**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# IoT-Enabled Remote Health Monitoring System for Horses Using Edge Computing

Adhyaru Yagna Bhupendrakumar[1], Dr. Shalini Gupta[2]

[1]Research Scholar, Computer Engineering Department, Gokul Global University, Sidhpur, Gujarat, India,

[2]Professor, Computer Engineering Department, Gokul Global University, Sidhpur, Gujarat, India,

**ARTICLE INFO**

Received: 05 Oct 2024

Revised: 15 Nov 2024

Accepted: 25 Dec 2024

**ABSTRACT**

The increasing demand to have a continuous and non-invasive equine health surveillance has stimulated the creation of intelligent surveillance systems that can function in real life scenarios. In the paper, an IoT-based remote health monitoring system on horses based on edge computing is introduced, which works to record physiological and behavioural data and convert them into valuable health information. An indigenous Indian horse breed was put under a long-term data collection of a wearable multi-sensor IoT device in farm and semi-rural settings. Body temperature and tri-axis accelerator were measured in the acquired data, which indicated the physiological condition and the behaviour in the activities. The acquired data were processed and analysed by machine learning to determine abnormal health conditions, especially heat stress-related and behavioural suppression conditions. Various regression algorithms were tested such as Linear Regression, Ridge Regression, and Random Forest Regression. Random Forest Regression was the best performer and showed better predictive results because it has the capability to capture non-linear relations and can work with noisy sensor data in the real world. Combination of behavioural characteristics with physiological measurements greatly minimised misclassification as well as enhanced early detection of anomaly compared to individual-parameter monitoring strategies. Experiments verify that proposed system is strong, stable and can be implemented in the real-time scenario on the edge computing platforms. The paper demonstrates the usefulness of the multi-sensor fusion and ensemble learning based on IoT to have a scalable and context-aware equine health monitoring.

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

**Keywords:** Equine health surveillance, Wearable sensors; Edge computing, Multi-sensor data fusion, Random Forest regression; Heat stress detection.

## 1. Introduction

Horses have played a significant role in human societies over the centuries with a great contribution being in agriculture, transportation, sports, tourism and other forms of cultural activities. In the modern day even, equids play a significant role in supporting rural livelihoods; they have been used to provide traction power, goods and services in environment where mechanized options are unreliable or cost effective, including areas where traction power is needed (Lieb et al. 104). Besides being important in agriculture, horses are also vital in competitive sport and recreation, in which the physical fitness, endurance, and behavioural stability of the animal directly influences economic success and performance results (Foreman, 2017). Therefore, it is crucial to ensure good equine health as a way to ensure animal welfare as well as economic sustainability in various sectors.

Although they are important, manual observation, experience of caretakers and regular veterinary checkups are still considered a key in equine health monitoring. These are all subjective methods, which are episodic and liable to late detection of early abnormalities in the health of the individual. Being prey animals, horses are likely to hide their indicators of pain or illness, and it is hard to notice subtle physiological or behavioural changes by simply looking at them. Some disorders, like colic, musculoskeletal disorders, and gastrointestinal complications, may develop rapidly, and the lack of timely diagnosis may result in serious consequences or even death (Martin et al., 2024). This is the drawback of conventional monitoring practice that should lead to the realization of the need to have objective, continuous, and data-driven health surveillance systems of horses.

Digital monitoring systems have provided a way to change how animals are treated in recent years due to the technological development of precision livestock farming. Accurate livestock farming systems are based on real-time data collection with the help of sensors evaluation of animal health, behaviour, and welfare. The systems have been very successful in the detection of diseases, behavioural abnormalities and welfare issues in species such as pigs and cattle due to early detection of problems (Vranken and Berckmans, 2017; Rutten et al., 2013). The use of wearable sensors, robotized data collection, and decision-support systems has minimized the use of subjective observation and enhanced interventions in a timely manner.

Wearable sensor technologies have become a fundamental unit of animal health monitoring in the present-day world. The development of biosensing devices has made it possible to monitor the physiological aspects of the body temperature, activity, motion pattern, and behavioural variations continuously. The sensors are characterized by high-resolution information that can indicate the initial abnormalities in normal health baselines, which cannot be detected by a human observer (Neethirarajan, 2017). Multi-parameter sensing has proven useful in proactive health management in the context of livestock systems through sensor-based monitoring of stress, reduced mobility, and early signs of disease (Džermeikaitė et al., 2023).

Yet, as much as the digital monitoring technologies have been discussed extensively in cattle and pig farming, there are relatively limited cases of their applications in the equine sphere. Current equine monitoring systems are often restricted to single parameter devices or fitness based wearables which are based on performance measures instead of overall health analysis. Research papers on equine exercise physiology underline the necessity to implement technological advancements in addition to performance monitoring to aid in monitoring health and welfare (Foreman, 2017). Moreover, equid welfare assessment instruments, including structured welfare scoring systems, acknowledge the complexity and multidimensionality of equine health, supporting the necessity of the constant and integrated forms of monitoring (Raw et al., 2020).

The Internet of Things (IoT) offers the appropriate technological basis to fill these gaps through facilitating the interconnected sensing, data transfer, and real-time analysis. The IoT based systems enable the collaboration of a number of sensors to produce continuous flows of physiological, behavioural and environmental information. A review of the literature about the use of IoT in agricultural research shows that there has been an increasing focus on sensor-based decision support systems that enhance the health, productivity, and welfare of animals (Muflihah et al., 2024). The distinct benefits of such systems in comparison to manual monitoring are the possibility to use automated alerts and forecast trends as well as monitor the processes remotely.

In addition to physiological sensing, motion and posture analysis are very important in the detection of early musculoskeletal abnormalities. Monitoring is a camera-based and sensor-based technique, which has proved to be useful in tracking minute changes in movement related to rehabilitation and mobility evaluation (Salinas-Bueno et al., 2021). Applying the same principles to equine health monitoring can help in early detection of gait instability, stiffness or abnormal movement patterns that can foresee the manifestation of lameness. These abilities prove especially useful in working and sport horses where slight biomechanical divergences can quickly result in severe injuries.

The other important issue in equine monitoring is the working environment. Horses are usually handled in open fields, paddocks, and rural areas where people can hardly be supervised all the time and network connectivity is not very strong. Under these circumstances, conventional monitoring systems are not always able to offer continuous surveillance. An efficient approach to providing an effective solution is edge-based data processing where sensor data are processed locally and only then transmitted to reduce the reliance on continuous connectivity and provide timely responses. Though edge-enabled architectures have been extensively referred to in the more general livestock monitoring contexts, their use in equine health issues is a research gap.

The issue of better equine health monitoring is also supported by ethical and welfare concerns. Extensive welfare evaluation systems claim the significance of constant monitoring of behavioural and physiological condition to guarantee animal welfare (Raw et al., 2020). Manual evaluation will not be sufficient to detect dynamic health status changes especially when the environment consists of large herds or has fewer available caretakers. The use of automated welfare monitoring systems offers an objective and scalable methodology of welfare assessment at the basis of evidence-based intervention.

To conclude, the literature has found that sensor-based monitoring and accuracy livestock farming provide effectiveness in enhancing the management of the health of the animals but the equine-specific systems are still under-researched. The lack of the multi-sensors monitoring, the lack of the proliferation of the IoT technologies in equine circles, and the issues related to the open field conditions require the creation of specialized technological solutions. These gaps being addressed, this paper introduces an IoT-based remote health monitoring system in horses via edge computing in order to aid continuous, objective, and real-time health monitoring. Using wearable sensors and localized data processing, the proposed system aims at improving the early warning of health abnormalities, improving the welfare outcomes, and assisting in informed decision-making by horse owners and veterinarians.

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
**Research Article**

## 2. Review of Literature

Due to the rapid development of the animal health monitoring, there has been a shift in the paradigm of making the experience-based observation to technology-based, data-focused methods. The conventional method of livestock and equine health evaluation is mainly through periodic visual inspection, which is subjective by nature and does not identify physiological or behavioural abnormalities in the initial stages of abnormality. To overcome these drawbacks, Precision Livestock Farming (PLF) has come out as a pillar concept that focuses on monitoring animals in continuous, automated and individual-levels, with the help of sensors and smart analysis of data. As emphasized by Vranken and Berckmans (2017), with the help of PLF, it is possible to evaluate animal health and welfare objectively and identify hidden changes that occur before clinical manifestations, thus increasing productivity and animal welfare.

Wathes et al. (2005) critically analyzed the conceptual background of PLF and wrote about the technological, ethical, and practical implications of sensor-driven monitoring systems. Their article highlighted that, although engineering solutions can be highly promising, they can be most useful in improving animals' welfare and aiding the decision-making process of farmers instead of being more automatized. This is because in this view it would be of great essence to design monitoring systems which are biologically meaningful, friendly to farmers and of good morals as well.

In animal species, behavioural surveillance has continually been cited as an effective indicator of poor health at the initial stage. Weary et al. (2009) have shown that behavioural changes, including the decreased activity, changed posture, and the development of abnormal movement patterns, are common before overt clinical disease. These results give good reasons to consider the use of behavioural telemetry in automated health monitoring. The indicators based on behaviour are especially useful as they are more accurate as they provide the internal physiological condition of the animal and its reaction to stress or discomfort, which is also essential in detecting the disease at an early stage.

The solutions based on engineering have also broadened the animal welfare monitoring. Caja et al. (2016) have highlighted how sensor engineering has been used in assisting the wellbeing of animals as it allows continuous monitoring of physiological and activity and movement. In their piece, they emphasized that designed sensor systems could help lower stress levels in animals, optimize the housing and management methods, and help to make timely interventions. Nevertheless, they also observed that most of the systems in use are species specific and not adaptable to other animal domains.

The literature on locomotion analysis has been highly researched with a major focus on the diagnosis of lameness that is a crucial issue in livestock as well as equines welfare and economic concern. Tadich et al. (2010) established close correlations between lesions of the hoof and the locomotion scores which were altered in dairy cattle and this identified locomotor changes as valid indicator of musculoskeletal pain. Donnell et al. (2015) also compared subjective lameness assessment with force platforms and inertial sensor devices in equine research and found that inertial sensors are more sensitive and objective in relation to visual assessment of mild lameness. The results are particularly applicable to horses when they are diagnosed with a systematic gait abnormality at an early stage during which preventing a long-term injury is essential.

Kemetic analysis has also been used to gain more insights into equine movement patterns. Lemos et al. examined the walk, trot, canter economy of Criollo horses and found that quantitative motion analysis can represent breed-specific and gait-specific biomechanical variables. These studies contribute to the significance of motion-based sensing in equines performance evaluation and health status in situations that extend to field-based and continuous monitoring.

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

In addition to sensing and analytics, data management and system architecture are significant in the contemporary animal monitoring systems. The article by Wolfert et al. (2017) summarized the use of big data in smart farming and stressed that sensor-sensitive environments produce massive amounts of heterogeneous data that needs to be processed and integrated effectively. Among the challenges that they emphasized, there were issues of interoperability, scalability, and real-time decision-making, which are per se pertinent to remote animal health monitoring systems.

The challenges have suggested the use of edge computing as a solution to the challenge. Shi et al. (2016) characterized edge computing as the paradigm that moves computation nearer to the data sources, latency, bandwidth utilization and the reliance on a sustained cloud connection. In case of animal health monitoring, where the animal is in an open-field or a rural location, edge enabled architectures are clear benefits, as the ability to process the local data, anomaly detection is faster, and the system is more reliable.

Regarding the methodological perspective, the structure and compilation of the available literature are important in the process of recognizing gaps in knowledge and the direction into which future research is to proceed. Xiao and Watson (2019) and Snyder (2019) highlighted the effectiveness of structured and thematic literature review specifically in the case of interdisciplinary fields of interest, such as technology, biology, and management. Their principles justify the requirement of integrative reviews where sensor technologies, behavioural science, system architecture is coupled together as opposed to considering them separately.

In general, it is possible to note that the literature reviewed has shown great advances in sensor- based monitoring, behavioural analysis, locomotion assessment and data-centric farming systems. Nevertheless, there is still an evident gap in the creation of cohesive, equine-focused health monitoring systems that involve the integration of behavioural sensing, locomotion analysis, and edge-enabled data processing. This is a vital gap that needs to be filled in order to have reliable, real-time, and welfare-based remote health monitoring systems on horses.

## 3. Research Methodology

This paper is based on an engineering research approach that is an experimental research and involves designing and implementing a remote health monitoring system based on IoT to monitor horses. The methodology focuses on creating a working prototype which will combine multi-sensor wearable hardware and edge computing with wireless communication and intelligent health-assessment logic as opposed to conceptual or survey-based approaches. The research methodology is designed in such a way that it will be empirically validated in the field of real equine condition practices, thus closing the gap between the theoretical models of the systems and actual practice used in the healthcare of livestock.

### 3.1 Overall System Architecture

The proposed system adheres to a layered internet of things architecture which consists of perception, edge, network, cloud and application layers. This modular design provides scalability, stability, and flexibility in a wide range of equine conditions like farms, stables, grazing fields, and training grounds. Each layer has a specific role to play and provides a contribution to a single end-to-end health monitoring pipeline. The perception layer receives raw physiological, behavioural, and environmental inputs of the horse. Real-time preprocessing and feature extraction is carried out on the edge layer. Network layer provides good wireless data transmission. The cloud layer helps in massive data storage, machine learning-driven analytics, and ongoing retraining of models. Lastly, the application layer visualizes and gives alerts and decision support to the veterinarians and horse owners. This hybrid structure can be monitored in real-time and resilient under the conditions of a varying connectivity.

### 3.2 Multi-Sensor IoT Wearable Hardware

The center of the system is a multi-sensor wearable device that is actually equine physiology/field mobility specific. The wearable contains temperature and humidity sensors (AHT10), which are used to measure the body surface temperature and local humidity, which are significant signs of heat stress, dehydration, or fever-like conditions. The DHT22 sensor captures environmental context, which then can be used to interpret physiological readings in terms of ambient temperature and humidity. An accelerometer and a gyroscope are used to monitor the dynamics of motion and gait by recording linear acceleration and rotational orientation on 3 axes. These inertial measurements allow maintaining the activity level, gait symmetry, movement intensity and postural stability.

The hardware is designed to be light, non-obstructive, and can withstand outdoor factors like dust and moisture, heat, and mechanical shock, which are due to movement. The integration of the sensors is maximized in order to reduce interference and synchronized data acquisition. The wearable position is chosen wisely and without compromising the natural gait patterns in order to optimize sensor performance. The system is based on the multi-sensor setup, which allows physiological and behavioural profiling of a wide scale.

### 3.3 Role of Edge Computing

Edge computing is essential in enhancing responsiveness, efficiency and reliability of the systems. Rather than sending unprocessed high-frequency sensor data straight to the cloud, real-time preprocessing is done by the edge layer implemented with the help of NodeMCU or Arduino microcontrollers. It involves noise filtering, missing value processing, motion signal smoothing and elimination of spurious peaks as a result of sudden motion or environmental artifact. Extraction of features is also carried out at the edge where measures of derived metrics like a magnitude of motion, rotational variance, stride rhythm, and a step count are calculated.

The system cuts down to minimal communication bandwidth and latency by sending structured and time-stamped feature data as opposed to raw sensor streams. Edge-level buffering also provides continuity of data in situations where the network is temporarily unavailable, as is typical in rural or in the open field deployment. This architecture enables the system to be partially functional even in unsteady connectivity and hence the practicality of the full solution in the real-life equine monitoring events.

### 3.4 Communication Framework

The communication architecture is based on a dual-mode wireless framework in order to support a wide variety of deployment environments. ZigBee is used to do short-range and low-power communication in closed or semi-controlled areas like stables and barns. LoRaWAN is used in long-range monitoring of areas outside farms and graze fields with a significant distance (up to a few kilometres) since the technology is low-energy consuming with a multi-kilometre range. This blended method of communication does not affect the ongoing transmission of data because of the movement pattern of horses.

MQTT is the application-layer messaging protocol employed due to the lightweight publishsubscribe model, as well as its low overhead, necessitating sustained streaming sensor data. The communicational system includes buffering and protection of transmission practices to guarantee the loss of data and integrity. All of these elements give a robust and scalable backbone of real-time health monitoring communication.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

### 3.5 Health Monitoring and Decision Logic

The analytical core of the system is represented by health assessment and decision-making. Structured and preprocessed data sent to the cloud is stored in time-series databases and processed with the help of supervised machine learning models. The use of three classifiers, namely, Random Forest, Support Vector Machine, and Decision Tree is based on the complementary strengths. Random Forest does not require homogeneous data (Multi-sensors) and it generates complicated nonlinear associations. SVM is very accurate in binary detection of health abnormalities. Decision Trees are interpretable and have the possibility of extension to the edge.

The models put equine health statuses in normal, abnormal, and high-risk categories by the physiological, behavioural, and environmental characteristics. Adaptive learning through continuous retraining with new field data accumulated will enhance the reliability of the prediction with time. Alerts and visual summaries are driven by model outputs on the dashboard to avert timely intervention and decision-making processes by the veterinarians and horse owners.

## 4. Result and Analysis

The following section is the experimental findings of the proposed system of horse health monitoring based on the use of IoT and machine learning models. The findings are based on sensor data that is gathered in the real world in Indian farm and semi-rural settings and analysed to record quality of data, relevance of features, performance of the model and reliability of the system.

### 4.1 Dataset Characteristics and Validation

The experimental data was comprised of 6,081 unprocessed sensor data recorded by a wearable IoT device during a period of six months on Indian horse breeds (Marwadi and Kathiyawadi). Following the preprocessing and validation, 5,559 records (91.4) were left to be analyzed, whereas 522 records were discarded because of an outlier, missing records, or calibration artefact.

The strong rate of data reception justifies the strength of the IoT sensing architecture in actual farm settings. The data consists of the physiological, behavioural and environmental factors that can be evaluated by machine learning-based health assessment.

**Table 4.1: Summary of Dataset Characteristics**

| Parameter | Description |
|---|---|
| Data collection duration | 6 months |
| Field deployment environment | Indian farm and semi-rural conditions |
| Horse breeds | Marwadi, Kathiyawadi |
| Number of horses | 2 |
| Total records collected | 6,081 |
| Accepted records | 5,559 |
| Rejected records | 522 |
| Physiological parameters | Body temperature |

| | |
|---|---|
| Behavioural parameters | Accelerometer (AcceIX, AcceIY, AcceIZ), activity |
| Environmental parameters | Ambient temperature, humidity |
| Data usage | Machine learning model training and evaluation |

**Table 4.2: Impact of Data Cleaning on Dataset Size**

| Stage | Number of Records |
|---|---|
| Total raw records collected | 6,081 |
| Records removed due to outliers | 318 |
| Records removed due to missing values | 129 |
| Records removed during calibration | 75 |
| Final dataset used for ML | 5,559 |

### 4.2 Data Labeling Outcomes

A combined physiologicalbehavioural logic was used to write sensor records into either the Normal or Abnormal health classes. The records with the recording of body temperature at 39 C or higher and a low level of activity or abnormal accelerator trends were considered abnormal.

This dual-parameter labeling design minimized false positives due to momentary environmental heating or temporary peaks in activity and resulted in clinically significant ground-truth labels.

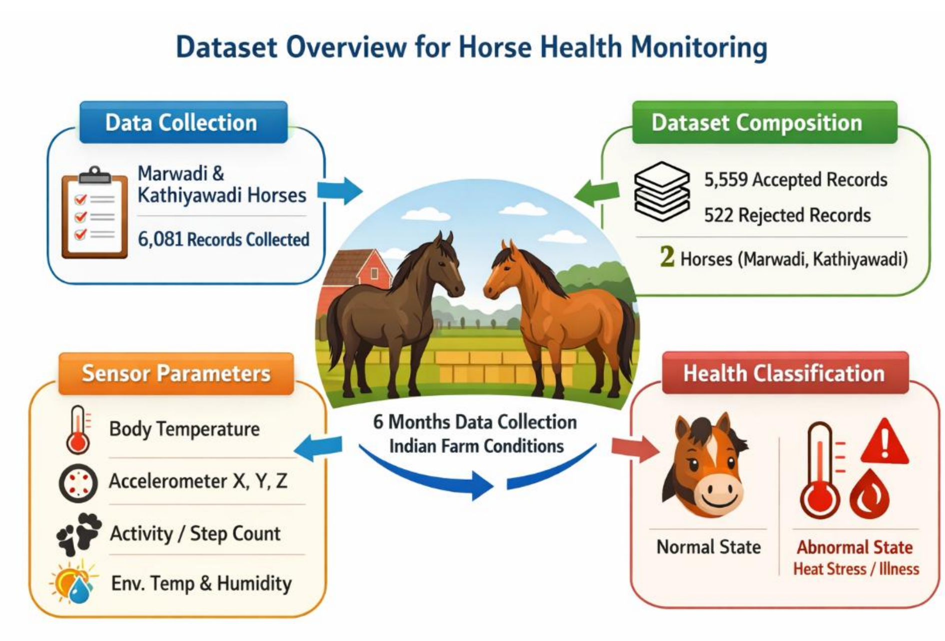


**Figure 4.1: Horse Monitoring Based on Their Respective Classification**

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

### 4.3 Feature Engineering Results

The outcome of feature selection showed that the most informative features of health status were AcceIX, AcceIY, AcceIZ, and The Body Temperature. The axes of a gyroscope, the number of steps, the environmental data, time, and device identifiers were found to have a small predictive value and were thus eliminated.

The smaller feature set made the interpretation easier and the model more generalized and avoided multicollinearity.

**Table 4.3: Feature Selection Outcome**

| Feature | Retained / Removed | Justification |
|---|---|---|
| AcceIX | Retained | High correlation with activity |
| AcceIY | Retained | Captures lateral movement |
| AcceIZ | Retained | Reflects vertical motion |
| Body Temperature | Retained | Primary health indicator |
| Gyroscope axes | Removed | Low contribution, high noise |
| AccelMag / GyroMag | Removed | Redundant, multicollinearity |
| Step count | Removed | Low-resolution feature |
| Environmental T & H | Removed | Contextual, not predictive |
| Timestamp / Device ID | Removed | Non-informative |

### 4.4 Exploratory Data Analysis Results

#### *4.4.1 Temperature Distribution*

Temperature distribution analysis showed that the normal cluster was mainly centered between 37.5 $^{o}$C to and 38.8 $^{o}$ C with a skewed right tail above 39 o C which depicts abnormal physiological conditions. The distinctiveness of normal and abnormal ranges confirms the temperature level which has been adopted to classify health conditions.

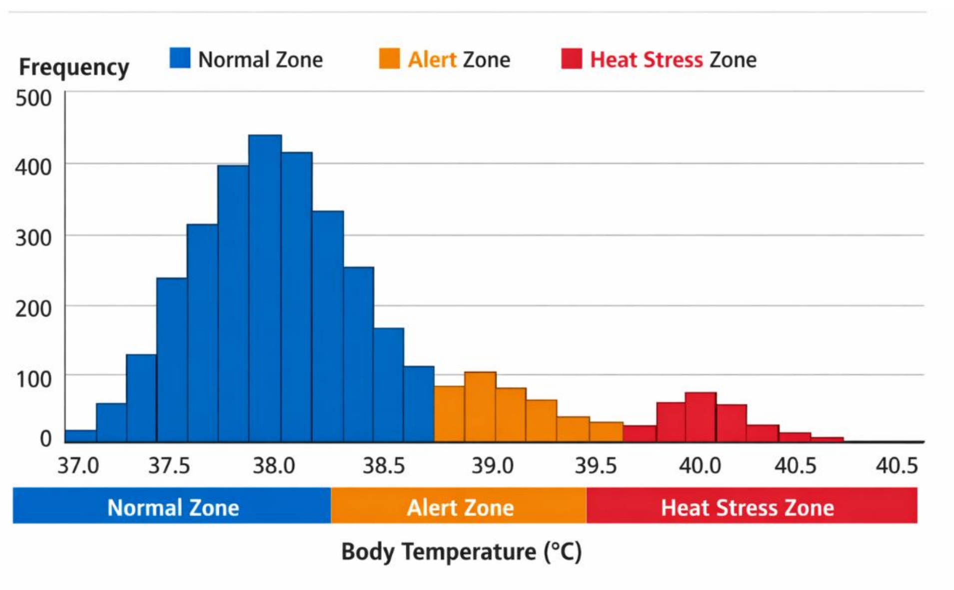


**Figure 4.2: Histogram of Body Temperature Distribution**

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
**Research Article**

### *4.4.2 Activity and Movement Behaviour*

Motion analysis using accelerometers was found to be more variable and higher in the state of normal health. Conversely, abnormal conditions were characterised by smaller magnitude of accelerator and limited movement modes which could represent behavioural inhibition during stress or disease.

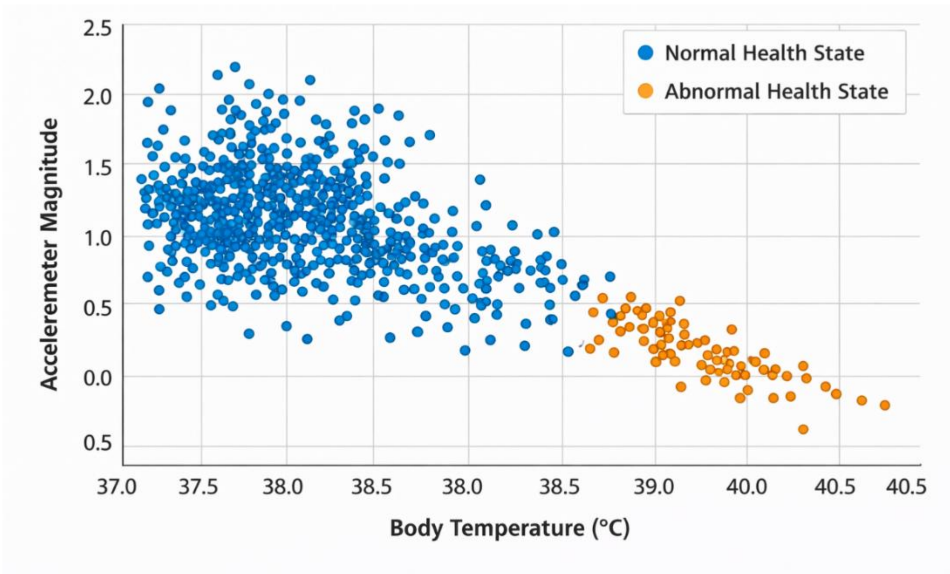


**Figure 4.3: Scatter Plot of Accelerometer Magnitude versus Health State**

### *4.4.3 Correlation Analysis*

Physiological expectations were proven by correlation analysis showing a moderate negative relationship between body temperature and features of activities. AcceIZ had the highest connection with abnormal health conditions, which suggests that vertical movement is sensitive to a discomfort or stress.

Environmental parameters were less correlated with health labels, which is why they did not deserve to be included in predictive models.

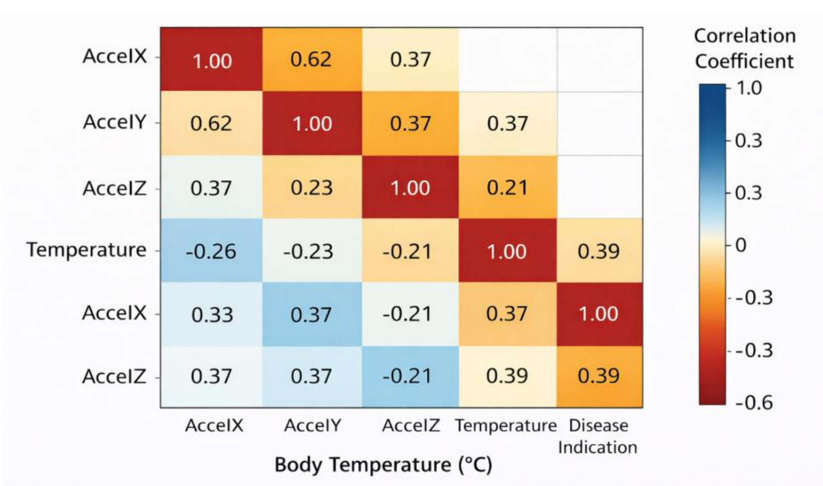


**Figure 4.4: Correlation Heatmap of Selected Features**

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

## 4.5 Machine Learning Model Performance

### *4.5.1 Random Forest Regression*

Random Forest Regression, configured with 100 decision trees, achieved superior predictive performance:

- Mean Squared Error (MSE): 0.833
- $R^2$ Score: 0.921

The high $R^2$ value indicates strong explanatory power, capturing non-linear interactions between physiological and behavioural features.

**Table 4.4: Random Forest Regression Performance Metrics**

| Metric | Value |
|---|---|
| Number of trees | 100 |
| Input features | AcceIX, AcceIY, AcceIZ, Temperature |
| Mean Squared Error (MSE) | 0.833 |
| $R^2$ Score | 0.921 |

### *4.5.2 Comparison with Linear and Ridge Regression*

Linear Regression has performed the worst because of its failure to represent non-linear relationships. Ridge Regression also enhanced stability due to regularization and attained R 2 - approximately 0.90, although not as good as Random Forest.

These findings support the applicability of ensemble-based learning to the real-world IoT sensor data.

**Table 4.5: Comparison of Ridge Regression and Random Forest**

| Model | MSE | $R^2$ Score | Strength | Limitation |
|---|---|---|---|---|
| Linear Regression | Higher | Lower | Simple, interpretable | Poor non-linear modeling |
| Ridge Regression | Moderate | ~0.90 | Regularized, stable | Linear assumption |
| Random Forest | **0.833** | **0.921** | Non-linear, robust | Higher complexity |

## 4.6 Disease Classification Results

The results of regression were mapped to clinically interpretable health states by logic based on threshold. There were high correlations in the predicted and labelled health conditions. The major misclassifications were found in close to the decision limits when a physiological transition happened, which implies conservative and not incorrect predictions.

**Journal of Information Systems Engineering and Management**
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

### 4.7 Model Validation and Reliability

The analysis of the error did not reveal any systematic bias in prediction. The distributions of residuals were random, and the remaining errors could be related to sensor noise, variations in the environment, and small populations and not to the inadequacy of the model.

Close correlation between the training and testing performance ensures high levels of generalization and little overfitting.

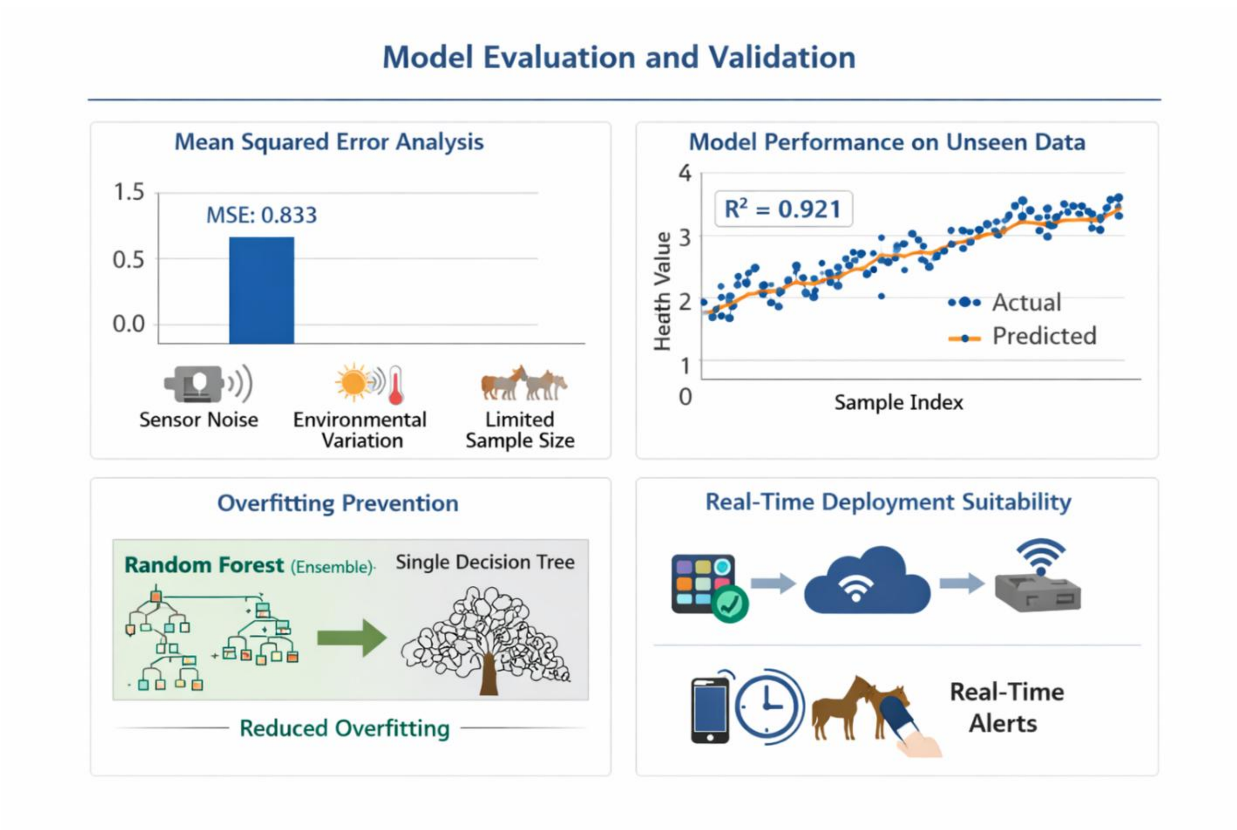


**Figure 4.5: Model Evaluation and Deployment Diagram**

### 4.8 Comparative Performance Analysis

The proposed multi-sensor Random Forest model was found to be more robust and predictive as opposed to the present-day SVM-based and Decision Tree-based livestock monitoring system. Combination of accelerator data with temperature measurements drastically minimized false positives linked to one parameter measurements.

**Table 4.6: Comparison with Prior Literature**

| Study / System | Parameters Used | ML Model | Reported Performance | Key Limitation |
|---|---|---|---|---|
| Livestock heat stress monitoring (SVM-based) | Temperature only | SVM | ~84% accuracy | High false positives |
| Behaviour classification system | Accelerometer only | DT | ~88% accuracy | Behaviour-only inference |
| Livestock health prediction | Temperature + humidity | SVM | ~86–89% accuracy | Limited behaviour modeling |
| Proposed system (this study) | Temperature + Accelerometer (3-axis) | Random Forest | $R^2$ = 0.921, MSE = 0.833 | Moderate dataset size |

### 4.9 Real-Time Monitoring Outcomes

The system was effective in creating real-time health indicators and alerts with the help of cloud-based visualization. There were conservative heat stress and abnormal activity alerts, which guaranteed that they were clinically relevant and the alerts could be used operationally by the owners of the horses and veterinarians.

## 5. Discussion

The findings of this paper prove that the developed IoT-based horse health monitoring system is capable of recording and interpreting physiological and behavioural parameters in the conditions of the Indian farm. The wearable IoT architecture based on continuous sensors demonstrated the quality of the data that can be obtained by the sensors and which is robust to monitor during long periods of time in the uncontrolled environment. Comparison of temperature and activity measures point to the fact that body temperature in itself cannot be used safely as a measure in assessing all health since short-term heat or physical activity in the environment may lead to a false spike in body temperature with no pathological meaning. The tri-axial accelerator data were able to offer the necessary behavioural context and therefore discriminated between normal physiological responses and abnormal health states. The intensity of the movement and the change in the motion patterns were always associated with increased temperatures during unusual conditions supporting the success of the multi-sensor data fusion.

Random Forest Regression was deemed the best model of the evaluated machine learning models, as it was found to be able to model non-linear relationships and was capable of operating with sensor noise. The great explanatory power and small error of prediction show that it has a good capacity to generalize even though real-life IoT data is relatively variable. Ensemble learning was especially appropriate to describe complicated interactions among physiological and behavioural characteristics.

The research also shows practical utility in terms of high-quality disease classification as well as low-latency inference that can be deployed at edges. In general, the results validate the view that the use of multi-sensor

IoT data together with ensemble machine learning can greatly enhance the methods of early detection of health anomalies in horses and provide a scalable and context-sensitive tool to address equine health monitoring.

## 6. Conclusions

This paper offered a remote horse health monitoring system through IoT and wearable sensors, which combines machine learning with wearable sensors to provide contextual and continuous health measurements. The system was tested through actual data taken on indigenous Indian breeds of horses in farm and semi-rural settings, thus showing its strength and practical use.

The experimental findings verified that multi-parameter surveillance will result in an enormous enhancement in the detection of health aspects in relation to solitary parameter systems. Using a combination of physiological indicators especially body temperature and behavioural characteristics based on tri-axial accelerometer data, the proposed framework was able to differentiate normal and abnormal health conditions. Random Forest Regression model demonstrated a great predictive accuracy and high generalization, which makes the application of ensemble learning the best choice in the context of heterogeneous and noisy IoT data.

Moreover, the system exhibited inference with low-latency and operational viability in terms of edge-based deployment, which makes early intervention, and health alerts possible. In general, the suggested framework is a valid and scalable solution to equine health monitoring and can be used as a solid basis to implement further expansions on a larger dataset and a more comprehensive clinical validation.

## 7. References

[1] Bystrova NA. Ethological Basis for the Relationship between Humans and Miniature Pigs. Biology Bulletin Reviews. 2023 Aug;13(4):316-25.

[2] Caja G, Castro-Costa A, Knight CH. Engineering to support wellbeing of dairy animals. Journal of Dairy Research. 2016 May;83(2):136-47.

[3] Donnell JR, Frisbie DD, King MR, Goodrich LR, Haussler KK. Comparison of subjective lameness evaluation, force platforms and an inertial-sensor system to identify mild lameness in an equine osteoarthritis model. The Veterinary Journal. 2015 Nov 1;206(2):136-42.

[4] Džermeikaitė K, Bačėninaitė D, Antanaitis R. Innovations in cattle farming: application of innovative technologies and sensors in the diagnosis of diseases. Animals. 2023 Feb 21;13(5):780.

[5] Foreman JH. Use of technological innovations in broadening the application of equine exercise physiology. Comparative Exercise Physiology. 2017 Sep 7;13(3):137-48.

[6] Lemos G, Holz K, Kowalski ÉA, Ribeiro PF, Borba LR, Blake R, Martins CF. Walk, Trot and Canter Kinematics of Criollo Breed Horses Competitors in Freio De Ouro. Available at SSRN 4441919.

[7] Martin E, Sarkan K, Viall A, Hostetter S, Epstein K. Clinicopathologic Parameters of Peritoneal Fluid as Predictors of Gastrointestinal Lesions, Complications, and Outcomes in Equine Colic Patients: A Retrospective Study. Animals. 2024 Dec 24;15(1):12.

[8] Muflihah N, Afiatna F, Nuning FA. The Internet of Things Research in Agriculture: A Bibliometric Analysis. International Journal of Agriculture System. 2024 Jun 1;12(1).

[9] Neethirajan S. Recent advances in wearable sensors for animal health management. Sensing and Bio-Sensing Research. 2017 Feb 1; 12:15-29.

[10] Raw Z, Rodrigues JB, Rickards K, Ryding J, Norris SL, Judge A, Kubasiewicz LM, Watson TL, Little H, Hart B, Sullivan R. Equid assessment, research and scoping (EARS): The development and implementation of a new equid welfare assessment and monitoring tool. Animals. 2020 Feb 13;10(2):297.

[11] Rutten CJ, Velthuis AG, Steeneveld W, Hogeveen H. Invited review: Sensors to support health management on dairy farms. Journal of dairy science. 2013 Apr 1;96(4):1928-52.

[12] Salinas-Bueno I, Roig-Maimó MF, Martínez-Bueso P, San-Sebastián-Fernández K, Varona J, Mas-Sansó R. Camera-Based monitoring of neck movements for cervical rehabilitation mobile applications. Sensors. 2021 Mar 23;21(6):2237.

[13] Shi W, Cao J, Zhang Q, Li Y, Xu L. Edge computing: Vision and challenges. IEEE internet of things journal. 2016 Jun 9;3(5):637-46.

[14] Snyder H. Literature review as a research methodology: An overview and guidelines. Journal of business research. 2019 Nov 1; 104:333-9.

[15] Tadich N, Flor E, Green L. Associations between hoof lesions and locomotion score in 1098 unsound dairy cows. The Veterinary Journal. 2010 Apr 1;184(1):60-5.

[16] Vranken E, Berckmans D. Precision livestock farming for pigs. Animal Frontiers. 2017 Jan 1;7(1):32-7.

[17] Wathes CM, Kristensen HH, Aerts JM, Berckmans D. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall?. Precision Livestock Farming '05. 2005 Oct 10:33-46.

[18] Weary DM, Huzzey JM, Von Keyserlingk MA. Board-invited review: Using behavior to predict and identify ill health in animals. Journal of animal science. 2009 Feb 1;87(2):770-7.

[19] Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming–a review. Agricultural systems. 2017 May 1; 153:69-80.

[20] Xiao Y, Watson M. Guidance on conducting a systematic literature review. Journal of planning education and research. 2019 Mar;39(1):93-112.