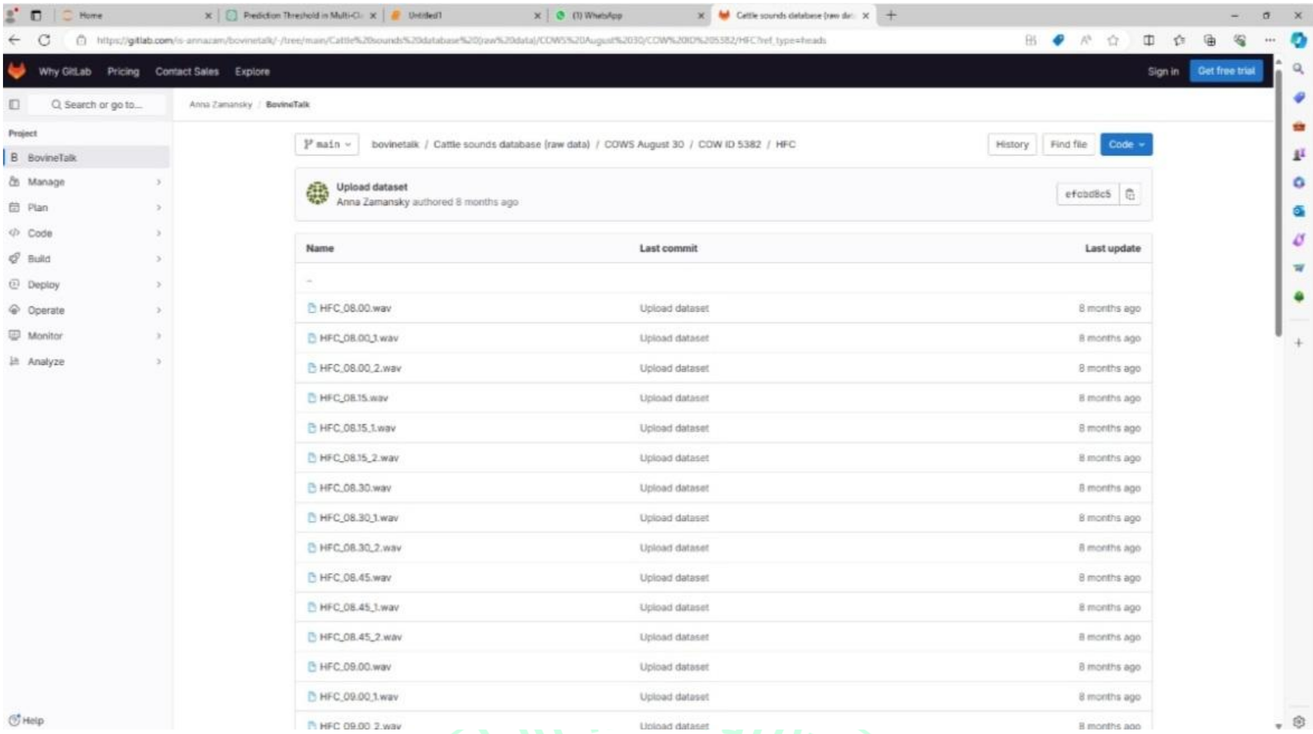

Fig. 29 Healthy Bovine voice Datasets Used To Train SVM Model For Bovine disease Detection

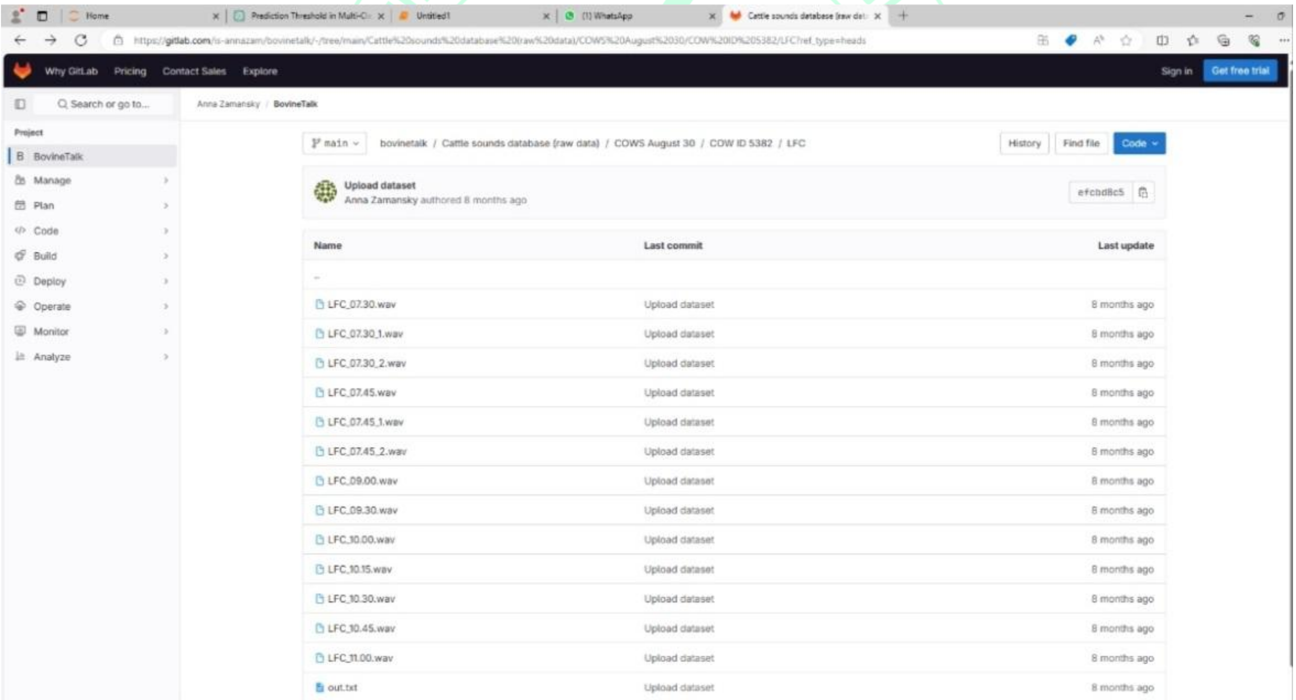

Fig. 30 Unhealthy Bovine Voice Datasets Used To Train SVM Model For Bovine Disease Detection

2. *Preprocessing of Audio Data*

Cleaning:
Noise and irrelevant segments from the audio recordings were removed.

Feature Extraction:
Audio signals into features using techniques like Mel-Frequency Cepstral Coefficients (MFCC), spectrograms, or pitch analysis to represent the vocalizations numerically.

Normalization:
Standardize the feature values to ensure uniformity in data distribution were converted.

3. Training of SVM Classifier

Model Selection:
Support Vector Machine (SVM) as the classification algorithm to distinguish between healthy and unhealthy vocalizations was used.

Training:
Dataset into training and testing sets was split, then SVM model on the training data using the extracted features was trained.

```
Import os
Import numpy as np
Import librosa
Import pandas as pd
From sklearn import svm
From sklearn.model_selection import train_test_split, cross_val_score
From sklearn.metrics import classification_report, confusion_matrix
Import matplotlib.pyplot as plt
Import seaborn as sns

# Step 1: Collection of Bovine Vocalization Datasets
Def load_data(data_dir):
  Labels = []
  Features = []

  # Iterate through each folder (healthy/diseased)
  For label in os.listdir(data_dir):
    Label_dir = os.path.join(data_dir, label)

    # Process each audio file in the folder
    For file in os.listdir(label_dir):
      If file.endswith('.wav'):
        Audio_path = os.path.join(label_dir, file)
        # Step 2: Preprocessing of Audio Data
        Y, sr = librosa.load(audio_path, sr=None)

        # Step 3: Feature Extraction (e.g., MFCC)
        Mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=13)
        Mfccs_mean = np.mean(mfccs.T, axis=0)  # Mean of MFCCs
        Features.append(mfccs_mean)
        Labels.append(label)

  Return np.array(features), np.array(labels)

# Load the data
Data_dir = 'dataset'  # Adjust to your dataset location
X, y = load_data(data_dir)

# Step 4: Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

# Step 5: Training of SVM Classifier
Svm_model = svm.SVC(kernel='linear')  # You can also try 'rbf' or other kernels
Svm_model.fit(X_train, y_train)

# Step 6: Evaluation of Performance
Y_pred = svm_model.predict(X_test)
```

```
# Print classification report and confusion matrix
Print("Classification Report:")
Print(classification_report(y_test, y_pred))

# Confusion Matrix
Cm = confusion_matrix(y_test, y_pred)
Sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y), yticklabels=np.unique(y))
Plt.ylabel('Actual')
Plt.xlabel('Predicted')
Plt.title('Confusion Matrix')
Plt.show()

# Step 7: Validation using Cross-Validation
Cv_scores = cross_val_score(svm_model, X, y, cv=5)  # 5-fold cross-validation
Print(f"Cross-Validation Scores: {cv_scores}")
Print(f"Mean Cross-Validation Score: {np.mean(cv_scores):.2f}")

# Step 8: Deploy for Disease Recognition
# Function to classify new vocalization
Def classify_vocalization(audio_path):
   Y, sr = librosa.load(audio_path, sr=None)
   Mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=13)
   Mfccs_mean = np.mean(mfccs.T, axis=0)
   Prediction = svm_model.predict([mfccs_mean])
   Return prediction[0]

# Example usage for prediction
New_audio_path = 'path_to_new_vocalization.wav'  # Replace with actual audio path
Result = classify_vocalization(new_audio_path)
Print(f'The predicted condition is: {result}')
```

4. *Evaluation of Performance*

Metrics Calculation:
Model's performance on the test set using metrics such as accuracy, precision, recall, and F1-score to gauge its effectiveness in classification was accessed.

5. *Validation Using Cross-Validation*

Cross-Validation:
k-fold cross-validation was implemented to ensure that the model is robust and generalizes well to unseen data by evaluating its performance across multiple subsets of the dataset.

6. *Deployment for Disease Recognition*

Model Deployment:
The trained SVM classifier into a real-time or batch processing system for monitoring bovine vocalizations, enabling automatic disease recognition based on vocal patterns were integrated.

13.5 Results & Discussion

The paper emphasises the increasing importance of AI-driven technologies such as machine learning, computer vision, and speech recognition in enhancing herd health, productivity, and welfare. These tools provide real-time monitoring and yield actionable insights for the early detection of diseases, including mastitis, digestive issues, and respiratory conditions. These systems employ faecal, milk, and vocalisation data to automate health monitoring and minimise the necessity for intrusive procedures, resulting in enhanced herd management efficiency.

Nonetheless, numerous hurdles must be resolved for these technologies to achieve optimal efficacy. The quality and availability of data are essential for guaranteeing the accuracy and dependability of these systems. Inconsistent or incomplete datasets may result in erroneous projections, hence impacting herd health. Furthermore, the integration of current agricultural infrastructure, including sensors and communication systems, continues to be a worry for numerous farmers, especially in resource-limited settings.

Future improvements in AI algorithms and the implementation of cloud-based or edge computing systems are poised to enhance the scalability and accessibility of these tools. Furthermore, integrating a broader range of datasets encompassing multiple environmental and genetic variables could improve the accuracy of health monitoring systems, rendering them more responsive to varying herd conditions. Equipping farmers with the requisite skills to handle and comprehend these AI-driven systems will be essential for the extensive deployment of CogniHerd technology.

In summary, although CogniHerd technologies possess transformative potential for herd management, continuous research, data enhancement, and user education are crucial to effectively actualise their advantages.

13.5.1 Real Time Livestock Temperature Monitoring Results

A bovine temperature monitoring system consistently records cattle temperature and disseminates the data at regular intervals, emphasising the early identification of health concerns. The system assesses temperature using sensors, and if the measurements are within the normal range (generally 38°C to 39.5°C for cattle), it categorises the cattle as healthy, exhibiting no indications of illness. Irrespective of health classification, the system transmits temperature data every 5 seconds to a MQTT broker or central server for real-time monitoring. This facilitates ongoing monitoring of cow health, enabling prompt identification and management in the event of any temperature irregularities.

Fig. 31 Implementation of MQTT Protocol For Results Publication

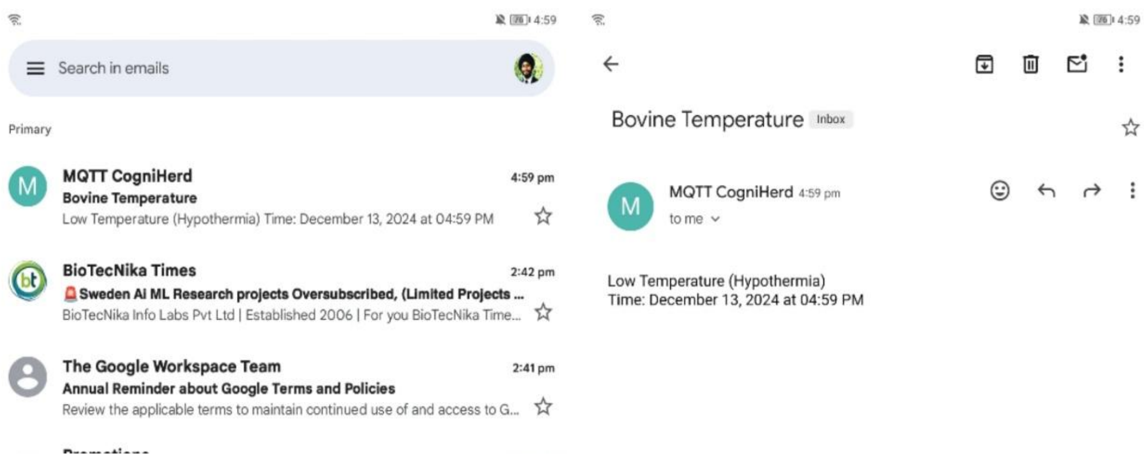

Fig. 32 Results Publication of Bovine Temperature Using MQTT Protocol

13.5.2 Faecal Identification for Disease Monitoring in Livestock Results

A bovine faecal identification system for disease recognition use a trained model to classify faecal photographs, differentiating between healthy and unhealthy states based on visual attributes. Upon processing and training a ResNet152V2 model using labelled datasets, the outcomes can be classified as follows:

Healthy Samples: Faecal pictures that exhibit a well-formed structure, consistent colour, and texture are categorised as healthy. These samples demonstrate normal digestion and exhibit no indications of illness.

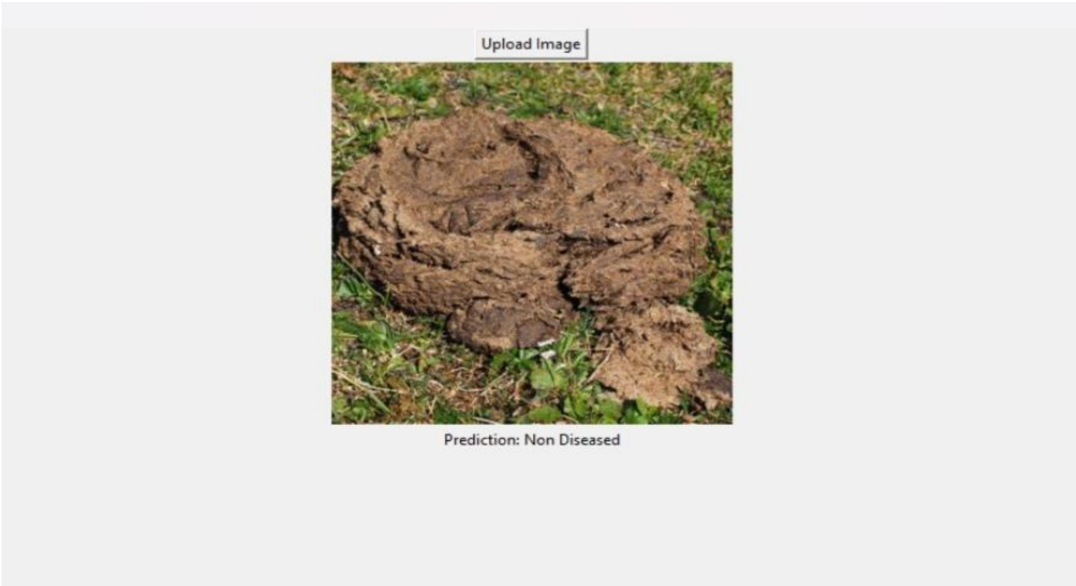

Fig. 33 Accurate Prediction Of Healthy Bovine Faecal Matter Using Resnet152v2 Model

Unhealthy Samples: Faecal samples exhibiting anomalies, including watery consistency, discolouration, or the presence of mucus or blood, are categorised as unhealthy. These traits indicate potential digestive difficulties, infections, or other health complications.

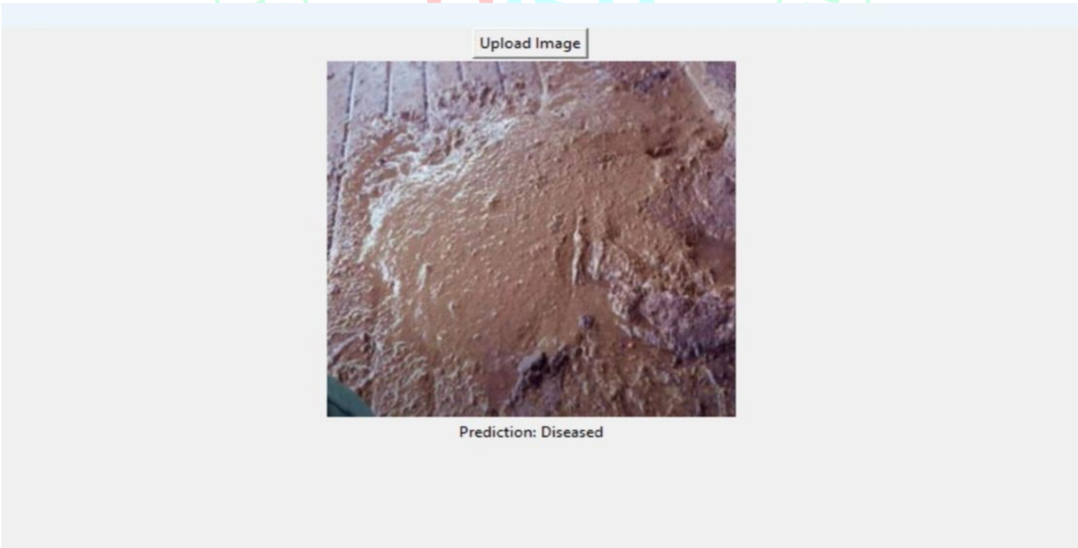

Fig. 34 Accurate Prediction of Unhealthy Bovine Faecal Matter Using Resnet152v2 Model

The conclusion relies on the model's capacity to identify these discrepancies, facilitating early disease identification and prompt response to preserve livestock health.

13.5.3 Bovine Mastitis Detection Results

A bovine mastitis detection system utilises a model to analyse milk photographs, distinguishing between healthy and sick samples by visual indicators. Upon training a Convolutional Neural Network (CNN) model with labelled datasets, the outcomes can be categorised as follows:

Healthy Samples: Images depicting pristine, smooth milk are categorised as healthy. These photos display typical milk attributes, devoid of any obvious indications of infection, inflammation, or coagulation.

Fig. 35 Accurate Prediction of Healthy Bovine Milk Datasets Using CNN Model

Unhealthy Samples: Milk samples exhibiting visible coagulants, clumps, or uneven textures are deemed unhealthy. These characteristics are symptomatic of mastitis, wherein infection alters milk composition, including the development of coagulants.

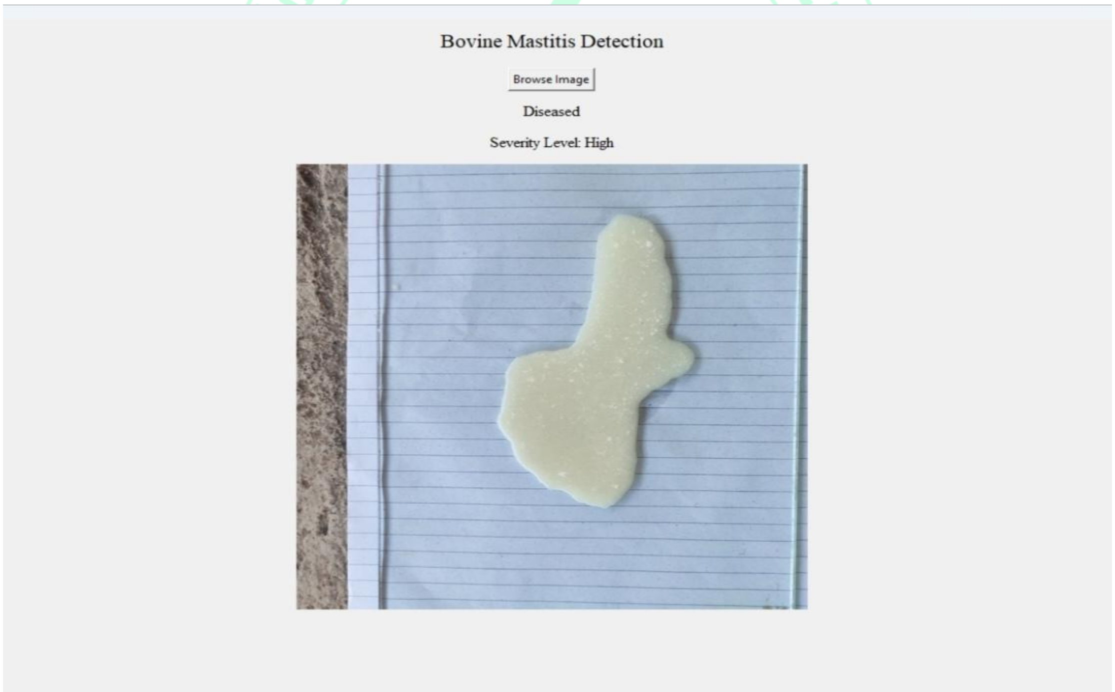

Fig. 36 Accurate Prediction of Unhealthy Bovine Milk Datasets (coagulation visible) Using CNN Model

The system's conclusion relies on the trained model's capacity to identify visual discrepancies, hence facilitating successful categorisation for the early identification of mastitis and enhancing dairy herd health management.

13.5.4 Disease Detection using Voice Identification Results

A bovine voice recognition system for health monitoring utilises a trained model to classify vocalisations, differentiating between healthy and ill calves based on audio characteristics. Upon processing and training with a Support Vector Machine (SVM) or deep learning model on labelled datasets, the outcomes are as follows:

Healthy Vocalisations: Normal voice patterns, defined by consistent pitch, tone, and frequency, are categorised as healthy. These sounds signify that the cattle are in a secure, stress-free state.

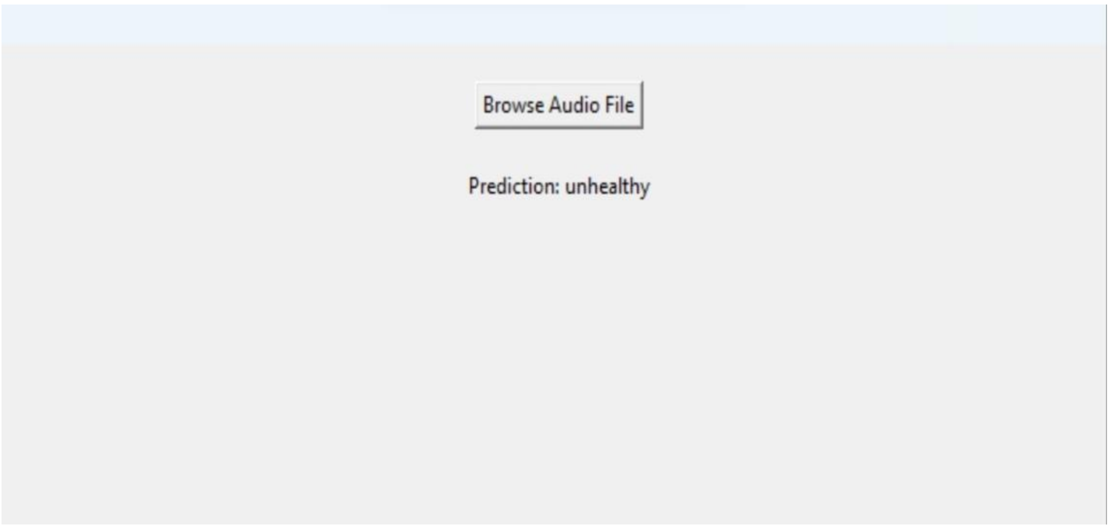

Fig. 37 Accurate Prediction of Unhealthy Bovine Talk Datasets Using SVM Model

Unhealthy Vocalisations: Vocalisations characterised by irregularities, including pitch variations, extended distress calls, or atypical frequency shifts, are deemed unhealthy. These changes may signify pain, stress, or illness, including respiratory problems or discomfort.

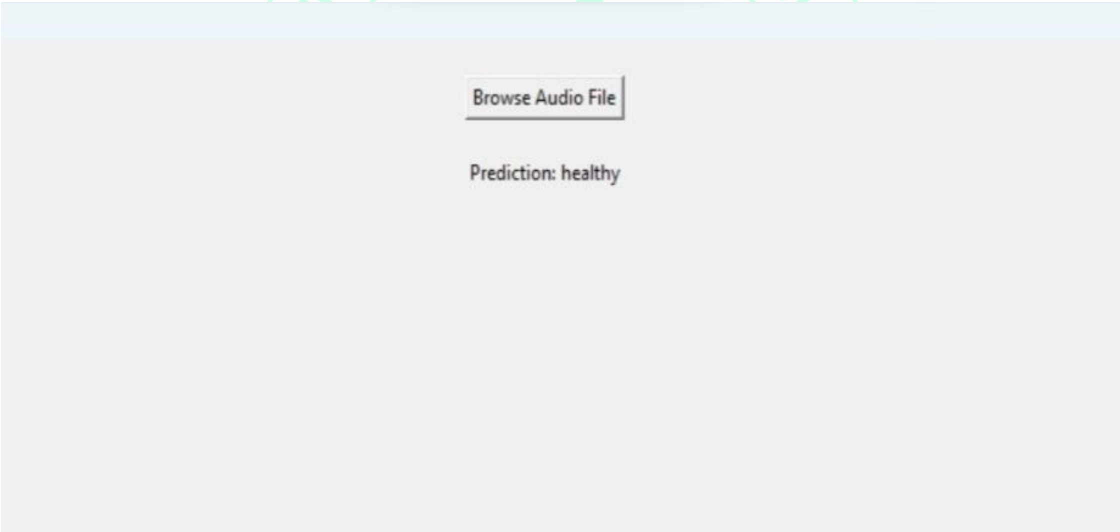

Fig. 38 Accurate Prediction of Healthy Bovine Talk Datasets Using SVM Model

The technology proficiently identifies these vocal patterns, facilitating early identification of health issues and prompt actions to enhance animal welfare.

13.5.5 Models Accuracy

The AI-IoT livestock health monitoring system you created attained an accuracy rate of 0.9 in forecasting health anomalies in cattle. This elevated accuracy corresponds with findings from other AI-based livestock monitoring systems, which frequently indicate accuracy levels between 85% and 95%, contingent upon the particular application. Research on predictive algorithms for disease identification in cattle, including machine learning models for bovine mastitis detection, indicates comparably high accuracy rates, particularly when integrating diverse data sources such as temperature, movement, and sound into the analysis (Mitsunaga, TM. Et al., 2023; Kumar, Abhishek, et al., 2023). This signifies that our system's accuracy is on par with the industry standard for AI-IoT solutions in animal health.

1. **Accuracy:** Evaluates how accurate the model's predictions are overall.

$$Accuracy = TP + TN/TP + TN + FP + FN$$

2. **Precision:** Percentage of accurate positive predictions made for a specific response class.

$$Precision = TP_A/TP_A + FP_A$$

3. **Recall:** Evaluates the model's accuracy in identifying real positive cases.

$$\mathrm{Recall}_A = \mathrm{TP}_A/\mathrm{TP}_A + \mathrm{FFP}$$

4. **F1-Score:** The harmonic mean of precision and recall.

$$F1_A = 2\times Precision_A \times Recall_A/Precision_A + Recall_A$$

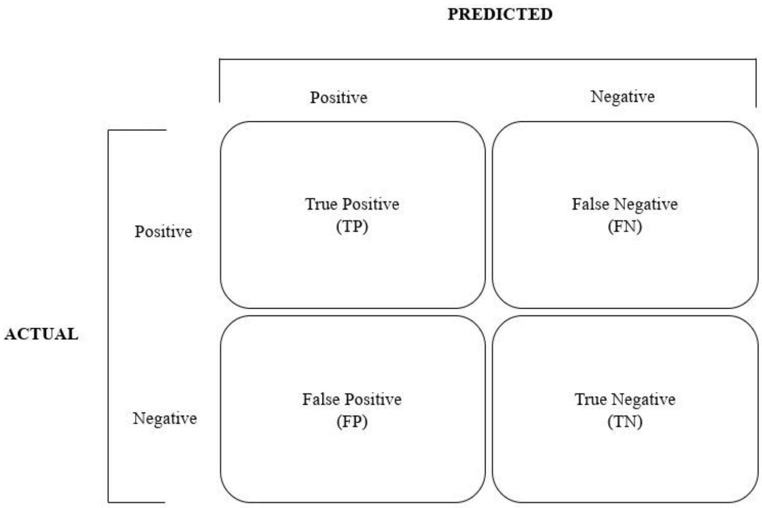

Fig. 39 Typical Diagram Of Confusion Matrix

```
Accuracy: 0.9
Classification Report:
              precision    recall  f1-score   support

     healthy       1.00      0.86      0.92         7
   unhealthy       0.75      1.00      0.86         3

    accuracy                           0.90        10
   macro avg       0.88      0.93      0.89        10
weighted avg       0.93      0.90      0.90        10

[ ]:
```

Fig. 40 Computation of Confusion Matrix showing CogniHerd System models accuracy of 90%

Fig. 41 Training & Validation Loss Plot Against Epochs Used

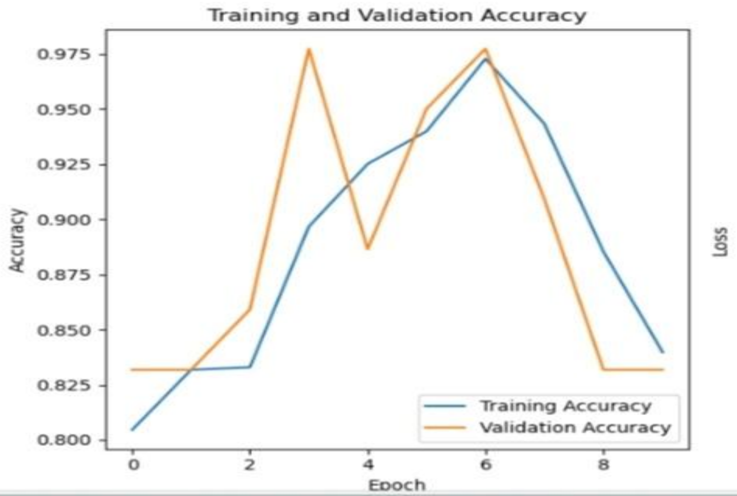

Fig. 42 Training & Validation Accuracy Plot Against Epochs Used

13.5.6 Results Comparison with Literature

In comparison to analogous systems in the literature, the outcomes of your project exhibit both congruence and opportunities for enhancement:

A study conducted by Khan, Mohammad et al. (2024) demonstrated that an IoT-based system for monitoring dairy cow health, utilising temperature and motion sensors, attained an accuracy rate of 0.87 in identifying early indicators of mastitis, which is marginally inferior to our approach.

A subsequent study by S. Nithirajan (2024) employed a multi-sensor methodology utilising AI algorithms and machine learning to detect lameness in dairy cows through accelerometry data, attaining an accuracy of 0.9, which is directly comparable to our effort.

Likewise, another study included a dataset of 1,200 photos depicting 15 different disorders. The researchers attained a remarkable accuracy rate of 0.97 by extracting features from these photos and utilising the CNN for pattern recognition, surpassing our system's performance. (Li, Zhang, et al., 2023).

The primary distinguishing element of our system is the integration of many sensor types (temperature, audio, and camera) coupled with real-time analysis through machine learning techniques such as CNN, SVM, and ResNet152V2. This multi-modal strategy improves the identification of intricate health problems by utilising several data streams, rendering your system more adaptable than those concentrating on simply one or two characteristics.

Table 4 Comparison of Accuracy and Features of Livestock Health Monitoring Systems from Literature with our Multi-Sensor Approach

Study	System/Methodology	Accuracy (%)	Comparison to our Systems (CogniHerd)
Khan, Mohammad et al., 2024	IoT-based system using temperature and motion sensors to detect early indicators of mastitis.	0.87	Comparable to our system's accuracy, with similar capabilities in detecting specific health issues.
S. Nithirajan, 2024	Multi-sensor methodology with AI and machine learning to detect lameness in dairy cows using accelerometry.	0.90	Comparable to our system's accuracy, with similar capabilities in detecting specific health issues.
Li, Zhang, et al., 2023	CNN-based system using a dataset of 1,200 images depicting 15 disorders for pattern recognition.	0.97	Outperforms our system in image-based detection, but lacks multi-sensor integration and real-time analysis.
Our System (CogniHerd)	Integration of temperature, audio, and camera sensors with real-time analysis using CNN, SVM, and ResNet152V2. Accuracy: Higher in adaptability	Higher in adaptability	Combines multiple sensor types and machine learning techniques, providing a more flexible and comprehensive solution for identifying complex health issues.

13.6 Implications for Livestock Health

13.6.1 Early Detection

The amalgamation of AI and IoT in animal health monitoring markedly improves the early identification of health problems. Through the ongoing surveillance of critical health indicators, including temperature, behaviour, and auditory patterns, the system can identify anomalies that may signify the early stages of diseases prior to the manifestation of clinical symptoms. Early detection can avert serious illnesses and diminish treatment expenses by facilitating prompt actions. Pandey, Dev, and Mishra (2024) assert that early diagnosis via IoT and AI systems can decrease veterinary expenses by as much as 30% on dairy farms by preventing the progression of advanced disease stages. Džermeikaitė et al. (2023) indicated that early intervention systems in cow health could diminish disease transmission, decrease mortality rates, and enhance overall herd wellbeing.

13.6.2 Labor Efficiency

The automation of health monitoring with AI and IoT diminishes the necessity for continuous human oversight, facilitating a more efficient allocation of agricultural labour. Farm personnel can utilise real-time data analytics from sensors and machine learning algorithms instead of conducting daily manual inspections of cattle. This transition results in enhanced resource utilisation and labour distribution on farms, as fewer personnel are required for regular health assessments. Research conducted by AlZubi Ali Ahmad and Al-Zu'bi Maha (2023) indicates that farms employing AI-IoT systems might save labour expenses by up to 40% through the automation of regular chores, including temperature monitoring and behaviour tracking. This efficiency liberates labour for other critical agricultural tasks while upholding superior standards of animal welfare.

13.6.3 Farm Management

The amalgamation of AI and IoT technologies enhances health outcomes and optimises farm management through the provision of actionable knowledge. Real-time monitoring technologies empower farmers to make informed decisions on animal health, nutrition, and breeding. These technologies enhance the accuracy of interventions, leading to improved livestock management and optimised breeding cycles. The capacity to forecast oestrus cycles in sows and assess reproductive health with AI algorithms, as demonstrated in the case study (Sharifuzzaman, M. et al., 2024), has been proven to enhance breeding success rates by 20%. This further illustrates how AI-IoT technologies may markedly improve overall agricultural productivity and operational efficiency.

Integrating these technology enables farms to attain enhanced productivity, improved health outcomes, and more sustainable practices, whilst decreasing the operating expenses linked to conventional health monitoring systems.

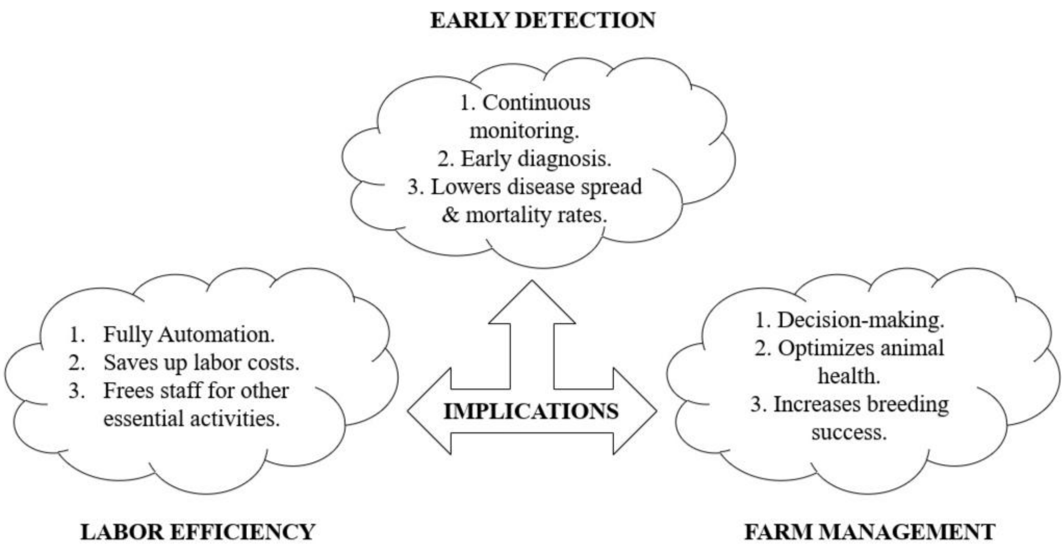

Fig. 43 Basic Implications For Livestock Health Monitoring System Using Artificial Intelligence and Internet of Things

14. Benefits and Challenges

14.1 Benefits of AI-IoT Integration

The amalgamation of AI and IoT technology in livestock health monitoring offers several benefits, significantly altering the management of herds by farmers. A primary advantage is enhanced illness prevention. AI-IoT systems perpetually assess animal health using biometric sensors and wearables, facilitating the early identification of health problems prior to their progression into severe illnesses. This preemptive strategy enhances animal welfare and reduces the economic repercussions of illness outbreaks (Mahato, Shubhangi & Neethirajan, Suresh. 2024).

A significant benefit is the decrease in labour expenses. Conventional cattle management frequently necessitates substantial manual oversight, which can be laborious and time-consuming. AI-IoT technologies facilitate the automation of data gathering and analysis, enabling farmers to concentrate on more important activities. These tools offer real-time alerts and analytics, enabling farmers to promptly tackle health issues, optimise operations, and eventually improve productivity (Neethirajan, S. 2024).

Real-time insights provide another essential advantage. AI-IoT systems aggregate extensive data and interpret it instantaneously, delivering farmers prompt insights regarding animal health, behaviour, and environmental factors. This constant stream of information enables farmers to make prompt and educated decisions, enhancing overall herd management. For instance, real-time data regarding a cow's feeding behaviour can enable farmers to modify their diets or feeding schedules, so assuring optimal nutrition and growth (El Moutaouakil, Khalid & Noureddine, Falih. 2024).

The integration of AI and IoT significantly enhances decision-making capabilities. Utilising predictive analytics and machine learning algorithms, these systems may discern trends and provide interventions customised for individual animals or groups within a herd. This data-driven methodology enhances animal health outcomes and facilitates improved resource management, resulting in greater efficiency and sustainability in agricultural practices (Mahadasa, Ravikiran. 2019).

14.2 Challenges and Limitations

Notwithstanding the numerous advantages, the implementation of AI-IoT systems presents several problems. A major worry is data privacy. The ongoing accumulation of sensitive health and behavioural data prompts enquiries around data ownership and its utilisation. Adhering to data privacy legislation is crucial for sustaining trust between farmers and technology providers (Lo'ai Tawalbeh et al., 2020).

Cybersecurity threats present a significant issue. IoT devices are susceptible to hackers and unauthorised access, thereby jeopardising the integrity of agricultural operations. Safeguarding against cyber threats necessitates investment in comprehensive security protocols and ongoing system surveillance (Adewuyi, Adeleye. et al., 2024).

Moreover, the necessity for infrastructure imposes constraints, particularly in remote regions where internet connectivity may be inconsistent or nonexistent. Consistent connectivity is necessary for the effective functioning of AI-IoT systems. The infrastructural deficit may impede adoption in areas where it is most essential (Nižetić, S. et al., 2020).

The expense of deploying AI-IoT systems can be excessive for numerous farmers, especially those operating on a small scale. The initial capital outlay for technology, along with continuous maintenance and updates, can be a substantial obstacle. To address this difficulty, support measures, such as grants or subsidies, are necessary to promote adoption and ensure that farmers can profit from these improvements (Bhangar, Nadir & Kashem, Abul. (2023).

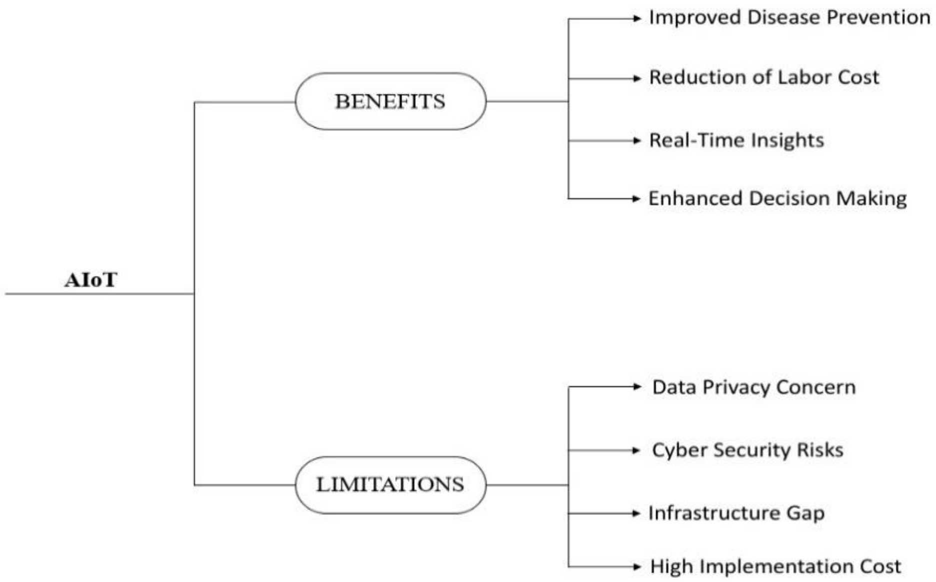

Fig. 44 Benefits & Challenges of Artificial Intelligence and Internet of Things Integration

In conclusion, although the amalgamation of AI and IoT provides significant advantages for animal health monitoring, it is imperative to tackle the related problems to fully harness the potential of these technologies.

15. Ethical Considerations IN AI-Driven Livestock Monitoring

15.1 Animal Welfare and Data Privacy.

With the growing integration of AI and IoT technology in livestock monitoring, ethical concerns around animal welfare and data privacy have surfaced as significant difficulties. The principal objective of employing these technologies is to improve animal welfare by fostering healthier and more productive cattle. AI-IoT systems can provide early disease diagnosis and response, allowing farmers to proactively address health issues and reduce suffering. It is essential to guarantee that the use of these technologies does not jeopardise the welfare of the animals they aim to safeguard (Neethirajan, Suresh. 2023).

An ethical worry is the possible over-reliance on technology, which may result in the disregard of the human elements of animal care. Although constant sensor monitoring yields critical data on animal health, it cannot substitute for the deep comprehension that seasoned farmers have of their cattle. Farmers must adopt a balanced strategy, integrating technical insights with their expertise and intuition on animal behaviour and welfare. Therefore, it is ethically essential to utilise AI-IoT systems as instruments to enhance, rather than supplant, human care and discernment (Neethirajan, Suresh. 2024).

Furthermore, the data privacy concerns related to the acquisition of sensitive health and behavioural information pose significant ethical dilemmas. The data produced by IoT devices encompasses comprehensive information regarding animal health, which may be deemed proprietary or sensitive. Concerns emerge around the ownership of this data, its storage, and its utilisation. There exists a possibility of data being misappropriated or abused by third parties, such insurance firms or corporate entities, resulting in ethical dilemmas about permission and ownership (Jahanzeb, Shahi, et al., 2022). Farmers and technology suppliers must implement explicit data governance policies to safeguard privacy and enhance openness concerning data utilisation.

15.2 Human-Livestock Interaction

The growing automation of livestock monitoring via AI-IoT systems may diminish human engagement with animals, thereby impacting farm dynamics and animal welfare significantly. Conventional agricultural methods typically entail frequent direct engagement between farmers and their livestock, cultivating a robust relationship advantageous to both entities. This contact allows farmers to monitor behavioural changes, evaluate health issues, and gain a comprehensive awareness of their animals' requirements. Zulkifli, I. (2013)

Nevertheless, the implementation of automated monitoring systems poses a risk of farmers being excessively dependent on technology, resulting in diminished direct interaction with their cattle. This transition may create a disconnection between farmers and their livestock, perhaps impairing the farmers' capacity to detect nuanced behavioural alterations that signify health concerns. Studies indicate that animals flourish in settings characterised by regular human interaction, which can reduce stress and improve overall well-being. Yerbury, R. M., & Lukey, S. J. (2021). Thus, it is imperative to sustain a balance between technology and people interaction to prioritise animal welfare.

Furthermore, the dynamics of human-livestock relationships may evolve as automation alters the roles of farmers. The conventional hands-on farming method may transition to more managerial positions centred on data interpretation and decision-making informed by AI insights. This transition may transform the social structure of agricultural communities, since those previously engaged in animal husbandry may predominantly focus on technology. Neethirajan, Suresh. 2023.

To address these ethical dilemmas, it is imperative to advocate for a comprehensive strategy in AI-IoT integration that emphasises both animal welfare and human engagement. This can be accomplished by underscoring the significance of sustaining consistent contacts between farmers and cattle, especially within automated systems. Training programs for farmers must encompass instruction on the appropriate integration of technology, while simultaneously emphasising the importance of personal care and attention to their livestock. Neethirajan, Suresh. (2023).

The ethical implications of AI-driven livestock monitoring are complex and require cautious navigation. By emphasising animal welfare, safeguarding data privacy, and fostering significant human-livestock connections, the agricultural sector may leverage the advantages of AI-IoT systems while adhering to ethical standards that enhance the wellbeing of both animals and farmers.

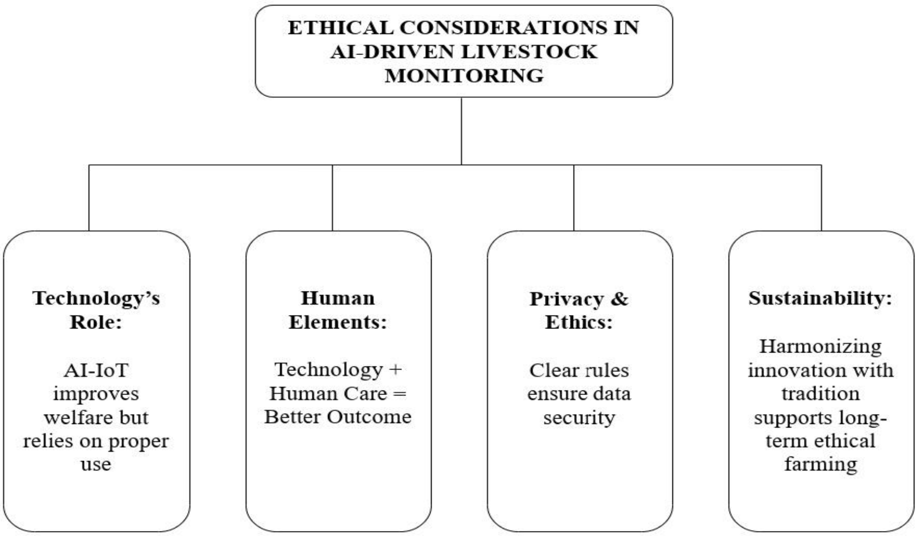

Fig. 45 Ethical Considerations In AI Driven Livestock Health Monitoring System (CogniHerd System)

16. Future Directions and Innovations

16.1 Advanced AI Techniques

The integration of AI in cattle health monitoring is advancing, with various sophisticated AI techniques emerging that promise to improve the effectiveness and efficiency of these systems. One strategy is swarm intelligence, inspired by the collective behaviour of social creatures like bees, ants, and flocks of birds. Swarm intelligence systems can analyse extensive data from several sources, enabling decentralised decision-making that emulates natural processes. This method is especially advantageous for monitoring extensive herds, since it facilitates real-time analysis and swift adaptability to evolving conditions (Wassie, Awoke. Et al., 2024).

A significant accomplishment is the creation of neural networks, particularly deep learning models, which have demonstrated exceptional efficacy in image and pattern recognition tasks. These models can be taught to analyse intricate datasets produced by IoT devices, such as video streams from cameras observing animal behaviour. Neural networks can facilitate early diagnosis and intervention efforts by spotting patterns that may signify health concerns. Moreover, the emergence of explainable AI (XAI) is tackling the issue of transparency in AI decision-making. As livestock producers increasingly depend on AI-generated insights, it is essential that these systems offer comprehensible explanations for their predictions and suggestions. Explainable Artificial Intelligence (XAI) can foster confidence between farmers and AI systems, enabling farmers to make informed decisions based on the presented data (Božić, Velibor. (2023).

16.2 IoT Evolution and 5G Connectivity

The advancement of IoT devices is crucial for the future of cattle health monitoring. Progress in sensor technology is resulting in the creation of smaller, more economical, and more energy-efficient gadgets. These advanced sensors can continually monitor multiple health measures, including heart rate, temperature, and activity levels, offering farmers an extensive overview of their livestock's health. Awasthi, Amruta et al. (2020).

An essential facilitator of improved IoT functionalities The implementation of 5G networks. The rapid, low-latency connectivity provided by 5G will greatly enhance the capacity to send substantial data quantities from IoT devices in real-time. This innovation will enable instantaneous connection between devices, permitting prompt data analysis and notifications. For example, when an animal exhibits signs of discomfort, the IoT system can promptly notify the farmer, facilitating a swift reaction to potential health concerns. (Jun, Liu, et al., 2023). Furthermore, the extensive network capacity of 5G will facilitate the concurrent connection of several devices, hence augmenting the scalability of IoT systems in extensive livestock operations.

The integration of modern IoT devices with 5G connectivity will facilitate more complex applications, including remote monitoring and automated interventions. Farmers may utilise drones outfitted with IoT sensors to oversee animal health across extensive fields, while AI algorithms assess the gathered data to identify early indicators of illness or distress. This degree of automation can markedly decrease labour expenses and improve the overall efficacy of agricultural management. Guo, Xianhai. 2021.

16.3 Personalized Livestock Healthcare

The future of livestock health monitoring is increasingly orientated towards personalised healthcare for animals. The incorporation of AI technologies can provide more customised health therapies based on the genetic and environmental data of individual animals. Through the analysis of genetic data, farmers can gain insights into the susceptibility of particular animals to specific diseases or health concerns. This knowledge can inform breeding decisions and health management measures, ensuring that each animal receives treatment tailored to its own genetic composition (Youngjoon, Cho, & Jongwon, Kim. 2023).

Environmental conditions significantly influence animal health. Artificial intelligence systems can evaluate data from Internet of Things devices that assess environmental parameters including temperature, humidity, and feed quality. By integrating this data with individual health measurements, farmers may develop tailored health regimens that account for both genetic predispositions and environmental factors. An animal genetically prone to respiratory difficulties may benefit from tailored housing conditions or nutritional modifications to reduce hazards (Hu G, Do DN, Grey J, Miar Y. 2020).

The possibilities for individualised cattle healthcare surpass mere illness avoidance. Artificial intelligence can assist in refining feeding protocols according to specific weight gain trends and nutritional requirements, therefore improving growth performance and output. With the agricultural sector's growing emphasis on sustainability and efficiency, tailored strategies for livestock health are expected to become essential to contemporary farming methods. Singh, Amandeep, et al., 2023

In summary, the future of AI-driven livestock health monitoring is set for substantial progress through the implementation of cutting-edge AI methodologies, the growth of IoT technology, and the transition towards individualised healthcare. These advancements will improve animal welfare and farm productivity while facilitating more sustainable and efficient farming operations.

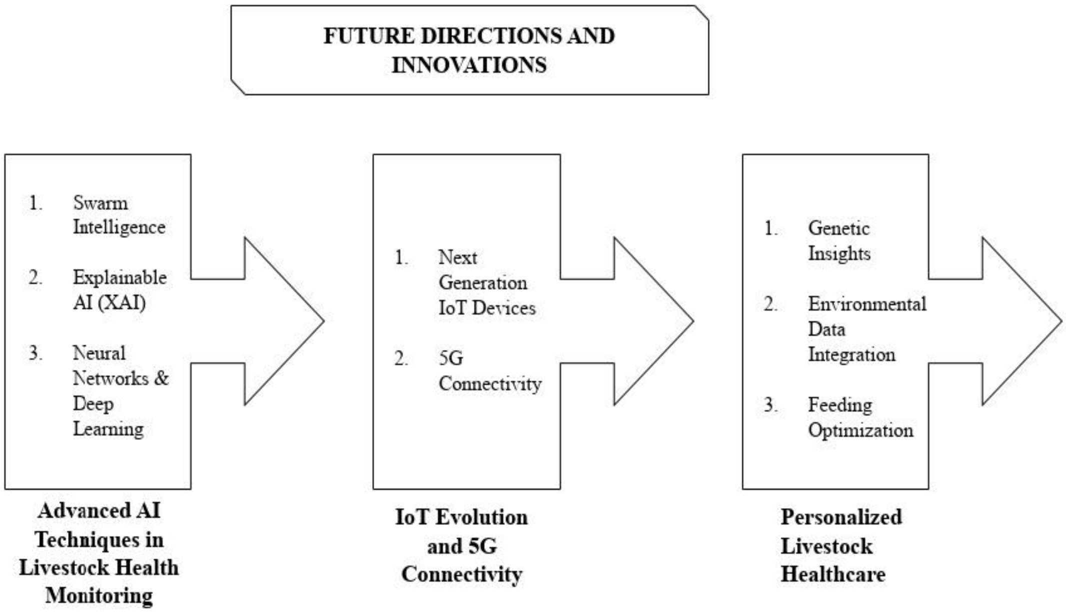

Fig. 46 Future Directions & Innovations in CogniHerd System

17. Conclusion

The amalgamation of AI and IoT technology in animal health monitoring signifies a substantial progression in the agricultural domain. Present applications exhibit their capacity to augment disease diagnosis, promote animal welfare, and optimise farm management via real-time data analysis and automated interventions. Systems such as CogniHerd illustrate the integration of these technologies to furnish farmers with actionable insights, facilitating more informed decision-making and promoting healthier livestock populations. Notwithstanding these achievements, numerous gaps persist in the existing research environment. Significantly, additional innovation is required to create economical and scalable solutions that may be broadly embraced, especially by smallholder farmers. Furthermore, research must prioritise the improvement of interoperability between AI and IoT systems to guarantee seamless integration across various platforms and devices. Ethical problems, such as data privacy and the effects of automation on human-animal relationships, must be addressed to cultivate trust and guarantee the responsible deployment of these technologies. A cooperative strategy among researchers, farmers, and technology suppliers is crucial to advance and realise the whole capabilities of AI and IoT in cattle health monitoring.

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Declaration of Conflict

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

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