Proceedings of the 3rd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS-2025)
DVD Part Number: CFP25DN7-DVD; ISBN: 979-8-3315-3883-5

IoT-Enabled Device for Predictive Monitoring and Disease Management in Cow

1st E. Chandralekha
Assistant professor, CSE
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology
Avadi, Chennai, India
echandralekha@veltech.edu.in

2nd Inturi Dhineesh
UG Scholar, CSE
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology
Avadi, Chennai, India
vtu19234@veltech.edu.in

3rd Ganta Lokesh Reddy
UG Scholar, CSE
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology
Avadi, Chennai, India
vtu19283@veltech.edu.in

4th Tailuru Ganesh
UG Scholar, CSE
Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology
Avadi, Chennai, India
vtu19235@veltech.edu.in

Abstract - Cattle health and welfare are crucial to the dairy and farming sectors, where early disease detection can improve animal welfare and reduce financial losses. An Arduino UNO, an ESP8266 microcontroller, and several sensors are integrated in this study's affordable and scalable Internet of Things-enabled system to continuously monitor critical parameters like temperature, humidity, heart rate, and respiratory rate in cows. For the purpose of tracking live animal conditions, the real-time data is sent to the ThingSpeak cloud platform and displayed using ThingView. Python's Pickle serialization is used to embed a machine learning-based predictive model that has been trained on both synthetic and real-time data within a Streamlit web application. The model achieves a prediction accuracy of 80% to 95% under controlled test conditions, classifying the health status of cattle into categories such as Normal, Fever, Heat Stress, or Respiratory Infection. Through the use of Random Forest classification and threshold-based logic, the system provides actionable insights via an intuitive dashboard and facilitates the early detection of possible health problems. The suggested solution supports both small and large-scale livestock operations by offering real-time, remote, and intelligent diagnostics for cattle health, thereby addressing the drawbacks of manual monitoring.

Keywords— Application Programming Interface, Central Processing Unit, Comma-Separated Values, Espressif Systems, Graphical User Interface, Internet of Things, Liquid-Crystal Display, Logistic Regression, Machine Learning, Pickle File, Random Forest, Support Vector Machine, User Interface, Uniform Resource Locator, Visual Studio.

I. INTRODUCTION

In modern day livestock management, maintaining animal welfare, increasing productivity, and reducing financial losses all depend on ongoing cattle health monitoring. The detection of new health problems is frequently delayed by traditional methods, which rely on fixed threshold alerts and recurring manual inspections. Real-time data collection and analysis is now feasible thanks to developments in wireless communication, sensor miniaturization, and cloud computing; however, there are still three major issues with current solutions: sporadic data collection, underutilized predictive analytics, and expensive deployment costs.

In order to address these constraints, this paper proposes an end-to-end IoT and machine-learning framework. Using an Arduino UNO and an ESP8266 microcontroller equipped with sensors for temperature, humidity, heart rate, and respiratory rate, our system collects and preprocesses data on-device. Dashboards from ThingView and Streamlit are used to visualize the cleaned data after it has been streamed to the ThingSpeak cloud platform. A Random Forest classifier, serialized using Python's Pickle and trained on both historical and live datasets, performs inference in real time, classifying each animal's condition as Normal, Fever, Heat Stress, or Respiratory Infection with 80–95% accuracy in controlled tests.

Key Contributions:

1. IoT architecture that is inexpensive and energy-efficient for ongoing cattle health monitoring.

2. Early disease prediction using a cloud-based analytics pipeline that combines Random Forest classification with rule-based thresholds.

3. Remote, real-time visualization of sensor data and health alerts is made possible by an interactive, Streamlit dashboard.

4. High predictive performance and scalability across small and large-scale farming scenarios are demonstrated by experimental validation.

II. LITERATURE REVIEW

Khan et al. [1] have presented an MSSO-ANFIS model-based healthcare monitoring system for heart disease diagnosis in an IoMT (Internet of Medical Things) cloud environment. To improve the accuracy and speed of medical pre dictions, the system combines intelligent cloud-based monitoring with machine learning techniques, specifically an enhanced version of the Adaptive Neuro Fuzzy Inference System (ANFIS). Their study demonstrates how IoMT can be used to improve healthcare delivery by enhancing predictive models and offering real-time diagnostic capabilities.

Chatterjee et al. [2] have presented Live Care is a framework for IoT-enabled livestock healthcare that combines sensors, cloud storage, and visualization. Their system exemplifies scalable smart agriculture solutions that enable real-time animal monitoring with the specific goal of enhancing the health of livestock. The frame work highlights the benefits of remote visualization and cloud-based data storage, which allow for ongoing health monitoring and the early identification of possible health problems in cattle. According to their research, IoT frameworks can improve the productivity and well-being of livestock.

Feng et al. [3] have presented Social Cattle is an Internet of Things (IoT) system that uses behavioral sensing to identify mastitis in cattle. This novel approach uses the social interaction patterns of cattle to identify early symptoms of disease, especially mastitis, a common condition that affects dairy cows. The system reduces the need for manual intervention and enables proactive health management by combining behavioral sensing with cloud-based analytics to provide real-time disease detection.

Nagasubramanian et al. [4] have presented an IoT-based pattern recognition system combined with an ensemble classification framework for the detection of crop diseases. To identify crop diseases, their system integrates IoT sensors with 5 a variety of machine learning approaches, including ensemble learning, decision trees, and support vector machines. The system gives farmers a more dependable and effective method of crop management by processing real-time sensor data and applying machine learning to forecast possible disease outbreaks.

Patle et al. [5] have presented LSTM (Long Short-Term Memory) networks are used in a field-tested smart sensor system to predict plant diseases. Based on real-time sensor data, the system predicts plant disease outbreaks using sophisticated machine learning models such as LSTM networks. By giving farmers precise forecasts and assisting them in taking preventive action before an outbreak happens, their method shows enhanced forecasting capabilities under actual farming conditions.

Costa et al. [6] 2021 have presented a thorough analysis of precision livestock technologies with an emphasis on how they can be used to manage dairy calves and increase agricultural output. In order to increase productivity, animal welfare, and resource efficiency in dairy farms, the paper explores a number of technologies, such as sensors, data analytics, and Internet of Things systems, and how they can be incorporated into precision livestock management.

Dutta et al. [7] have presented MOOnitor is a multi-sensory, Internet of Things-enabled tool for tracking cattle activity. Accelerometers and physiological sensors are integrated into the system to provide real-time cattle behavior monitoring and continuous health tracking. Cattle welfare and farm management can be enhanced by using the data gathered to track animal health, identify behavioral changes, and anticipate possible health problems.

Qazi et al. [8] have presented a critical analysis of smart agriculture enabled by AI, emphasizing present obstacles and potential paths for IoT-based farming technologies. With an emphasis on issues like data integration, sensor calibration, and real-time data processing, their paper offers a thorough examination of the application of AI and IoT in agriculture. They talk about how AI could improve agricultural practices' sustainability and efficiency.

Arshad et al. [9] 2022 have presented the installation of a wireless sensor network 6 to monitor animals intelligently. Temperature, heart rate, and movement patterns are just a few of the health data that the system continuously gathers and sends via wireless sensors. Particularly in remote locations where conventional monitoring techniques are impractical, this real-time data is utilized to produce actionable insights for improved livestock health management and more productive farming practices.

Arshad et al. [10] have presented a safe system for tracking the health of cattle that incorporates encryption protocols and intelligent modules to ensure data integrity. To guarantee the privacy and security of the data gathered from cattle health monitoring sensors, this system integrates cutting-edge security measures. Real-time data analysis is made possible by the system's intelligent modules, which also guarantee data security and integrity and enable the early identification of health problems

Research Gap:

IoT-based monitoring and predictive analytics have made great strides, but there are still a number of important gaps. Without offering an integrated framework that combines ongoing data collection with real-time predictive analytics, many current systems function in silos, concentrating on distinct monitoring facets. The implementations of Khan et al. [1] and Chatterjee et al. [2] frequently lack smooth integration between hardware components, cloud data management, and intelligent decision-making modules, despite the fact that they have established solid foundations in healthcare and livestock monitoring, respectively. Early disease detection through machine learning models is possible with systems like those suggested by Feng et al. [3] and Nagasubramanian et al. [4], but they still face difficulties like sensor calibration and data heterogeneity. Similarly, Patle et al.'s deep learning methods [5] and Costa et al.'s review of precision livestock frameworks [6] highlights important developments but also point to shortcomings in terms of scalability, adaptability, and energy efficiency. Furthermore, there is still a clear gap in systems that combine various sensor inputs with strong encryption and real-time analytics, even after wireless sensor networks were implemented in research by Dutta et al. [7] and Arshad et al. [8, 10]. The fragmented nature of current IoT applications across various do mains is further highlighted by additional reviews by Qazi et al. [11], Moutaouakil et al. [13], and Poyyamozhi et al. [14]. Islam et al. [15] show that comprehensive early detection systems are scarce even in aquaculture. This project intends to close these enduring gaps by creating a comprehensive monitoring solution that integrates several physiological sensors with an Arduino-based CPU, enables wireless data transfer via ESP8266, supports cloud visualization, and uses a state-of-the art machine learning pipeline. In order to overcome the drawbacks of the current IoT-based monitoring systems, the suggested integrated approach aims to increase system scalability, guarantee energy efficiency, and enhance personalized care and predictive accuracy.

III. Proposed Work

The proposed Animal Health Monitoring System integrates cloud computing, machine learning, and the Internet of Things to enable real-time disease prediction in cattle. Through the use of a sensor array, the system continuously gathers critical data, including temperature, humidity, heart rate, and respiratory rate. An ESP8266 wirelessly sends the data to the ThingSpeak cloud platform after an Arduino UNO processes the raw sensor signals and carries out basic filtering and digital conversion. A Streamlit-based web application retrieves real-time data from a mobile app called ThingView and uses it to feed a pre-trained machine learning model (serialized with Pickle) that categorizes cattle health into sections like normal, fever, heat stress, and respiratory infection. While an alert system quickly alerts farmers and veterinarians to critical conditions, a rule-based system offers backup for quick risk assessment and offers suggestions for useful interventions. The system is designed to be both affordable and scalable, which will ultimately improve farm efficiency and animal welfare. It can be used in both small and large scale farming operations.

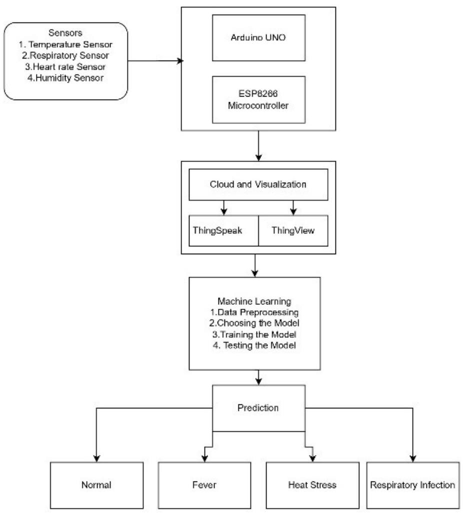


Figure 1 shows overall Architecture of the Cow Health Monitoring System

A. COMPONENT DESCRIPTION:

1. Sensors:

The sensor module is in charge of recording the vital physiological and environmental characteristics of the cattle. In order to identify fever or other indications of infection and heat stress, it has a temperature sensor that measures body temperature. Monitoring ambient moisture levels with a humidity sensor is crucial for spotting respiratory problems and avoiding dehydration. Additionally, a respiratory rate sensor continuously tracks breathing patterns to identify any anomalies that could indicate metabolic problems or infections. A heart rate sensor measures changes in cardiac rhythm that may be early indicators of stress or cardiovascular issues. Together, these sensors provide comprehensive information for effective health monitoring.

2. Microcontrollers:

Data collection and communication are managed by two micro controllers. The Arduino UNO is the primary data acquisition device, using interfaces with all sensors to precisely gather and preprocess raw signals into usable digital readings. The ESP8266 microcontroller then provides wireless connectivity for the transmission of the processed sensor data to the ThingSpeak cloud platform. This combination enables seamless, real-time remote monitoring and ensures data integrity through robust error handling.

3. Display:

The system includes an LCD display to show the temperature, humidity, heart rate, and respiratory rate sensor readings in real time. With the help of this feature, farmers can keep an eye on the health of their cattle without constantly accessing the cloud.

B. DATA ACQUISITION:

Processing raw sensor outputs and wirelessly sending the formatted data to the cloud platform are the two primary steps in the data acquisition process.

1. Arduino UNO Data Processing:

Raw digital signals via the sensors are collected by the Arduino UNO, which serves as the main microcontroller. Along with performing preliminary data formatting and filtering, it transforms those signals into digital numerical readings. After processing, the data is sent to the ESP8266 microcontroller via a serial communication protocol.

2. ESP8266-Based Wireless Data Transmission:

Using HTTP requests, the ESP8266 microcontroller wirelessly transmits the formatted data from the Arduino UNO to the ThingSpeak cloud. The sensor data is also sent to ThingSpeak by the ESP8266 for storage and visualization. If there are network problems, data is retransmitted thanks to basic error-handling procedures.

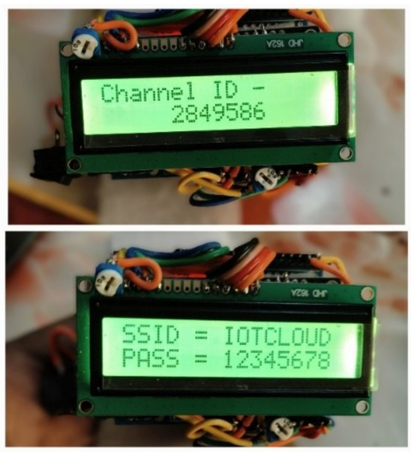
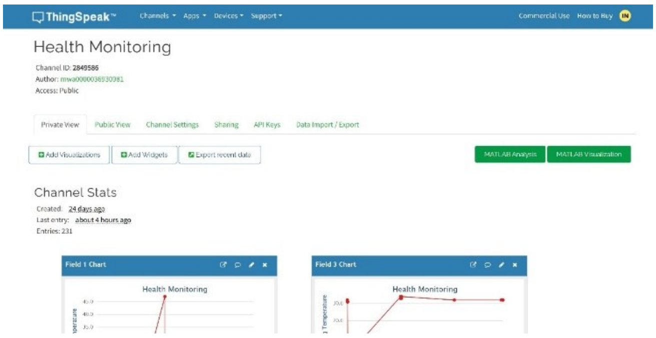


Figure 2 shows steps involved in Hardware Connection with ThingSpeak

The picture shows various phases of Wi-Fi connectivity and cloud integration for the Animal Health Monitoring System using an Arduino-based Internet of Things device with an LCD display. "Initializing..." indicates the system's startup, and "Connected..." confirms a successful Wi-Fi connection. The ThingSpeak Channel ID (2849586), which connects the device to cloud-based data storage, is shown on the third screen. The Wi-Fi SSID (IOTCLOUD) and password (12345678) used to access the network are displayed on the last screen. This configuration guarantees the transmission and monitoring of cattle health data in real time through cloud services.



The ThingSpeak website interface is displayed in Figure 3.

The picture shows the Animal Health Monitoring System's ThingSpeak dashboard, where sensor data is uploaded and shown. Since the Channel ID (2849586) is open to the public, cattle health metrics can be tracked in real time. Additional insights are made possible by the dashboard's visualization, data export, and MATLAB analysis options. According to the channel statistics, there were 231 data entries, with the most recent one occurring roughly four hours ago.

IV. MACHINE LEARNING MODEL DEPLOYMENT

We trained and implemented three supervised learning models Random Forest, Support Vector Machine (SVM), and Logistic Regression to automatically classify the health status of cattle. To provide real-time predictions based on sensor inputs, the trained models were serialized using Python's Pickle module and incorporated into a Streamlit web application.

Algorithms:
Three machine learning models were tested for binary classification tasks in our deployment framework. Here is a description of the models.

Logistic regression: It is a linear model that uses a logistic function to estimate the likelihood of a binary outcome. By applying the sigmoid activation function, logistic regression converts input features into a probability. For input vector ***x****, model weights w, and bias b, the prediction ŷ is given by:*

$$\hat{y} = 1/(1 + exp(-w^T x + b))$$

A binary label for the class is then generated by thresholding this output.

Support Vector Classifier (SVM): The Support Vector Classifier maximizes the margin between classes to determine the best separating hyperplane. The expression for its decision function is

$$\min_{w,b,\xi} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{N} \xi i$$

subject to

$$y_i \ (w^T \phi(x\_i) + b) \geq 1 - \xi i, \xi i \geq 0, \ \forall i$$

Here, $\phi(\cdot)$ is the cost parameter, and C is a nonlinear mapping to a higher-dimensional space. The function that makes decisions is:

$$f(x) = sign(w^T \phi(x) + b)$$

Random Forest: To increase accuracy and decrease overfitting, the Random Forest ensemble approach combines the predictions of several decision trees. The final prediction for classification is established by:

$$\hat{y} = mode \ \{h\_1 \ (x), h\_2 \ (x), \ldots, h\_T \ (x)\}$$

Using Gini Impurity, which is defined for a node D as follows, each decision tree chooses the optimal split at each node:

$$\text{Gini(D)} = Gini(D) = 1 - \sum_{i=1}^{k} p_i^2$$

Where p_i is the probability of class i in node D. Lowe Gini values indicate purer splits.

V. EXPERIMENTAL RESULTS

A. Experimental Setup

A synthetic dataset with 2,300 labeled records representing the health conditions of cattle was used to test the system. Heart rate, temperature, humidity, and respiratory rate were among the characteristics. Every data instance was classified as either Respiratory Infection, Heat Stress, Fever, or Normal. Eighty percent of the dataset was used for training, and twenty percent was used for testing.

Label encoding and feature normalization were part of the data preprocessing process. Python 3.9 and the scikit-learn library were used to create the models. The front-end web application was built using the Streamlit framework, and ThingSpeak was used to gather and store sensor data. The web dashboard was used for both real-time predictions and model inference.

B. Model Evaluation:

Random Forest, Support Vector Machine (SVM), and Logistic Regression were the three machine learning models that were trained and assessed. The classification accuracy for every model is compiled in Table I:

TABLE 1 MODEL PERFORMANCE

Algorithm	Accuracy
Logestic Regression	76
Support Vector Classifier	83
Random Forest	91

Table 1 shows the highest accuracy of 91%, the Random Forest model performed better than the others. It was chosen to be the last model to be used for the health monitoring.

C. *Classification Report:*

```
Model Accuracy: 0.91
Classification Report:
                       precision    recall  f1-score   support

               Fever       0.93      0.99      0.96       597
         Heat_Stress       0.96      1.00      0.98       611
              Normal       0.87      0.72      0.79       500
Respiratory_Infection      0.86      0.89      0.88       592

            accuracy                           0.91      2300
           macro avg       0.90      0.90      0.90      2300
        weighted avg       0.91      0.91      0.91      2300
```

Figure 3 displays the Random Forest model's classification report, which includes information on each class's F1-scores, precision, and recall. While maintaining respectable performance on the Normal and Respiratory Infection classes, the model excels on the Fever and Heat Stress classes.

D. *Sensor Data Collection:*

The system uses an Arduino Uno and an ESP8266 to monitor sensor data in real time. Trends in the physical and environmental variables recorded are shown in Figures 4–7.

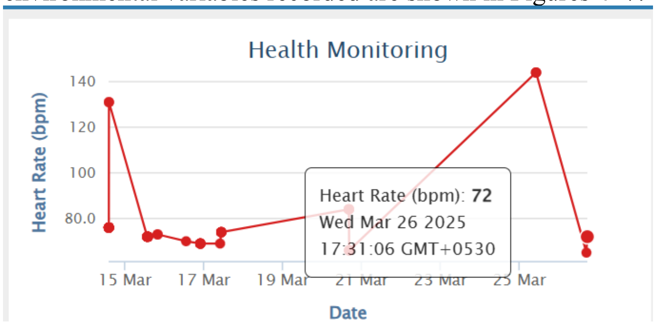


Figure 4 shows Real-time cow heart rate readings that are continuously tracked and displayed through the ThingView application . Heart rate (bpm) data from March 15–26, 2025. It displays health fluctuations with a steep increase on March 15 and a subsequent decline and gradually normalization by March 26.

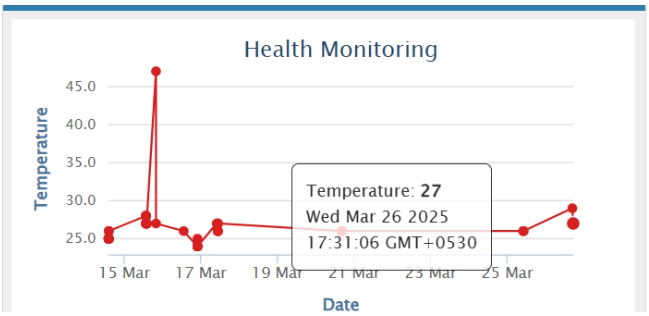


Figure 5 provides real-time temperature readings for the cattle, which are monitored and shown via the ThingView app. shows the temperature changes that were noted between March 15 and March 26, 2025. Around March 16, there is a sharp increase that might be a sign of fever or heat stress, highlighting the importance of routine monitoring.

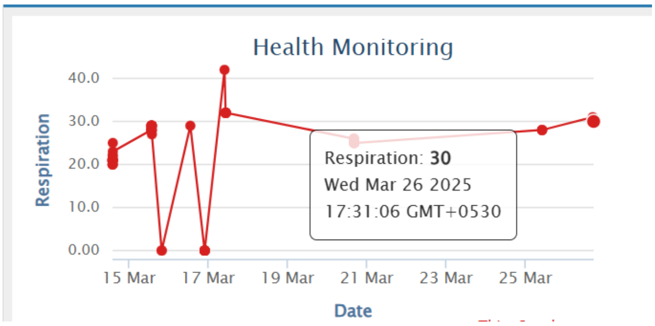


Figure 6 demonstrates how the cattle's real-time respiratory rate readings are continuously monitored and visualized using the ThingView application. It shows the measurements of the respiration rate taken between March 15 and March 26, 2025. Significant increases and dips around March 17 are among the fluctuations that could indicate difficulties with respiration or irregular breathing patterns

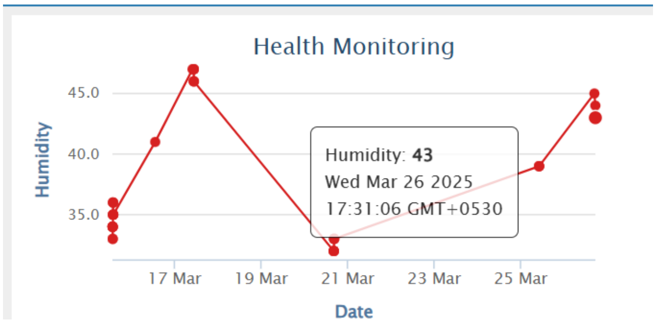


Figure 8 shows the cattle's surroundings' real-time humidity levels, which are tracked and displayed via the ThingView app. Humidity levels during the same time frame. The significance of preserving ambient comfort to avoid heat stress or dehydration is highlighted by a discernible increase around March 17, followed by a decline and a gradual increase toward March 26

E. *Predection Result:*

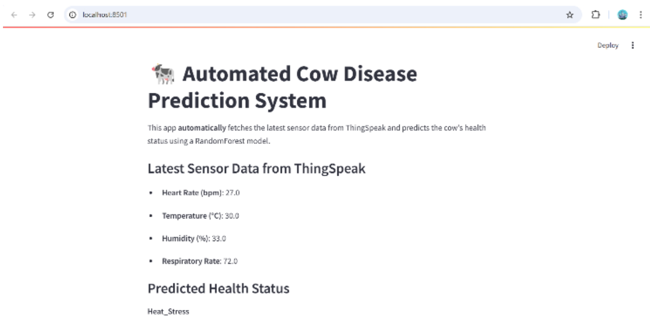


Figure 9 shows the interface visualized here is built with Streamlit and connects to the ThingSpeak platform to collect live sensor readings. Based on the received data, such as heart rate and temperature, the system predicts the cow's health status. The displayed output confirms the predicted condition as 'Heat Stress', supporting the system's real-time detection capability.

VI. LIMITAIONS AND FUTURE WORK

Our IoT-ML system performs well in real-time and with high accuracy, but there are still a number of real-world issues. Extreme temperature or humidity fluctuations can cause sensor drift and radio frequency interference in hardware integration, and relying solely on constant Wi-Fi puts distant farms at risk for data gaps. Monitoring just four vital signs could cause other early warning signs to be missed, and models that were developed in a controlled environment might deteriorate in the field. Large-scale implementation is hampered by battery life and device maintenance, and existing error-handling might not completely recover from network or sensor failures.

We will address these by implementing advanced sensor-fusion algorithms, expanding our sensor suite (e.g., SpO_2 and activity trackers), introducing edge-computing for on-device preprocessing, and switching to lightweight protocols (MQTT/LoRaWAN) for lower power consumption; experimenting with deep-learning architectures and augmenting our datasets to improve generalization; and developing self-healing routines with automated calibration and an improved, mobile-friendly dashboard to ensure robust, scalable livestock health monitoring.

VII. CONCLUSION

The IoT-enabled framework for ongoing cattle health monitoring and predictive risk assessment is presented in this paper. It is based on sensors that measure heart rate, temperature, humidity, and respiratory rate, as well as an Arduino UNO for data collection and an ESP8266 for wireless transmission. A pre-trained machine-learning model (serialized with Pickle) provides real-time health-status predictions and intervention recommendations based on sensor feeds that are streamed to cloud platforms (ThingSpeak/ThingView) and visualized via a Streamlit dashboard. According to experimental findings, combining data-driven Random Forest classification with rule-based thresholds can achieve up to 91% accuracy, facilitating early disease detection and preventative veterinary care that improves farm productivity and animal welfare.

However, the system's practical limitations include its reliance on dependable wireless connectivity, its narrow range of physiological parameters, and its power limitations in field deployments. The sensor suite will be expanded, deep-learning architectures will be investigated using larger and more varied datasets, and edge computing and energy management techniques will be optimized for scalable, resilient operation in future work. All things considered; this economical approach presents a positive first step toward data-driven, sustainable livestock management.

REFERENCES

[1] Khan, Mohammad Ayoub, and Fahad Algarni."A health care monitoring system for the diagnosis of heart disease in the IoMT cloud environment using MSSO ANFIS." IEEE Access 8 (2020): 122259-122269.

[2] Chatterjee, Pinaki S., Niranjan K. Ray, and Saraju P. Mohanty. "LiveCare: An IoT-based healthcare framework for livestock in smart agriculture." IEEE Transactions on Consumer Electronics 67, no. 4 (2021): 257-265.

[3] Feng, Yunhe, Haoran Niu, Fanqi Wang, Susan J. Ivey, Jie Jayne Wu, Hairong Qi, Raul A. Almeida, Shigetoshi Eda, and Qing Cao. "SocialCattle: IoT-based mastitis detection and control through social cattle behavior sensing in smart farms." IEEE Internet of Things Journal 9, no. 12 (2021): 10130-10138.

[4] Nagasubramanian, Gayathri, Rakesh KumarSakthivel, Rizwan Patan, Muthura malingam Sankayya, Mahmoud Daneshmand, and Amir H. Gandomi. "Ensem ble classification and IoT-based pattern recognition for crop disease monitoring system." IEEE Internet of Things Journal 8, no. 16 (2021): 12847-12854.

[5] Patle, Kamlesh S., Riya Saini, Ahlad Kumar, and Vinay S. Palaparthy. "Field evaluation of smart sensor system for plant disease prediction using LSTM net work." IEEE Sensors Journal 22, no. 4 (2021): 3715-3725.

[6] Costa, Joao HC, Melissa C. Cantor, and Heather W. Neave. "Symposium re view: Precision technologies for dairy calves and management applications." Journal of Dairy Science 104, no. 1 (2021): 1203-1219.

[7] Dutta, Debeshi, Dwipjyoti Natta, Soumen Mandal, and Nilotpal Ghosh. "MOOnitor: An IoT-based multi-sensory intelligent device for cattle activity 51 monitoring." Sensors and Actuators A: Physical 333 (2022): 113271.

[8] Qazi, Sameer, Bilal A. Khawaja, and Qazi UmarFarooq. "IoT-equipped and AI enabled next-generation smart agriculture: A critical review, current challenges and future trends." IEEE Access 10 (2022): 21219-21235.

[9] Arshad, J., A. U. Rehman, M. T. B. Othman, M. Ahmad, H. B. Tariq, M. A. Khalid, and H. Hamam. "Deployment of wireless sensor network and IoT plat form to implement an intelligent animal monitoring system." Sustainability 14, no. 10 (2022): 6249.

[10] Arshad, J., T. A. Siddiqui, M. I. Sheikh, M. S. Waseem, M. A. B. Nawaz, E. T. Eldin, and A. U. Rehman. "Deployment of an intelligent and secure cattle health monitoring system." Egyptian Informatics Journal 24 (2023): 265–275.

[11] Rajendran, Jai Ganesh, Manjunathan Alagarsamy, Vaishnavi Seva, Paramathi Mani Dinesh, Balamurugan Rajangam, and Kannadhasan Suriyan. "IoT-based tracking cattle health monitoring system using wireless sensors." Bulletin of Electrical Engineering and Informatics 12, no. 5 (2023): 3086-3094.

[12] Casella, Enrico, Melissa C. Cantor, Megan M. Woodrum Setser, Simone Sil vestri, and Joao HC Costa. "A machine learning and optimization framework for the early diagnosis of bovine respiratory disease." IEEE Access 11 (2023): 71164-71179.

[13] Moutaouakil, Khalid El, Hamza Jdi, Brahim Jabir, and Noureddine Falih. "Dig ital Farming: A Survey on IoT-based Cattle Monitoring Systems and Dash boards." AGRIS on-line Papers in Economics and Informatics 15, no. 2 (2023): 31-39.

[14] Poyyamozhi, Mukilan, Balasubramanian Murugesan, Narayanamoorthi Ra jamanickam, Mohammad Shorfuzzaman, and Yasser Aboelmagd. "IoT—A 52 Promising Solution to Energy Management in Smart Buildings: A Systematic Review, Applications, Barriers, and Future Scope." Buildings 14, no. 11 (2024): 3446.

[15] Islam, Sk Injamamul, Foysal Ahammad, and Haitham Mohammed. "Cutting edge technologies for detecting and controlling fish diseases: Current status, outlook, and challenges." Journal of the World Aquaculture Society 55, no. 2 (2024): e13051.

[16] Sharma, Kushagra, and Shiv Kumar Shivandu. "Integrating artificial intelli gence and internet of things (IoT) for enhanced crop monitoring and manage ment in precision agriculture." Sensors International (2024): 100292.

[17] Jafar, Abbas, Nabila Bibi, Rizwan Ali Naqvi, Abolghasem Sadeghi-Niaraki, and Daesik Jeong. "Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations." Frontiers in Plant Science 15 (2024): 1356260.

[18] Liao, Yuxuan, Zhong Tang, Kun Gao, and Mohammad Trik. ”Optimization of resources in intelligent electronic health systems based on Internet of Things to predict heart diseases via artificial neural network.” Heliyon 10, no. 11 (2024).

[19] Michelena, ´ Alvaro, ´ Oscar Fontenla-Romero, and Jos´ e Luis Calvo-Rolle. ”A review and future trends of precision livestock over dairy and beef cow cattle with artificial intelligence.” Logic Journal of the IGPL (2024): jzae111.

[20] Zhao, Yanan, Lu Zhang, Aihua Wang, and Dong Zhou. ”Biosensor Technol ogy: Advances and Applications in Livestock Infectious Disease Diagnosis.” Veterinary Sciences 12, no. 1 (2025): 23.