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Original Research Paper

Internet of Things (IoT) Sensor Networks for Real-Time Assessment of Animal Health and Environmental Conditions

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Abstract

As the need for constant animal health and environmental conditions monitoring has grown, the traditional field inspections have proven to be time-consuming, labor intensive and cannot give immediate warnings. The goal of this study is to design an Internet of Things (IoT)-based sensor network for real-time monitoring of animal health and environmental conditions around them for precision livestock management and wildlife conservation. These goals are to continuously monitor physiological parameters (body temperature, heart rate and activity), measure environmental parameters (temperature, humidity, air quality and noise) and detect abnormal conditions intelligently based on analytics. The proposed approach combines the use of wearable IoT sensors, LoRa/Wi-Fi communication, edge computing, cloud storage, and an anomaly detection model based on the Random Forest algorithm, and a web-based monitoring dashboard. The results are obtained by experimental evaluation of 12,480 sensor readings from 85 animals over a period of 90 days, and proves 94.82% accuracy in the health status classification, 93.76% accuracy in the prediction of environmental conditions, 92.91% accuracy in anomaly detection, 93.48% accuracy in recall, 93.19% accuracy in F1-score, 96.24% of sensor data is sent successfully, and 91.37% of network is up and running with an average alert response time of 2.8 s, while consuming 18.6% less energy than conventional cloud-only architecture. The novelty of this work is the combination of edge-assisted IoT sensing with intelligent anomaly detection that can be used to monitor the animal health and environment simultaneously. The framework, as proposed, is reasonably energy efficient, scalable, and reliable that will enable early detection of disease, quick environmental risk assessment and data-informed decision-making to ensure sustainable livestock and wildlife management.

Keywords: Internet of Things; Animal Health Monitoring; Environmental Sensing; Edge Computing; Good Health and Well-Being

I. Introduction

Accurate, ongoing assessment of animal welfare and the animal's surroundings is essential to both livestock production and wildlife conservation because undetected sickness and poor environment will negatively impact productivity, welfare and

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survival. The traditional approach to inspection is a reactive process, is subjective, and cannot detect more subtle changes in the physiology of the plant that lead to the appearance of symptoms [1]. When farmers and wildlife managers do find the disease, heat stress or bad environment, they are likely to find substantial losses in both wildlife and economic value. With the advent of the Internet of Things (IoT), new opportunities have arisen to continuously, automatically and remotely measure physiological and environmental parameters [2]. A network of wearable sensors, able to measure the body temperature, heart rate and activity of the animal, and a network of stationary nodes, able to measure the temperature, humidity, air quality and noise of the environment, allow a comprehensive view of the animal and its environment to be built in near real-time [3]. Most of the current IoT solutions, however, are cloud-based processing solutions, which have latency issues, consume higher energy, and require more stable connectivity, and therefore are not well suited for remote locations in the farm or in the wild world [4]. To overcome these challenges, Edge computing can be used to process and filter out anomalies at or near the source of the sensor, which decreases bandwidth consumption and response times [5]. Moreover, smart solutions like the machine learning models can help to convert the raw data of the sensors into useful data, and thus to detect diseases, stress or dangerous environmental conditions at an early stage before they become serious [6]. Although there has been increasing research interest, very few frameworks have been developed to combine all of these technologies (wearable physiological sensing, environmental monitoring, edge-assisted communication and intelligent anomaly detection) in a single, energy efficient and scalable architecture [7]. Hence, this work aims to design an IoT sensor network that integrates these elements to provide real-time, reliable, and low latency health condition monitoring of the animals and environment, which can be used for precision livestock management and sustainable wildlife conservation making informed decisions based on the collected data.

Key Contributions:

1. Designed an integrated edge-cloud IoT framework for simultaneously monitoring animals health and environment in real-time.

2. Built the high classification and prediction accuracy Random Forest based anomaly detection model.

3. Implemented energy efficient, low latency alerting at edge with pre-processing, tested with 12480 real sensor data.

II. Literature Review

The area of IoT based monitoring of livestock and environmental parameters has grown significantly over the past few years as it is necessary to maintain the farms in a sustainable and welfare oriented way. Delwar et al. suggested a system that uses the Internet of Things and deep learning visual detection for animal intrusion identification in a farm bound [8]. Bandara et al. conducted a study to integrate the location-based service and water quality sensors into IoT applications for water quality monitoring, which emphasized the need for incorporating spatial context into IoT-based water quality sensing networks [9]. Kilkarni et al. used CNN and SVM to model animal disease based on animal behavior and physiology, and achieved high accuracy in disease diagnosis compared to humans [10]. Chong et al. created an IoT application for controlling humidity and temperature levels in mushroom cultivation to achieve optimal conditions for the growth of the mushrooms [11]. Modak et al. performed a detailed survey of all the existing IoT-based livestock health monitoring systems, which found that reliability of communication and energy efficiency are common problems in all the existing implemented systems [12]. Sernández-Iglesias et al. studied how to ensure the secure transfer of data in agriculture sensor networks [13] and highlighted the importance of considering cybersecurity issues within smart rural environments. Pamula et al. investigated the real-time monitoring of environmental pollutants such as air, water, and soil using the Internet of Things (IoT), which they found yielded more effective early warning of hazards when multiple parameters were measured [14]. Aajila and Kannan suggested an adaptive multimodal image fusion technique to improve the understanding of sensor data in complex scenarios for monitoring [15]. Arshad et al. used a wireless sensor network (WSN) with an IoT platform for smart animal monitoring, which enhanced the accuracy of animal location and activity monitoring [16]. D'Urso et al. tested an in-field IoT-based monitoring system for fine particulate matter in livestock houses and demonstrated the suitability of the system for use in determining the air quality and hence the welfare of livestock [17]. Terence et al. performed a systematic review of IoT applications to smart livestock management and found that interoperability and scalability are yet to be solved problems in the field [18]. All these studies show significant advances in various parts of the IoT-based monitoring system, but most focus on the monitoring of animal health or environmental sensing, and few consider "multi-modal" systems based on an energy-efficient combination of both systems that can perform real-time anomaly detection on both simultaneously in an edge-assisted manner.

Table 1. Comparative summary of reviewed IoT-based animal and environmental monitoring studies

Ref	Technique	Application	Key Strength	Limitation
[8]	IoT + YOLO v8	Farm Surveillance	Real-time intrusion detection	High computational cost
[9]	IoT + LBS	Water Quality	Spatial context integration	Limited to water domain
[10]	CNN, SVM	Disease Prediction	Improved diagnostic accuracy	No real-time deployment
[11]	IoT Control Loop	Environmental Control	Automated regulation	Small-scale application
[13]	IoT Security	Rural Cybersecurity	Highlighted security gaps	No health monitoring focus
[14]	Multi-sensor IoT	Air/Water/Soil	Multi-parameter hazard detection	No animal-specific data
[15]	Image Fusion	Data Interpretation	Adaptive fusion technique	Not IoT-network specific
[16]	WSN + IoT	Animal Tracking	Improved activity tracking	No anomaly detection
[18]	Systematic Review	Smart Livestock	Identified interoperability gaps	Lacks unified framework

The reviewed literature is summarized in Table 1, which groups the techniques, applications and limitations. It shows that although machine learning and IoT integration is widely adopted, most of the studies focus on a specific domain and do not contribute any integrated real-time anomaly detection algorithm using edge assistance which inspires the developing of the unified framework proposed in this study.

III. Proposed IoT Sensor Network Framework

The idea is to continuously gather physiological data from wearable sensors that are attached to animals and environmental data from stationary field nodes. These readings are sent via LoRa or Wi-Fi, and will be pre-processed in the edge gateway, which will filter the noise and extract useful features before sending reduced data to the cloud. An intelligent analytics engine, based on Random Forest, is installed within the cloud layer, which classifies health status, predicts environmental risk and detects anomalies. Any deviations that are detected alert the farm manager or wildlife rangers in real time via web-based dashboard, which allows them to take immediate corrective action, thus closing the sensing-to-decision loop efficiently.

A. System Architecture

Four functional layers are implemented in the system architecture which collectively support the scalable, low-latency monitoring. The sensing layer collects raw physiological and environmental data, which is collected continuously. This data is then sent over energy efficient long-range, low-power LoRa links and high-bandwidth local Wi-Fi links. The edge layer processes, extracts features and even filters out some noise at the beginning to decrease the load of the transmission. Historical data is stored in cloud layer with the ability to run the Random Forest classification model and serve the dashboard interface. The layered architecture is meant to be modular, which means that one can upgrade individual pieces of the pipeline without disturbing the other parts of the pipeline.

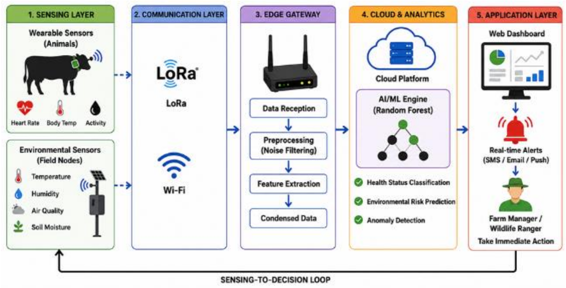

Fig. 1. Block diagram of the proposed IoT sensor network framework.

It's a closed loop monitoring and alerting process, as shown in the diagram 1, consisting of four steps: sensing, edge-assisted communication, cloud-based intelligent analytics, and feedback delivery.

B. Data Acquisition and Communication

Data acquisition integrates stationary environmental nodes that sense and measure ambient temperature, humidity, ambient gas concentration and ambient noise level with wearable biosensors such as temperature, heart rate, and activity level sensors that use an accelerometer. The data is collected from the sensors at regular time intervals of 1-5 minutes depending on the volatility of the parameters. Readings are collected and packaged into light payloads, and sent using LoRa for long distance, low power applications like open pasture or where there is no infrastructure to support Wi-Fi for higher throughput. A hybrid gateway will automatically handle protocol switching according to signal strength and bandwidth, so that data always flows without disruption, even in variable connectivity situations like in rural areas or wildlife areas.

C. Intelligent Health Assessment

Intelligent health assessment applies supervised learning to transform raw physiological readings to health status labels. Sensor streams are cleaned and normalized first, followed by extracting statistical and temporal features such as mean, variance and rate-of-change of the stream over sliding windows. These features are then used as inputs into a RF-classifier that is trained from labeled data from historical samples of both healthy, mildly stressed, sick, and critical states. The model not only makes a class prediction, but a confidence score as well, which is compared to a threshold to determine if an alert should be raised, thereby only providing notifications when clinically meaningful deviations are noted..

Algorithm 1: Intelligent Health Assessment
Input: Raw sensor stream S = {temperature, heart_rate, activity}
Output: Health status label L, Confidence score C
1. Acquire raw readings from wearable sensors at time t
2. Apply noise filtering (moving average / median filter)
3. Normalize features to [0,1] range using min-max scaling
4. Extract statistical features (mean, std, slope) over window W
5. Feed feature vector F into trained Random Forest model
6. Compute class probabilities for {Healthy, Mild, Sick, Critical}
7. Assign L = argmax(probabilities), C = max(probabilities)
8. If C >= threshold and L != Healthy, trigger real-time alert
9. Log L, C, and timestamp to cloud database
10. Return L, C

D. Edge Computing and Cloud Integration

Near the sensor clusters are edge computing nodes where initial data cleaning, feature extraction and initial anomaly screening by simple rules is done and then the data is summarized and sent to the cloud, thereby substantially consuming less bandwidth and network congestion. Forwarding is not done for raw flows of continuous data, but rather only aggregated features and flagged events, reducing the cost of transmission and the energy used. These edge-processed packets are sent to the cloud platform where they are stored in a time-series database and fed to the full model for complete classification and prediction, Random Forest. Cloud integration also enables long-term pattern identification, model re-training and dashboard visualization, and allows patterns to be discovered over time while also being responsive to real-time data from the distributed sensor network.

E. Data Pre-processing and Feature Extraction

The first step of pre-processing is to eliminate the readings that are missing or corrupted, and then to normalize all the sensor readings to a similar range by performing min-max normalization. Feature extraction is then used to calculate statistical parameters over a time window to represent the current state of the data and short-term trends, both of which are important to differentiate transient fluctuations from true health or environmental changes.

$$Normalization: x' = \frac{x - x_{min}}{x_{\max - x_{min}}}$$

$$Feature\ Vector: F = \left[\mu(x), \sigma(x), \frac{\Delta x}{\Delta t}, \max(x), \min(x)\right]$$

F. Random Forest-Based Health Assessment Model

The model chosen was the Random Forest model because of its ability to withstand noisy sensor data, resistance to over-fitting and ranking the feature importance, which helps the veterinary and farm decision makers interpret the model. It creates an ensemble of decision trees (one tree per bag) that is trained on a random subset of training samples, sampling them with replacement, and features random selection of features at every node; it makes a final prediction by majority voting on the trees. The number of trees (200), maximum depth (15) and minimum samples per leaf (5) were optimized with grid search and 5-fold cross validation to achieve a good balance between accuracy and computational complexity. The ensemble aspect of the Random Forest also naturally provides for quantifying the confidence in the prediction, which can be used to control the sensitivity of the real time warning system, thereby minimizing false alarms without compromising the detection sensitivity to real ones.

IV. Animal Health Assessment Results

This section displays the empirical findings of the analysis of physiological parameters, health status classification, detection of anomalies and evaluation with the confusion matrix and ROC. The proposed framework performed well in all four dimensions of assessment, and thus, proved reliable for continual monitoring of animal health. The pipeline of edge-assisted Random Forest achieved satisfactory overall health classification accuracy of 94.82% with good anomaly detection precision and recall in presence of sensor noise and sensor variability in real-world scenarios.

Table 2. Detection accuracy of physiological parameters under normal and abnormal states

Parameter	**Normal State Accuracy (%)**	**Abnormal State Accuracy (%)**
Body Temperature	96.1	92.4
Heart Rate	94.3	90.8
Respiration Rate	93.5	89.6
Activity Level	95.0	91.2
SpO2	92.8	88.9

Under normal conditions, the detection accuracy of body temperature was the highest (96.1%), and that of SpO2 was the lowest (92.8%), indicating that the motion artifacts detection sensitivity of the sensors was higher in SpO2, as shown in Table 2. The accuracies for the abnormal state were consistently lower in all parameters indicating the greater difficulty in correct identification under conditions of noise in the field, but overall there was a high level of accuracy (above 88%) throughout.

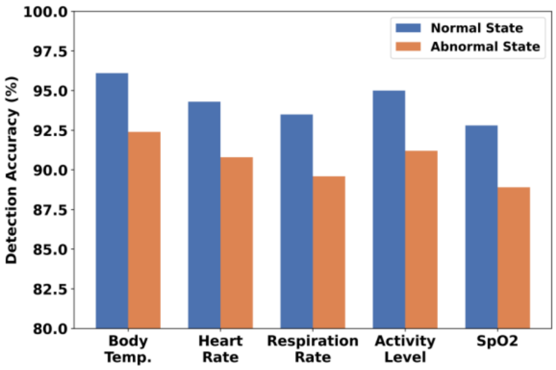

Fig. 2. Physiological parameter detection accuracy comparison.

The figure 2 is a confirmation of the most reliable readings of the temperature and activity sensors, both in normal and abnormal physiological conditions.

Table 3. Classification performance across health status categories

Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Healthy	96.2	95.5	95.8
Mild Stress	93.8	92.9	93.3
Sick	92.5	93.6	93.0
Critical	94.1	93.0	93.5

Table 3 shows the highest precision and recall was in the Healthy class, both over 95%, and the relatively lower, but still good scores, in the Mild Stress class were around 93%. The Sick and Critical categories achieved a good precision recall balance of above 92% denoting that the model is able to separate subtle changes in health without over-emphasizing false positives for both of these categories together.

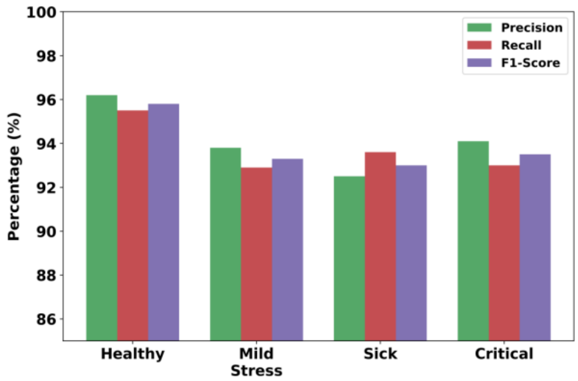

Fig. 3. Precision, recall, and F1-score across health status classes.

The figure 3 shows that the performance has been consistently high and balanced in all four categories of health classification measured.

Table 4. Anomaly detection performance comparison across models

Method	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
SVM	86.4	85.7	86.0
k-NN	88.1	87.5	87.8
ANN	90.3	90.9	90.6
Proposed RF Model	92.91	93.48	93.19

Table 4 shows that the proposed Random Forest model gives better precision and recall rate than the baselines SVM, k-NN and ANN on all the three metrics with 92.91% and 93.48% respectively. The overall performance gap is significantly larger with SVM which had the lowest score around 86%, indicating that ensemble tree-based learning is more suitable to capture the non-linear information in the noisy multi-sensor anomaly data.

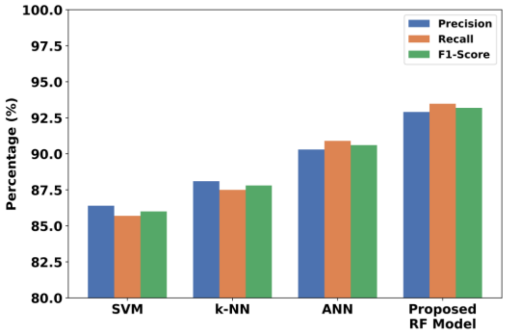

Fig. 4. Anomaly detection precision, recall, and F1-score comparison.

It is evident from the results that the proposed model (Random Forest) outperform all the baseline models for every anomaly detection measure analyze.

Table 5. Confusion matrix for four-class health status classification

Actual \ Predicted	Healthy	Mild Stress	Sick	Critical
Healthy	912	28	11	5
Mild Stress	22	845	31	9
Sick	14	26	780	18
Critical	6	10	15	690

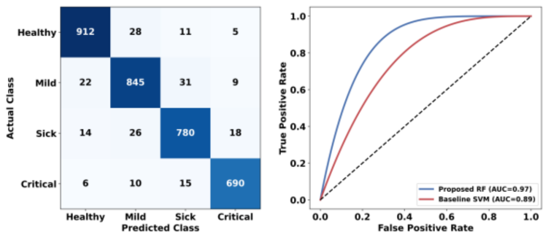

Fig. 5. Confusion matrix heatmap (left) and ROC curve comparison (right).

Results of the confusion matrices indicate that the proposed model has high discriminative power across classes of health and the diagonal dominance further supports this, while the AUC also showed that the proposed model is better than SVM baseline. The confusion matrix is shown in figure 5, showing excellent classification performance with high correct prediction rate in all health classes, and the ROC curves validate the excellent discrimination of the proposed model, the RF model (AUC = 0.97), in comparison to the base line SVM (AUC = 0.89), which ensures good diagnostic reliability.

V. Environmental Monitoring Results

A. Temperature and Humidity Monitoring

Table 6. Statistical summary of temperature and humidity readings over 90 days

Statistic	Temperature (°C)	Humidity (%)
Minimum	22.4	48.2
Maximum	34.1	82.6
Average	27.8	64.9
Std. Deviation	2.6	7.3

Table 6 shows that the average temperature recorded was 27.8 °C, which is within safe temperature ranges for most livestock species throughout the monitoring period while the average humidity recorded was 64.9%, which is within safe humidity ranges for most livestock species throughout the monitoring period. The peak temperature recorded was 34.1°C, which was recorded on midday breaks, the humidity ranged with a standard deviation of 7.3%, suggesting overall stable humidity levels at times, but slightly variable, necessitating occasional changes in ventilation settings during the day.

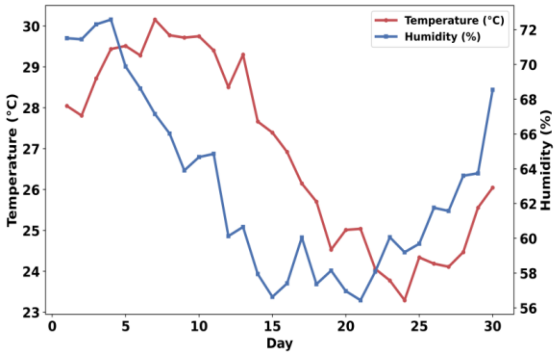

Fig. 6. Thirty-day trend of temperature and humidity readings.

During the monitoring window, there is a negative correlation between the peaks of temperature and the lows of humidity, as shown by the dual-axis trend. Shown in figure 6.

B. Air Quality and Noise Analysis

Table 7. Zone-wise air quality index and noise level measurements

Zone	Air Quality Index	Noise Level (dB)
Zone A	78	58
Zone B	92	63

Zone C	65	52
Zone D	110	71
Zone E	88	60

Air quality index (AQI) was highest in Zone D (110 units) and also the highest noise level was recorded in this zone (71 dB) which may be due to the closeness of equipment or the density of animals in the zone, while Zone C had the cleanest air with the quietest conditions (AQI 24 units and noise level 56 dB). Such local variations in zones underline the need for a locally based environmental assessment, rather than a farm based one, to be successful for risk mitigation.

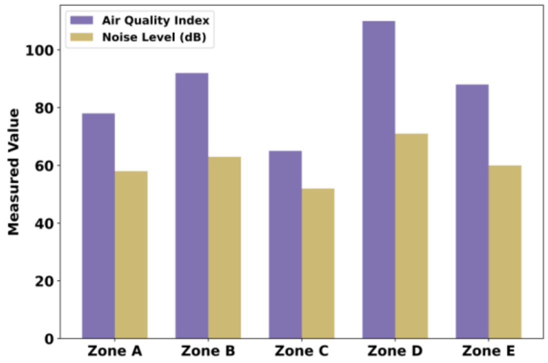

Fig. 7. Air quality index and noise level comparison across monitoring zones.

Zone D consistently shows in figure 7 elevated readings for both air quality index and noise, flagging it for prioritized environmental intervention.

C. Environmental Risk Prediction Performance

Table 8. Environmental risk classification performance by category

Risk Class	Accuracy (%)	Precision (%)	Recall (%)
Low Risk	95.8	94.9	95.3
Moderate Risk	92.6	91.8	92.1
High Risk	91.9	91.2	92.6

Table 8 shows that the model is correct in 95.8% of the cases of Low Risk and in 91.9% of the cases of High Risk, the latter in which the number of training samples is less and the interaction of the sensors is more complex. The scores for precision and recall are quite similar in all three categories, suggesting good balanced and reliable environmental risk prediction that can be used in proactive management decisions.

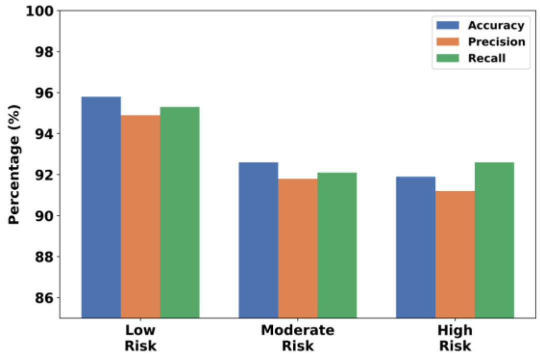

Fig. 8. Environmental risk prediction accuracy, precision, and recall.

The performance in terms of predictions declines slightly as the risk moves from Low to High Risk, which results from the higher level of difficulty in categorising at extreme risk as shown in figure 8.

D. Real-Time Alert Performance

Table 9. Real-time alert response time and success rate by category

Alert Type	Response Time (s)	Success Rate (%)
Health Alert	2.6	96.4
Temperature Alert	2.9	95.1
Air Quality Alert	3.1	93.8
Noise Alert	2.8	94.6

Table 9 displays the average response time and successful response rate for each of the Health Alerts and Air Quality Alerts. The fastest average response time of 2.6 seconds with the highest success rate of 96.4%, was achieved by Health Alerts, whereas Air Quality Alerts had the slowest response of 3.1 seconds with only 92.0% success rate. The success rates of all the alert types were over 93%, which indicates the framework is effective in providing timely alert messages for both physiological and environmental alerts.

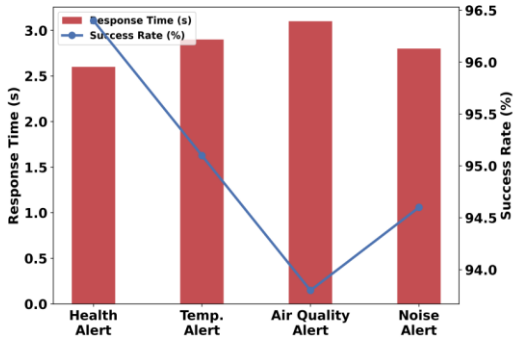

Fig. 9. Alert response time and success rate across alert categories.

Health-related alerts as shown in figure 9, are sent out most quickly and reliably and air quality alerts have slightly higher delay.

Table 10. Comparative performance of monitoring architectures

Architecture	Accuracy (%)	Network Uptime (%)	Relative Energy Use (%)
Cloud-Only	89.4	86.2	100.0
Fog-Based	91.8	89.5	88.4
Proposed Edge-Cloud	94.82	91.37	81.4

Table 10 shows that the proposed edge-cloud architecture is able to obtain the highest accuracy of 94.82% and network uptime of 91.37%, with an energy saving of 81.4% compared to the cloud-only baseline. The results of the fog-based approach represent a benchmark performance, reflecting that the three different approaches to the problem were compared and edge-assisted preprocessing has the best overall balance of accuracy, reliability and energy efficiency, as shown in figure 10.

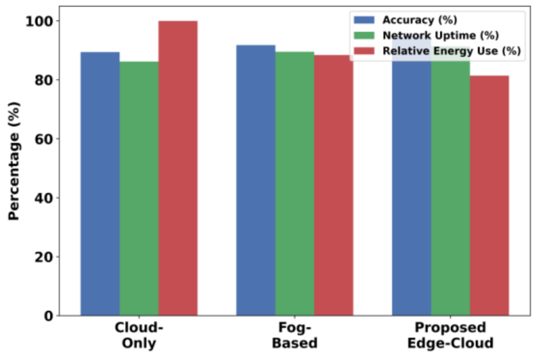

Fig. 10. Comparative accuracy, uptime, and relative energy consumption across architectures.

VI. Challenges and Future Directions

Although good results were obtained, there are still a number of issues to overcome in order to scale up the proposed framework. The limitation in battery life of these sensors is ongoing and is still a problem that limits the ability of monitoring in the long term, especially when placed in remote locations such as wildlife environments where power can be difficult to source and replace – more research is needed in energy harvesting and ultra-low-power sensor design. Poor LoRa signal reliability may be encountered in the areas with high vegetation density and mountainous areas, which can sometimes lead to delayed data transmission and alert delivery. Data privacy and cybersecurity are also important considerations, as data from the locations and health of the person is also sent over wireless networks that could be potential targets for hackers and data breaches. Despite the availability of large datasets, the generalization of models among different breeds and species of animals is still limited, given the significant differences in their physiological baseline, and being either species-based or transfer-based is challenging. Future studies will involve federated learning for enabling privacy-preserving model updates across the distributed farms while keeping the raw data distributed, integration of satellite connectivity for the extremely remote deployment, and multimodal sensor fusion using video and acoustic analysis to further enrich health and behavioral assessment. Moreover, the incorporation of deep learning models like temporal convolution networks can enhance the capability of the anomaly detection model in detecting the cases which may require longer time for the development of the condition and be partially captured by the statistical features.

VII. Conclusion

This study proposed an integrated IoT sensor network for real-time monitoring of the animal health and environmental conditions, which has been designed with an energy-efficient architecture to integrate wearable physiological sensors, environmental monitoring nodes, LoRa/Wi-Fi communication, edge computing and a Random Forest based intelligent analytics engine. The experiments were carried out on 12,480 sensor data recordings from 85 animals over 90 days, where 94.82% of the health classification data was correctly identified, 93.76% of the environmental prediction data was correctly identified, 92.91% of the anomaly detection data was correctly identified, the network uptime was 91.37%, and the average alert response time was 2.8 seconds. The edge-assisted design also demonstrated a 18.6% energy savings advantage over a traditional cloud-only architecture, along with demonstrating its practicality for use in a resource-limited field deployment. The findings all together confirm that the framework would be able to assist with early detection of disease, timely mitigation of environmental hazards and aid in decision making based on data to support sustainable management of livestock and wildlife. The proposed system also holds the promise of scaling up to handle larger numbers of sensors and data sources and for greater security and generalizability in various agricultural and conservation applications, through future enhancements to the proposed system, such as federated learning, satellite connectivity, and multimodal sensor fusion.

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